ON THE PROCESS OF MAINTENANCE DECISION-MAKING IN THE OFFSHORE OPERATIONAL ENVIRONMENT OF THE OIL AND GAS INDUSTRY

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Tese de Doutorado apresentada ao Programa de Pós-graduação em Engenharia de Produção, COPPE, da Universidade Federal do Rio de Janeiro, como parte dos requisites necessários à obtenção do título de Doutor em Engenharia de Produção.

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TESE SUBMETIDA AO CORPO DOCENTE DO INSTITUTO ALBERTO LUIZ COIMBRA DE PÓS-GRADUAÇÃO E PESQUISA DE ENGENHARIA (COPPE) DA UNIVERSIDADE FEDERAL DO RIO DE JANEIRO COMO PARTE DOS REQUISITOS NECESSÁRIOS PARA A OBTENÇÃO DO GRAU DE DOUTOR EM CIÊNCIAS EM ENGENHARIA DE PRODUÇÃO.

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To Stella, Sidnea and Vitoria

The three stars of my life

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"It always seems impossible until it's done."

Nelson Mandela
(1918 – 2013)

Resumo da Tese apresentada à COPPE/UFRJ como parte dos requisitos necessários para a obtenção do grau de Doutor em Ciências (D.Sc.)

SOBRE O PROCESSO DE TOMADA DE DECISÃO DE MANUTENÇÃO NO AMBIENTE OPERACIONAL OFFSHORE DA INDÚSTRIA DE ÓLEO E GÁS

Mario Marcondes Machado

Fevereiro/2019

Orientadores: Mario Cesar Rodríguez Vidal
Cecilia Haskins

Programa: Engenharia de Produção

O objetivo geral desta pesquisa é desenvolver um arcabouço de apoio à decisão para implementações de programas de manutenção preventiva no ambiente operacional offshore da indústria do petróleo. A tese investiga os problemas que envolvem o processo de tomada de decisão de manutenção, cujos elementos são sistematicamente identificados e categorizados, incluindo aspectos organizacionais. A interface com operações é considerada para promover a integração entre os cronogramas de manutenção e produção. Esta tese é composta de pesquisa qualitativa e quantitativa. Os objetivos subjacentes são identificar, entre os principais atores offshore do setor, o estado das práticas e, a partir da literatura, as principais técnicas utilizadas para decisões de manutenção, a fim de propor alternativas para apoiar futuras implementações de programas de manutenção preventiva. Por meio de uma abordagem baseada na Engenharia de Sistemas, assistida por revisão da literatura, entrevistas com especialistas (na Noruega e no Brasil), pesquisa on-line e estudos de caso, os resultados desta tese complementam um ferramental para engenheiros de manutenção e gestores visando facilitar o compartilhamento de informações e a cooperação interdisciplinar no ambiente operacional. As principais contribuições desta pesquisa são: (i) Um mapa conceitual para a ontologia do processo de tomada de decisões de manutenção; (ii) Um plano para implementação de programas de manutenção preventiva; (iii) A sugerida solução inter-setorial: lista mínima de equipamentos; (iv) Um nomograma markoviano para a confiabilidade; (v) Um modelo de aplicação do Processo de Decisão de Markov.

Abstract of Thesis presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Doctor of Science (D.Sc.)

ON THE PROCESS OF MAINTENANCE DECISION-MAKING IN THE OFFSHORE OPERATIONAL ENVIRONMENT OF THE OIL AND GAS INDUSTRY

Mario Marcondes Machado

February/2019

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The overall objective of this research is to develop a comprehensive decision support framework for preventive maintenance program implementations in the offshore operational environment of the oil and gas industry. The thesis investigates the problems surrounding the maintenance decision-making process, which elements are systematically identified and categorized, including organizational aspects. The interface with operations is considered in order to promote integration between maintenance and production schedules. This thesis has been a mix of qualitative and quantitative research. The research subjacent objectives have been to identify, among major oil and gas offshore players, the state-of-practices regarding the maintenance decision-making process and identify, in the literature, the main techniques used for maintenance decisions and optimization in order to propose alternatives for supporting future preventive maintenance program implementations. By means of a Systems Engineering based approach, assisted by a literature review, interviews with experts (in Norway and in Brazil), an on-line survey and case studies, the results of this thesis complement a toolkit for maintenance engineers and managers aiming to facilitate information sharing and interdisciplinary cooperation in the operational environment. The main contributions of this research are: (i) A concept map for the maintenance decision-making process ontology; (ii) A plan for preventive maintenance program implementations; (iii) The suggested cross-sector solution: the minimum equipment list; (iv) A Markovian dependability nomogram; (v) A Markov decision model application.

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List of abbreviations

BCS	– Brazilian Continental Shelf
BEP	– Best Efficient Point
CBM	– Condition Based Maintenance
CM	– Condition Monitoring
CMC	– Condition Monitoring Center
CM&D	– Condition Monitoring and Diagnostics of Machines
CMMS	– Computerized Maintenance Management Information System
CTMC	– Continuous Time Markov Chain
DTMC	– Discrete Time Markov Chain
ERP	– Enterprise Resource Planning
FMECA	– Failure Modes, Effects and Criticality Analysis
FOM	– Figures of Merit
FPSO	– Floating Production, Storage and Offloading platform
HQ	– Headquarters
ICAO	– International Civil Aviation Organization
INCOSE	– International Council of Systems Engineering
ISO	– International Organization for Standardization
IPO	– Input-Process-Output diagram
KPI	– Key Performance Indicator
LCC	– Life Cycle Cost Analysis
MDP	– Markov Decision Process
MEL	– Minimum Equipment List
MMEL	– Master Minimum Equipment List
MOE	– Measures of Effectiveness
MTBF	– Mean Time Between Failures
MTTF	– Mean Time to Failure
MTTR	– Mean Time to Repair
NCS	– Norwegian Continental Shelf
ODF	– On Demand Failure
OEE	– Overall Equipment Effectiveness
O&M	– Operations and Maintenance
OREDA	– Offshore Reliability Data Handbook
PHM	– Prognosis and Health Management
PM	– Preventive Maintenance
RAMS	– Reliability, Availability, Maintainability and Safety
RCM	– Reliability Centered Maintenance
SE	– Systems Engineering
SOI	– System of Interest
SPADE	– Stakeholders, Problem, Analysis/Alternatives, Decision and Evaluation
TOC	– Total Operating Cost
TPM	– Total Productive Maintenance

List of symbols

A_s	Set of available actions *a* in state *s*
S	Set of states *s (origin states)*
j	A given destination state
$d(s)$	Action chosen by decision rule *d* in state *s*
d^∞	Stationary policy which uses decision rule *d* in every period
$d_\varepsilon(s)$	Optimal decision in state *s* in respect to the tolerance ε
D^K	Set of decision rules where *K=MR, MD, HR, HD*
π	Policy ($d_1, d_2, \ldots, d_{N-1}$); $N \leq \infty$
π^*	Optimal policy
ε	Error tolerance (stopping/convergence criteria)
$sp(.)$	Span semi-norm
$argmax$	Subset of elements at which the maximum of a function is obtained
n	Iteration index
N	Number of iterations
V	Set of values $v^n(s)$ with n denoting the iteration number
v^π	Expected total reward under policy π
$v^0(s)$	Value at the iteration 0, $v^0(s) \in V, \forall\, s \in S$
$v^{n+1}(s)$	Value of state *s* at iteration *n* + 1
$r(s, a)$	Reward by chosen action a in state *s*
$p(j\|s, a)$	Probability that system occupies state *j* at *t* +1 when action *a* is chosen in state *s*
$g^\pi(s)$	Gain or expected average reward of policy π
λ	Component failure rate
μ_1	Minor repair rate (preventive)
μ_2	Major repair rate (corrective)
α	Standby utility
β	On demand failure probability (ODF)
$Prev$	Prevention factor
m	Scenario's severity (λ / μ_1)
L	Power required by the FPSO
l_s	Power generated per component
S_t	State vector
x_1	Number of components in operation in state *s*
x_2	Number of components in standby in state *s*
x_3	Number of components in corrective maintenance in state *s*
x_4	Number of components in preventive maintenance in state *s*
u_s	Utility of state *s*
$lact$	Component activation load
lt	Target load for a component (i.e., the load factor)
$lmin$	Unit minimum component load
$E(s)$	Expected sojourn time in state *s*
π^*	Optimal policy
$g^\pi(N)$	Gain or expected average reward (Utility) of policy π *at iteration N*

1 Introduction

In search of a balanced availability, operational efficiency and optimization, oil field operators must be able to make decisions in an environment of uncertainties and where logistic aspects have a great impact on production and costs such as offshore operations. Given that approaches aiming to coordinate/synchronize production and maintenance are among the key-elements of the so-called Industry 4.0 (Vatn, 2018), this thesis is opportune, since it investigates the maintenance decision-making process including organizational aspects, with emphasis on the interface with operations.

The overall objective of this research is to develop a comprehensive decision support framework for preventive maintenance program implementations in the offshore operational environment of the oil and gas industry. The subjacent objectives are: (i) identify, among major oil and gas offshore operators, the state-of-practices regarding the maintenance decision-making process and; (ii) identify, in the literature, the main techniques used for maintenance decisions and optimization in order to; (iii) propose alternatives for supporting future preventive maintenance program implementations.

The thesis is composed of complementary approaches from qualitative and quantitative research methods. The qualitative approach, with the assistance of Systems Engineering methods, includes a literature review, case studies, a survey, and interviews with maintenance experts in the oil and gas industry. In the quantitative approach, the Markov analysis is discussed, and a Markov decision model proposed. The research is developed from the offshore operator's headquarters perspective and is limited to the technical information flowing in the maintenance decision-making process at the tactical and operational levels.

The results of this research complement a toolkit for maintenance technicians, engineers and managers aiming to facilitate information sharing and interdisciplinary cooperation in the offshore operational environment. Among the results and propositions are: (i) a concept map for the maintenance decision-making process ontology; (ii) a plan for preventive maintenance program implementations and; (iii) a cross-sector solution (the minimum equipment list). In the quantitative approach, the Markov analysis and the

Markov Decision Process (MDP) are considered and an application towards the integrated Operations and Maintenance (O&M) policies is proposed.

1.1 Problem background

In a broad review of maintenance optimization applications, Dekker (1996) states that among the problems encountered in applying maintenance optimization models are: (i) deficient data collection and analysis; (ii) the need for the development of a generic modelling such that standard models can be used and; (iii) the need for a good formulation of the problem within an ambiguous terminology environment, since most concepts allow various interpretations.

A series of organizational skills and expertise are necessary and, according to Vatn *et al*. (1996), the need for a diverse set of expertise may be one of the reasons why it is so hard to implement model-based maintenance approaches. For Welte *et al*. (2006), one reason for the lack of models/methods usage, despite broad coverage in the literature, can be difficulties in providing the proper amount of data. Although those statements have been made long ago, according to the field research among major offshore oil and gas operators performed in this thesis, those difficulties are still there, especially regarding the decision-making process. In that sense, the ability to find an optimum balance between costs and benefits of maintenance decisions emerges as a key factor in a highly competitive business context.

According to Machado and Haskins (2016), significant benefits can be achieved when, for example, major maintenance interventions such as equipment overhaul are scheduled based on conclusions from the results of models and, among the promising approaches are the Markov chains and decision process. Experience has shown that, beyond a thorough operational experience, among the organizational key-elements are: (i) methods for expert's judgment use; (ii) strong notification culture (not a search for a culprit); (iii) data collection systems and condition monitoring routines; (iv) the use of a common recordkeeping system (i.e. routines for machine/assets event's and maintenance intervention recording etc.) and; (v) intelligent analytics and IT support systems (i.e. tools and database infrastructure). All these aspects underlie the motivation to investigate the decision-making process in the offshore operational environment of the oil and gas industry. Based on a preliminary literature review and early interviews with experts,

Table 1.1 presents a summary of factors impacting the offshore operator's maintenance support performance.

Table 1.1 – Factors impacting the offshore operators' maintenance support

Problem related to	From the literature	According to interviewed maintenance experts
Data	Deficient data collection and analysis (Dekker, 1996)	Lack of analysis, (i.e., root-cause, cost-benefits, life-cycle and decision) (Declared)
	Difficulties in providing the proper amount of data (Welte *et al*., 2006) (Declared)	
Models	Lack of model robustness in an ambiguous terminology environment (Dekker, 1996), (Declared)	
Technical competences	The need for diverse expertise/skills in the organization (e.g., decision analysis, expert judgement and a thorough operational experience) (Vatn *et al*., 1996)	Need for communication skills within and across the organizations (on- and off-shore personnel) (Declared)
Decision-making	The need for a more explicit use of decision logic and compiling the results into maintenance schedules (Vatn *et al*., 1996)	Deficient justification of analyst's preferences to convince management. (e.g., lack of life cycle evaluations) (Declared)

(Declared) = Interviews with experts

In summary, from the operators' side, there is a need for: (i) a better coordination of the condition monitoring and diagnostics (CM&D) activities in the offshore operational environment; (ii) operation and maintenance integration; and, (iii) culture change towards prevention. Moreover, deficient data collection and analysis and a poor quantification/demonstration of gains make it difficult to enhance the operator's maintenance support performance, resulting in high maintenance costs due to poor asset performance and limited interdisciplinary cooperation, mainly regarding the implementation of preventive maintenance programs.

1.2 Problem formulation

In the course of the research, it became clear that a Systems Engineering (SE) approach could help better understand the viewpoints in the maintenance decision-making contexts. The research started with the assumption that: by identifying the main actors, their roles and relationships, discussing the most relevant elements mentioned in the literature from recent applications and interviewing the experts in the field on the main aspects of the condition monitoring and diagnostics of machines (CM&D), it would be possible to contribute to paving the way for future implementations of preventive maintenance (PM) programs, such as Condition-Based Maintenance (CBM), Reliability-Centered Maintenance (RCM) and Total Productive Maintenance (TPM). As scope delimitation, the focus of this research is on the flow of information and operational data related to the maintenance decision-making process in the offshore operating environment of the oil and gas industry. The research problem can be stated as:

"How can the oil and gas industry improve the maintenance decision-making process towards a calibrated preventive maintenance program in the offshore operational environment?"

The Basic hypothesis is that *"The results from a systemic and systematic investigation of the state-of-practices assisted by a literature review regarding the state-of-knowledge on maintenance decision-making can contribute to developing a comprehensive decision support framework in this industry sector."*

This thesis is organized as follows: Chapter 2 describes the research methods; Chapter 3 presents the findings from literature review; Chapter 4 presents the findings from the field research; Chapter 5 summarizes and discusses the main thesis constructs and Chapter 6 concludes and indicates future research lines.

2 Research methods

This section describes the methods used in this research project.

From the point of view of its nature and purpose, since this thesis aims to generate knowledge for practical application and is directed to the solution of specific problems, it is classified as applied research using qualitative and quantitative approaches. This research can also be classified as exploratory research since it involves literature review, interviews and case studies. Moreover, as it is concerned with the direct description of experience, it may be classified as phenomenological. And, finally, by considering the Markov decision approach and analysis, it has also an experimental character. Table 2.1 presents the research objectives, methods and outcomes.

Table 2.1 – Research approach

Research objectives	Methods / Approach	Main outcomes
- Identify, among major oil and gas offshore operators, the state-of-practices - Identify, in the literature, the main techniques used for maintenance decisions and optimization, the state-of-knowledge - Propose alternatives for supporting future preventive maintenance program implementations	Literature review (Maintenance, Reliability, Decision Analysis and, Markov decision process) SPADE method 1. Stakeholders 2. Problem 3. Alternatives 4. Decision-making 5. Evaluation State-of-practices among the major offshore operators Case studies, interviews and on-line survey	- A concept map for the maintenance decision-making process ontology - A plan and decision framework for preventive maintenance program implementations - A Markovian dependability nomogram[1] (Submitted Article) - A suggested cross-sector solution: the minimum equipment list - Article "Maintenance Optimization Approaches for Condition Based Maintenance: a review and analysis" - Model and application of the Markov decision process to optimize O&M policies of parallel systems (Submitted Article)

See supporting documentation in Appendix A-C

[1]Nomogram – also called nomograph or abaque, is a graphical calculating device, a two-dimensional diagram designed to allow the approximate graphical computation of a mathematical function.

Interviews and survey were important methods to identify the state-of-practices regarding the maintenance decision-making process by understanding how major E&Ps' maintenance organizations deal with the inherent flow of information in the offshore operational environment.

The questions were grouped under five major headings as follows:

Axis 1 - Roles and responsibilities;

Axis 2 - Maturity of the CM&D related processes;

Axis 3 - Decision-making and learning;

Axis 4 - Key Performance Indicators;

Axis 5 - Barriers encountered and recommended ways of overcoming.

In summary, this research has proceeded in stepwise iteration. After an initial literature review on maintenance optimization applications and on reliability theory, other theoretical foundations were included. Starting from the problem identified and after more than a decade working in a major Brazilian oil and gas operator, the author's research project was planned in a three layers scheme as illustrated in Figure 2.1.

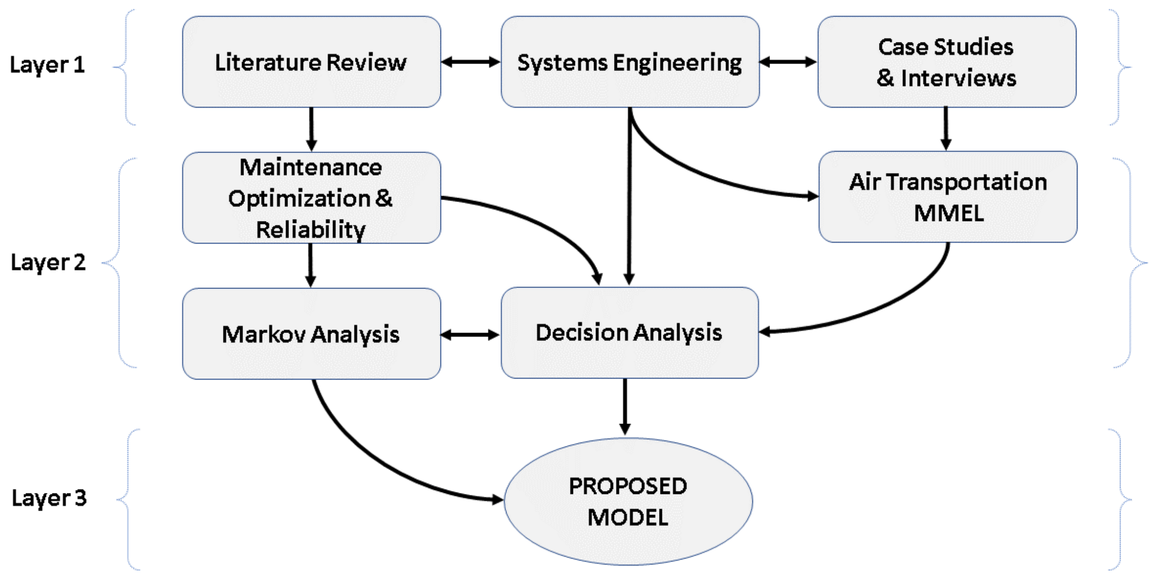


Figure 2.1 – Research overview

Layer 1: Initial literature review, case study, interviews among offshore operators. In this phase, the study also assesses the state-of-practices regarding maintenance optimization models and program implementation aspects in the offshore operational environment.

Layer 2: According to the results of the Layer 1 and based on the operating scenario observed in the Brazilian Continental Shelf (BCS), additional literature review (e.g., decision analysis) and alternative solutions (e.g., MMEL) were assessed.

Layer 3: According to the results of the layers above, the third layer contains the research results and contributions. As a quantitative approach, the development of a Markov decision model is proposed to optimize O&M policies and support maintenance backlog management of an offshore power plant.

3 State-of-the-knowledge

Starting with the Systems Engineering approach and methods, and then Decision Analysis tools, and Maintenance and Reliability theory, this chapter presents the fundamental elements collected to support this research project. A schematic overview of the research topics, e.g., the maintenance decision processes, is pursued in which the elements obtained from the literature, such as tables and flow diagrams were, to some extent, adapted to the research objectives. From the section on maintenance onwards, in order to draw parallels between theory and practice, some discussion topics are complemented with the experts' testimony, whose summaries of interviews transcripts are provided in Appendix C.

3.1 Systems engineering

According to Ludwig von Bertalanffy (1968), a system is regarded as a "whole" consisting of interacting "parts." From the ISO/IEC/IEEE 15288: 2015, **systems** *"... are man-made, created and utilized to provide products or services in defined environments for the benefit of users and other stakeholders.*" From INCOSE (2015:6), **engineering** *"can be regarded as the practice of creating and sustaining services, systems, devices, machines, structures, processes, and products to improve the quality of life.*"

From INCOSE (2015:11), **Systems Engineering (SE)** *"is an interdisciplinary approach and means to enable the realization of successful systems, and it includes both technical and management processes, both depending on good decision making."*

According to Haskins (2008:8), "… *the need for systems approach is exacerbated by the high degree of networking enabled by today's internet technology [...] Systems engineering research is served best by interdisciplinary approaches.*" This suggests that research within systems engineering should include a variety of methods ranging from mathematical modeling and simulation to case studies including surveys and interviews. In summary, the idea of systems engineering is: (i) obtain a systemic understanding of the requirements; (ii) identify the consequences of the decisions; (iii) understand the system complexity and its boundaries; and (iv) identify dynamic elements of the system of interest.

3.1.1 The SPADE methodology

In this research, a methodology derived from systems engineering practices by Haskins (2008) is chosen. The SPADE's graphical representation presented in Figure 3.1 is circular to communicate the incremental and iterative nature of following this approach. The acronym describes the process where: "S" stands for Stakeholders; "P" for Problem formulation; "A" for Analysis/Alternatives; "D" for Decision-making and; "E" for Evaluation.

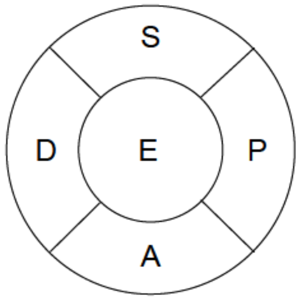


Figure 3.1 – SPADE methodology/framework representation (Haskins, 2008:27)

According to Haskins (2008) the SPADE methodology incorporates the SE principles of systematic collection of information, constant communications to keep stakeholders informed, and ongoing process development to establish guidelines for how to define the problem, consider alternatives, make a decision that balances the requirements, monitor the resulting situation, and adjust as needed within the context of the current situation.

3.1.2 The Heilmeier's catechism

Another systematic approach, according to Shapiro (1994), is the so-called "Heilmeier Catechism" from George H. Heilmeier. These are 9 questions that provide high level guidance for what information a project proposal should contain. These questions are:

I. *What are you trying to do? Articulate your objectives using absolutely no jargon. What is the problem? Why is it hard?*
II. *How is it done today, and what are the limits of current practice?*
III. *What's new in your approach and why do you think it will be successful?*
IV. *Who cares?*
V. *If you're successful, what difference will it make? What impact will success have? How will it be measured?*
VI. *What are the risks and the payoffs?*
VII. *How much will it cost?*
VIII. *How long will it take?*
IX. *What are the midterm and final "exams" to check for success? How will progress be measured?*

Especially questions I to VI are important both for the researcher and for communicating what is to be accomplished.

3.1.3 Measures of effectiveness

Solution success must be measurable and, according to Sproles (2000), the so-called Measures of Effectiveness (MOE) are the essential properties of a successful solution and must be formulated based on the user requirements. "*When asking, if a candidate solution cannot do this, would I reject it?*", if the answer is "*yes*" it is a critical issue. It is useful to think of MOEs as follows (Sproles, 2000:52):

(i) MOEs represent the viewpoint of the stakeholders "who have the right to impose requirements on a solution";

(ii) MOEs assist in making the right choice by indicating "how well" a solution meets the stakeholders needs and;

(iii) MOEs should be quantifiable in some manner.

Underlying MOEs, measurements can be considered as Figures of Merit (FOM) in the composition of a successful solution. Table 3.1 presents the proposed MOEs and respective FOM for a successful maintenance program.

Table 3.1 – MOEs and FOMs in PM program

Measurements of effectiveness	Figures of merit
ROI, Project Payback and Life cycle cost, OPEX-CAPEX	NPV, Stream of Cash flows and other monetary indicators, Overall Equipment Effectiveness (OEE).
Positive trend of the: - Rate of solution's implementations and - Diagnostic performance (generation and re-use). (Learning)	- Network connectivity, Dominance and Coverage (by the Operator Headquarters). - # of successful diagnostics analysis / total number of analysis. - # of hours (per annum) of courses and training the maintenance personnel receive in additional to the minimum required training.
Negative trend of the: - Corrective maintenance costs in relation to the total maintenance costs - Maintenance and failure related losses. (Predictability)	- # of failures (unplanned corrective actions) over the year. - # of incidents that increase the risk to human safety and the environment as consequence of performing maintenance actions or the occurrence of equipment failures.
Negative trend and/or stabilization of the: - Total maintenance costs/production level - Difference between production targets and the assets' actual capacity. (Uncertainty reduction and efficiency improvement)	- Total maintenance costs (preventive and corrective) on the production level. - Difference between the production performance of the facility and the planned production, as result of performing maintenance actions or occurrence of equipment failures.

3.1.4 Stakeholders' roles, interests and responsibilities

In order to answer the question IV of the Heilmeier's catechism - "*Who cares?*" - it is necessary to identify all the stakeholders involved and their role, interests and responsibilities regarding the solution approach. In that sense, Table 3.2 presents the E&P stakeholders, their role, interests and responsibilities with respective degree of involvement in the offshore operation, in the context of the maintenance decision processes.

Table 3.2 – E&P stakeholders' role in a maintenance decision-making process

E&P stakeholders	Role	Interests	Responsibility
DECISION MAKERS **(**E*&P operator's top management* Managers and O&M experts at the E&P operator' headquarters)	Approval	A + S	Verify
	Make strategical decisions		Evaluate the decision situation and asks for the required information Negotiates frame agreements with suppliers and vendors
DECISION ANALYSTS (Maintenance engineers and technicians at the operations base)	Present decision contexts indicating justified preferences Support decisions	RAMS	Support the decision maker (providing the required information in time) Communicate decisions to Offshore Technicians.
OPERATORS / MAINTAINEERS (Maintenance engineers and technicians at the offshore platforms)	Implement		Implement decisions and Provide condition monitoring information.
Suppliers and vendors	Support	R* and Sales	Supply customers with proper documentation, material and resources at a fair price Demonstrate commitment to their product/service's performance
Brazilian Regulatory Authority	Consent	R + A + S	Sanction

RAMS: Reliability, Availability, Maintainability and Safety, R* = Inherent reliability

The emphasis of this study is given to the primary stakeholders in a maintenance decision-making process and Table 3.3 presents their respective needs from the tactical and operational decision levels.

Table 3.3 – Primary stakeholders' needs in a maintenance decision-making process

DECISION MAKERS (Managers and O&M experts at the E&P operator' headquarters)	• Have access to a standardized, concise and consistent panel with the maintenance KPIs; • Have access to the issues reported by the assets' O&M personnel (onshore and offshore).
DECISION ANALYSTS (Asset manager, maintenance engineers and technicians at the operations base)	• Have access to (and discuss) the adequacy of the production plan with maintenance plans and the respective performance criteria with HQ managers; • Have access to the asset's maintenance KPIs. • Reliability and maintenance data from the CMMS system.
OPERATORS / MAINTAINEERS (Maintenance engineers and technicians at the offshore platforms)	• Have access to (and discuss) the maintenance plans, respective tactics and criteria with the asset manager; • Have access to: o Technical documentation, related standards, according to the assets' technology (i.e., maintenance plans, troubleshooting tables, training material, minimum requirements as a policy and procedures manual) o Reliability and maintenance data from the CMMS system (i.e., updated record/logbook databases, data from ERP system, etc.). o Appropriate tools and procedures (i.e., monitoring systems, routines and resources) to properly operate, inspect and repair the assets

3.1.5 Operation and maintenance processes from a SE perspective

According to ISO/IEC/IEEE 15288:2015, SE activities are categorized into four groups of processes that support a system life cycle as follows: (i) technical processes; (ii) technical management processes; (iii) agreement processes and; (iv) organizational project-enabling processes. In this study, the focus is given to two of the technical process, namely, the maintenance process and its interface with the Operations process. The purpose of the maintenance process, as defined in (ISO/IEC/IEEE 15288:2015 def. [6.4.13]) "*is to sustain the capability of a system to provide a service.*" Figure 3.2 presents the IPO[2] diagram for the maintenance process. The diagram for the Operation process is presented in Figure 3.3.

A socio-technical system such as the maintenance organization and its decision-making process, needs a method to maintain consistency of the sequence of decisions on the operational level. In that sense, this thesis proposes: (i) a cross-sector solution, the Master Minimum Equipment List (MMEL) which is a policy and procedures manual used in the

[2] IPO – Input Processing Output

air transportation sector; and (ii) the development of a Markov decision model to optimize operation and maintenance policies.

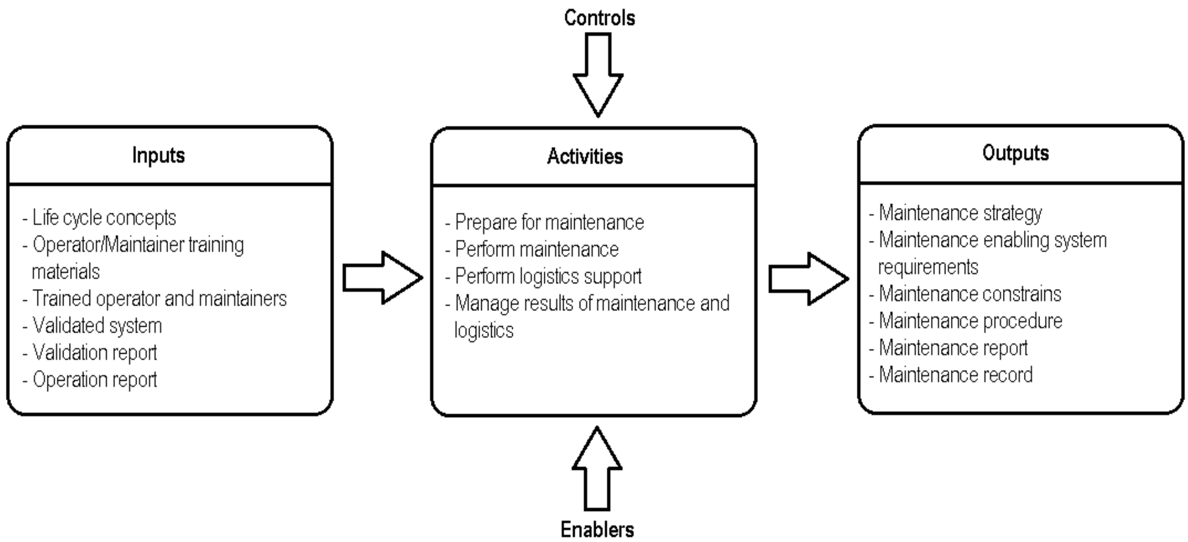


Figure 3.2 – IPO diagram for the maintenance process. (INCOSE 2015:97)

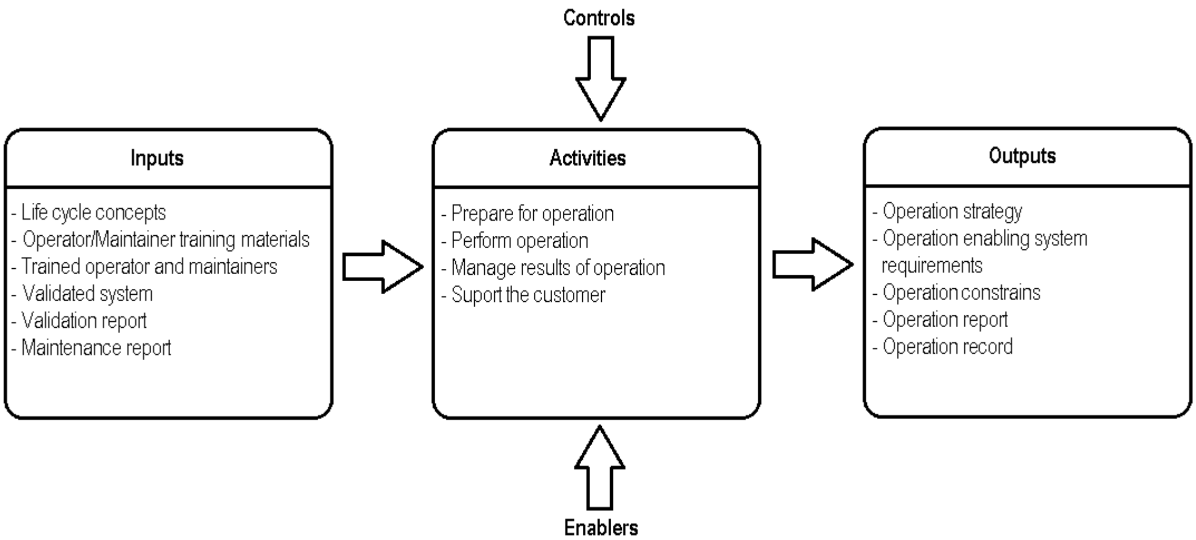


Figure 3.3 – IPO diagram for the operation process (INCOSE 2015:95)

3.1.6 Maintenance enabling systems

Among the maintenance enabling systems mentioned in the INCOSE (2015:100) are: (i) the operational environment as the circumstances surrounding and potentially affecting the operation; (ii) the supply system; (iii) the training systems; (iv) technical data (i.e. procedures, guidelines, and checklists needed for proper maintenance); (v) facilities and infrastructure required for system maintenance; (vi) tools and support equipment; and (vii) maintenance planning and management. For a condition-based maintenance (CBM) program, for example, the technical documentation should include information on how the condition monitoring and diagnostics capabilities are used to support maintenance decisions and trigger maintenance actions.

3.2 Decision analysis

This section presents a brief exposition of the decision analysis tools and data flows. The following exposition is based on (Clemen, 1996) with ideas from (Ferreira-Filho, 2015), (Koller and Friedman, 2009) and (Vatn *et al.*, 1996).

According to Clemen (1996), values are things that matter whilst objectives are specific things to achieve (or targets). Some objectives may be inter-related and, as such, may define values, that is, what is important. Each decision situation refers to specific objectives and that setting is called the decision context.

On scientific methods for decision-making, according to Ferreira-Filho (2015), operations research (OR) methods consist of a procedure for the description of a system with the aid of a model in order to, through experimenting with the model, discover the best way to operate the system. An OR study typically involves six stages, as follows:

Stage 1 - Formulation of the problem;
Stage 2 - Construction of a model of the system;
Stage 3 - Calculation of solution through the model;
Stage 4 - Testing of model/solutions;
Stage 5 - Establishment of controls of the solution and;
Stage 6 - Implementation and follow-up.

These stages were considered in the development of the plan presented in this thesis.

Once the objectives of the maintenance organization are defined, a structured decision-making process must be implemented. In a decision context, for Koller and Friedman (2009), each of available actions can lead to one among several outcomes, which can be preferred to different degrees. When outcomes are partially random, it is necessary to consider both the preferences and the probabilities of all these outcomes, which can depend not only on monetary, but also on all other relevant aspects.

Regarding the maintenance decision-making process in a preventive maintenance (PM) program, e.g., CBM, sequential decisions are required, since new information such as remaining useful life (RUL) estimates, condition and diagnostics reports are obtained periodically. Among the uncertain events are degradation and failure mechanisms and repair completion events. As consequences (or outcomes), after the last decision has been made and all the events have been resolved, the decision maker's choice is finally determined. A fundamental issue for Clemen (1996) is how far into the future to look. Once the dimensions of the consequences and the planning horizon have been determined, the next step is to figure out how to assess the consequences. To understand how decisions can contribute to consequences, influence diagrams and decision trees are considered.

3.2.1 Influence diagrams

In a model developed by Vatn *et al.* (1996) to identify the optimal maintenance schedule for components of a process plant, a maintenance optimization approach is presented, and the authors used the influence diagrams in the conception and communication of the model among the stakeholders (i.e. asset manager, maintenance and reliability engineers). See Figure 3.4.

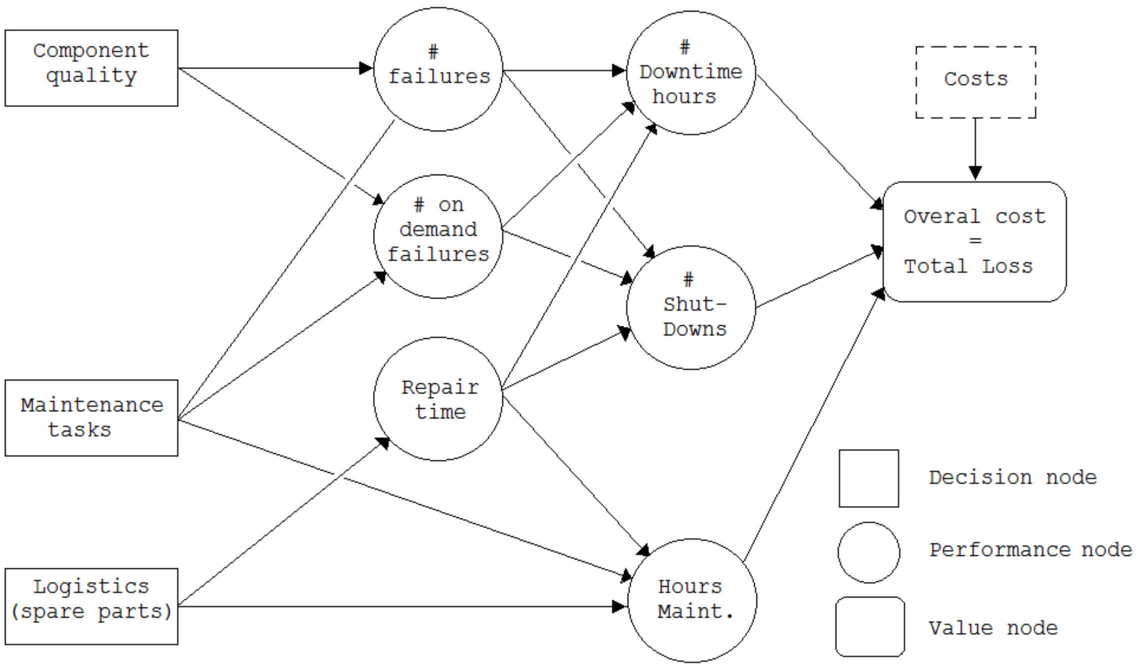


Figure 3.4 – Influence diagram for maintenance optimization (Vatn *et al.*, 1996:244)

An influence diagram is a directed graph $G = (N, E)$ where N is a set of nodes and E is a set of arcs (edges) connecting the nodes such that these structures can be further investigated. In their model, the objective-function is stablished according to the manager's prioritization and preferences, considering an overall measure for goal achievement. As future work, the authors mentioned the following topics:

- To include models for condition-based maintenance;

- Present a practical approach for large systems;
- Allow for use of true utility functions where the effect of the alternatives on the attributes are unknown;
- More explicit use of decision logic and;
- Compiling the results into maintenance schedules.

When using the influence diagrams, normally square rectangles are decision nodes, ovals are chance nodes (i.e., events), rounded rectangles are the consequence nodes (calculation or value node) and also circles can be used to represent intermediate calculations or constants. According to Clemen (1996), influence diagrams are snapshots of the decision-making understanding of the current situation. It is an acyclic graph where arrows from decision or chance nodes into chance or consequence nodes are *relevance arcs* whilst arrows ending at decision nodes are *sequence* arcs. To properly design an influence diagram, a requisite model containing everything that the decision maker considers important is necessary. That is, all the important concerns are to be fully incorporated and the decision elements must be clearly presented such as: (i) decision alternatives, (ii) uncertain events and outcomes and; (iii) consequences. An example of influence diagram for a typical maintenance sequential decision-making is presented in Figure 3.5.

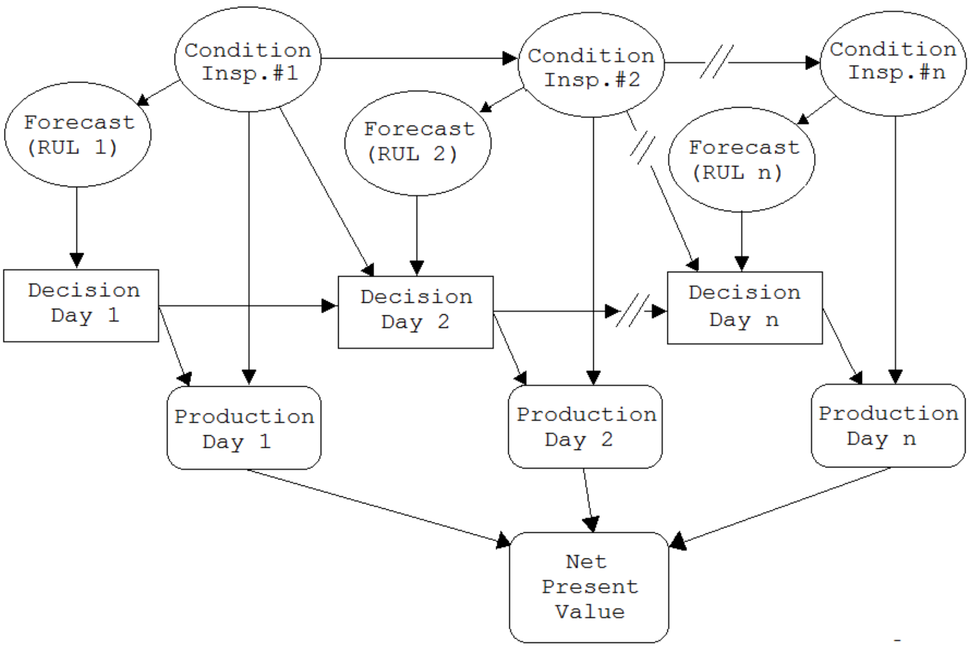


Figure 3.5 – Influence diagram for sequential decision. Adapted from (Clemen, 1996)

3.2.2 Decision trees

Another important decision analysis tool is the decision tree. On a decision tree the branches from decision nodes must be such that only one can be chosen. From each chance node, branches must correspond to a set of mutually exclusive and collective exhaustive outcomes, i.e., no other possibility exists and one of the outcomes must occur. Once uncertainty is resolved, one and only one of the outcomes occurs. A decision tree can display more details of the decision situation with nodes occurring in time-sequence. For Clemen (1996:68) “A decision-tree represents all of the possible/relevant paths that the decision maker might follow, including all possible decision alternatives and outcomes of chance events.” An example of a decision tree adapted to a typical replace/repair sequenced decision is presented in Figure 3.6. When a multi-objective decision is the case, a decision tree can be of the form in Figure 3.7.

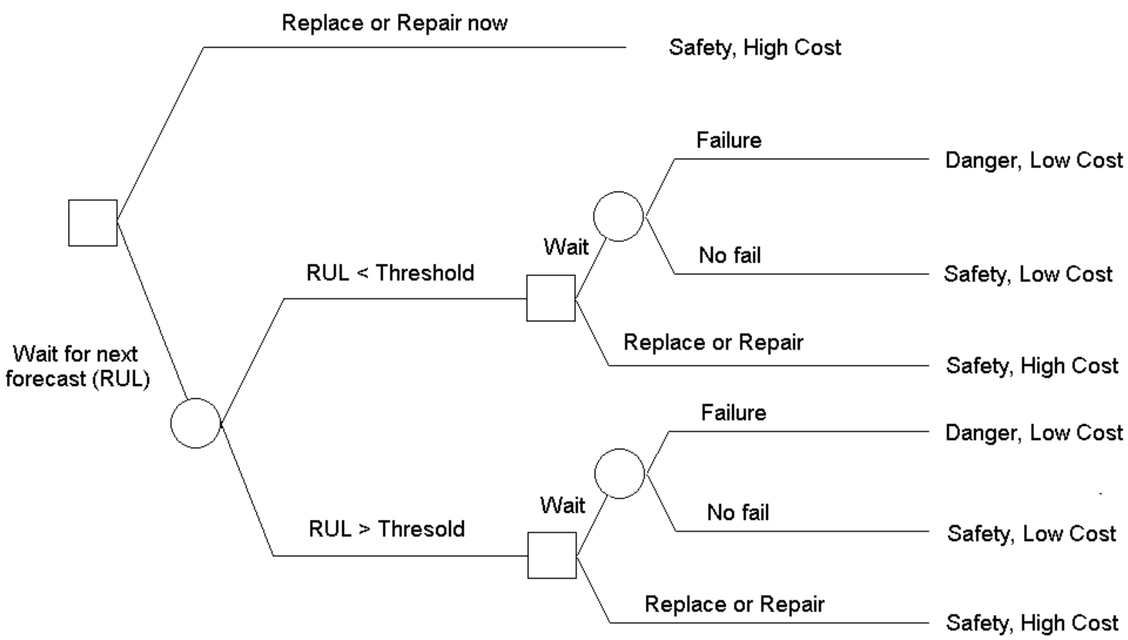


Figure 3.6 – Decision-tree of a sequential decision. Adapted from (Clemen, 1996)

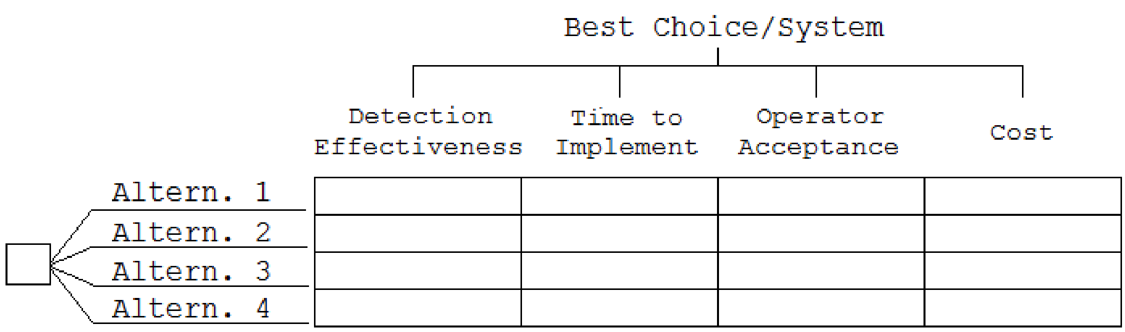


Figure 3.7 – Decision-tree of a multi objective decision. Adapted from (Clemen, 1996)

Since most of the maintenance decision contexts involve sequential decision problems, an appropriate approach could use the Markov Decision Processes (MDP).

3.3 Maintenance

This section presents some of the main maintenance concepts, maintenance categories, lists the maintenance agents and their roles and the types of decisions with the respective contexts. In order to enrich the discussions drawing parallels between theory and practice, some topics are supported by experts' testimony. Boxes with interview citations are coded with the interview and question number, e.g., (I3Q4) meaning that it is from the third interview on question four. A summary of interviews transcripts is available in Appendix C.

There are two basic categories of maintenance: corrective and preventive. Corrective maintenance actions are carried out after fault recognition and intended to put an item into a state in which it can perform a required function. Preventive maintenance is carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item (ISO 14224:2006). Preventive maintenance (PM) has sub-categories, which should be selected in accordance with the system's failure mechanisms, failure effects and consequence criticality. That can be assessed, among others, by a Failure Mode, Effects and Criticality Analysis (FMECA), a central analysis in a Reliability Centered Maintenance (RCM) approach, for example. These categories are defined by the International Atomic Energy Agency (IAEA, 2007:101) as follows:

> *<u>Preventive maintenance</u> are actions that detect, preclude or mitigate degradation of a functional structure, system or component to sustain or extend its useful life by controlling degradation and failures to an acceptable level, and <u>corrective maintenance</u> are those actions that restore, by repair, overhaul or replacement, the capability of a failed structure, system or component to function within acceptance criteria.*

According to IEC 50 (191), **maintenance** – *is the combination of all technical and corresponding administrative actions, including supervision actions, intended to retain an entity in, or restore it to, a state in which it can perform its required function* and **maintenance support performance** *is the ability of a maintenance organization, under given conditions, to provide upon demand, the resources required to maintain an entity, under a given maintenance policy*. See Figure 3.8.

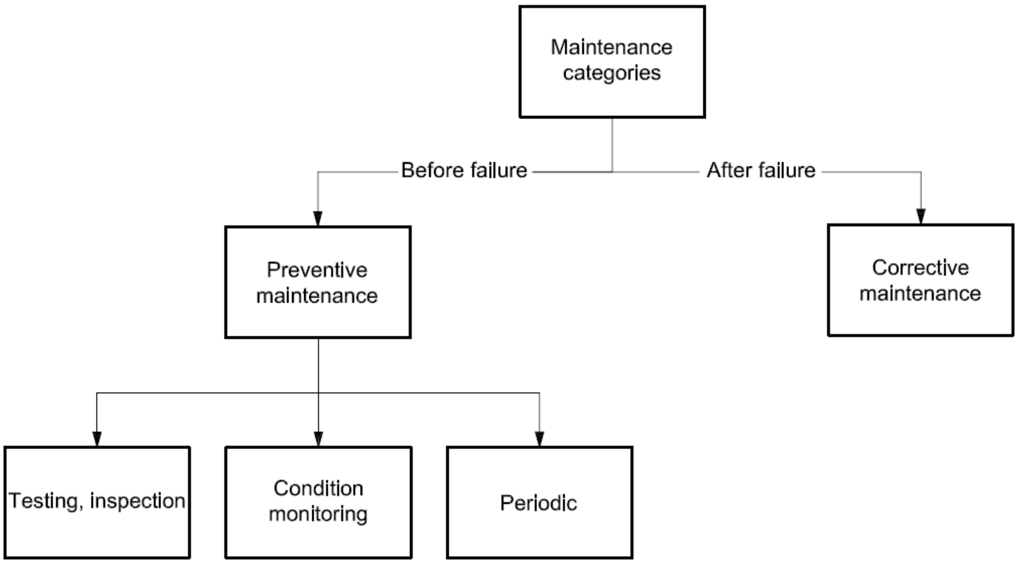


Figure 3.8 – Maintenance categorization (ISO 14224:2006)

In an attempt to reduce the ambiguity of terms in the field of maintenance, Pintelon and Parodi-Herz (2008) suggest definitions for three important terms: *maintenance action*, *maintenance policy* and *maintenance concept*. For them, **maintenance action** is the answer for the question "What to do?", that is, a basic maintenance intervention, elementary task carried out by a technician, whilst **maintenance policy** answers the question "How is it triggered?", being the rule or set of rules describing the triggering mechanism for the different maintenance actions. And **maintenance concept** is a set of maintenance policies and actions of various types, and the general decision structure in which these are planned and supported, i.e., an answer for "What logic and maintenance recipe are used?"

Bringing these together is a maintenance organization that aims to provide decision support after having adopted one or more maintenance concepts in its preventive maintenance (PM) program. Looking at how these sets of policies and actions work in the long-run, the maintenance organization will certainly observe some tradeoffs. For example, a preventive maintenance program may consist of a set of maintenance concepts (e.g., CBM, RCM, TPM, etc.), which in turn contain a set of maintenance policies and all the respective maintenance actions/tasks.

3.3.1 Maintenance agents, their roles and responsibilities

After discussing some concepts, this section refers to the people involved in the maintenance related processes. Among the main agents in a maintenance organization are: (i) operations and maintenance (O&M) technicians; (ii) maintenance/reliability engineers and; (iii) asset managers and experts. From the literature, a reliability engineer may be focused on the system's functions and its respective failure characteristics while a maintenance engineer will be focused on maintenance schedules and logistics.

According to Rausand and Høyland (2004) the main concern of a reliability engineer is to identify potential failures (regarding a functional block) and to prevent these failures from occurring. It is necessary to identify all relevant functions and the performance criteria related to each one.

For the maintenance engineer, the main concern is to keep the system in a continuous and smoothly running operation by using routines of condition monitoring and inspections, aiming to: (i) perform maintenance planning and execution; (ii) sustain the production plans; (iii) reduce the incidence of costly breakdowns; and (iv) develop strategies to improve overall reliability and safety of the assets, personnel and production processes at minimum costs. The O&M technicians on the shop floor (e.g., offshore production platforms) should be oriented to troubleshooting and situation awareness whilst maintaining routine support activities, such as data collection on assets' related events and intervention recordings, preferably, in a common recordkeeping system.

The maintenance team should work in a coordinated manner to provide adequate prevention and decision support information towards an appropriate operation of the assets. The recommendations from the condition monitoring assessments must be well discussed and the alternatives communicated to the decision-maker. Afterwards, decisions must be implemented under the assumption that, every action may affect the final overall asset's performance and results.

Among the asset manager's primary responsibilities are: (i) leading the operation and maintenance staff; (ii) coordination of operations including production, logistics and maintenance while ensuring compliance with all labor, safety, environmental and corporate policies and regulations; and (iii) develop and manage the strategies, production planning, spare parts' stock, instrumentation calibration, modifications and innovative systems and processes utilizing all available technology. In summary, the asset manager should consider the costs and benefits of each decision ensuring that the assets are maintained, supported and available as measured by KPIs such as Overall Equipment

Effectiveness (OEE) while influencing the socio-technical system to produce efficiently. Afterwards, in a feedback loop, the results and findings must be subject to analysis, in order to give traceability and lessons learned on the process.

On the titles and roles of the reliability and maintenance engineers, a different perspective is provided by interviewee#5:

(I5Q1*) "...one of the biggest companies in the world ...to give maintenance a better profile, because the image of maintenance has not been good unfortunately in the past. Top management doesn't really understand maintenance. They just see that it uses a lot of money. So, this company changed the titles of all the Maintenance Engineers and call them Reliability Engineers. And then suddenly it is a positive thing instead of a negative thing, because management associate maintenance with spending money just to keep something going. But they do understand some of them… at least reliability. Ah that's rather important. Uptime and Reliability. So, if you call someone a Reliability Engineer and it has a bit more credibility and a bit less baggage than if you call them Maintenance Engineer."*

In conclusion, at least for some operators, reliability and maintenance engineers are different names for the same position/role. This can be observed in the results of the on-line survey discussed in this thesis.

3.3.2 Strategy development

According to Rausand and Høyland (2004:400) "Maintenance tasks and resources have traditionally been allocated based on: (i) requirements in legislation; (ii) company standards; (iii) recommendations from manufacturers and vendors of the equipment; and (iv) in-house maintenance experience." As shown in Figure 3.9 , one operator's maintenance strategy should contain a combination of the legislation, manufacturers' recommendations and suitable models, in addition to a maintenance operational experience.

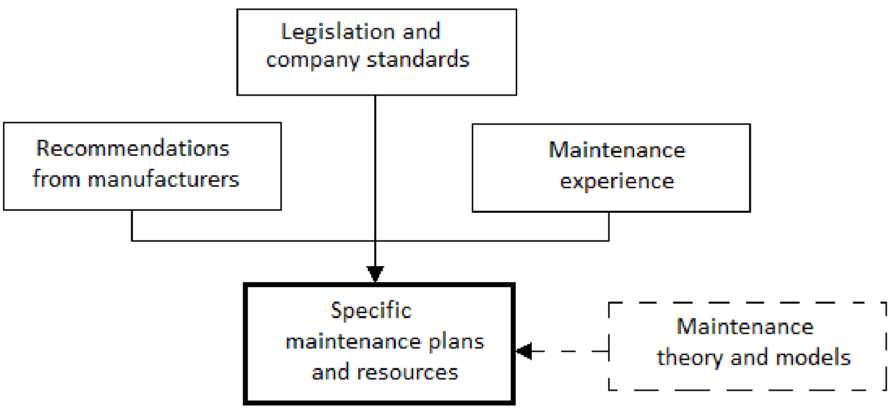


Figure 3.9 – Maintenance strategy development (Rausand and Høyland, 2004:401)

As can be seen, operators need to manage different interfaces. Beyond the interface with the regulatory authorities (i.e., legislation etc.) and with manufacturers (i.e., maintenance and operation plans and procedures), an interface with suppliers and vendors, toward defining specifications and minimum requirements, is established. In that sense, operators should establish the so-called frame agreements, as explained by Interviewee#5:

(I5Q6) *"All companies at their HQ or Head Office or from their operations base […] they are going to specify what standards are required and what specifications are required. And they will also, if they are smart, negotiate Frame Agreements with vendors. The HQ works on that level. Setting up Frame Agreements in accordance with the specifications and standards that are required."*

In conclusion, establishing the frame agreements, from the headquarters, is a way for the operators to achieve an appropriate level of compliance among the surrounding elements of its operational environment.

3.3.3 Maintenance decisions

There are many kinds of decisions towards maintenance optimization and some of them are listed in (Vatn, 2007): (i) the amount of preventive maintenance; (ii) whether to do first line maintenance (on site or at the workshop); (iii) the right number of spare parts in stock; (iv) preparedness for corrective maintenance; and (v) time of renewal and grouping of maintenance activities.

On the support of the maintenance optimization and decision-making, according to Machado and Haskins (2016) the most frequent analysis techniques used in recent maintenance optimization applications are Markov analysis and the decision methods, followed by Monte Carlo Simulation, Gamma process, Weibull distribution and Wienner process. The idea of such approaches is to model degradation and provide reasoning for decision-making, i.e., to find the best way to operate and maintain production assets.

3.3.4 Reliability centered maintenance

According to Rausand and Høyland (2004), the reliability centered maintenance (RCM) approach and concept was founded in the sixties, initially oriented towards airplane maintenance. This reliability concept emerged just after World War I and was then used in connection with comparing operational safety of one-, two-, and four-engine airplanes. Reliability was measured as the number of accidents per hour of flight time. Defined in

(ISO 8402), **reliability** "*is the ability of an item to perform a required function, under given environment and operational conditions and for a stated period of time*".

Reliability may be measured as suggested by (Rausand and Høyland, 2004):

1. Mean time to failure (MTTF);
2. Number of failures per time unit (failure rate);
3. The probability that the item does not fail in a time interval (0, *t*] (survival probability);
4. The probability that the item is able to function at time *t* (availability at time *t*)

If the item is not repaired after failure, 3 and 4 coincide.

The IEC 60300-3-11(IEC 1999) defines **RCM** as "*a systematic approach for identifying effective and efficient preventive maintenance tasks for items in accordance with a specific set of procedures and for establishing intervals between maintenance tasks*." From a Systems Engineering perspective in (INCOSE, 2015:101) RCM "*is a cost-effective maintenance strategy to address dominant causes of equipment failures that improves system reliability by reducing the amount of time the system is unavailable while conducting routine or preventive maintenance.*"

According to Rausand and Vatn (2008), RCM is a method for maintenance planning. They propose a maintenance task assignment decision logic as presented in Figure 3.10 .

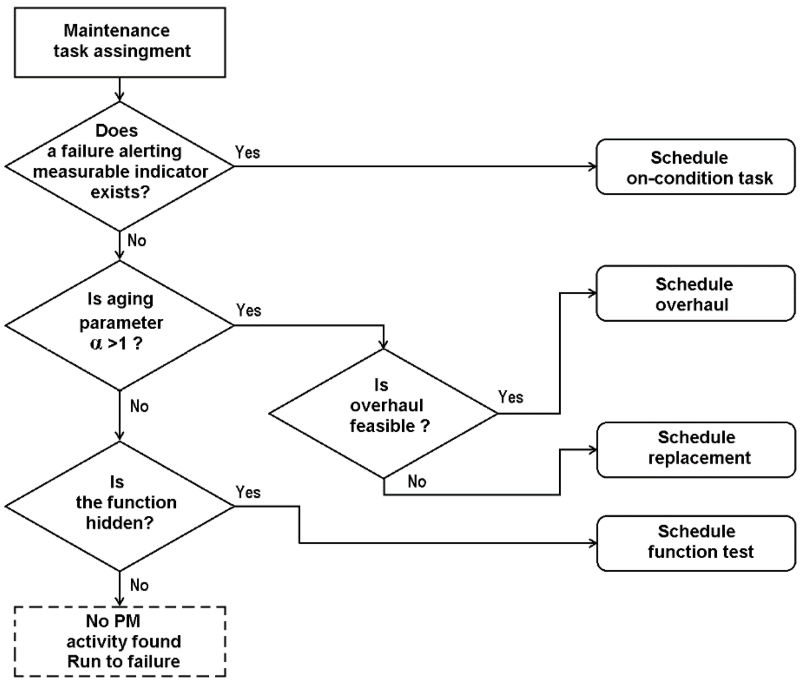


Figure 3.10 – Flow chart for task assignment. (Rausand and Vatn, 2008)

3.3.5 Total productive maintenance

According to Kister and Hawkins (2006) the concept of total productive maintenance (TPM) is connected with the industrial movement initiated by "Taiichi Ohno" the father of the Toyota Production System (TPS), the so-called *Lean Thinking*, which espouses the identification and elimination of waste in a production system. That movement produced an important development in the concepts of maintenance. The starting point for a TPM program is the set of fundamental laws of manufacturing maintenance, such as: (i) properly maintained equipment makes many quality products; (ii) improperly maintained equipment makes fewer products of questionable quality; and (iii) inoperable equipment makes no products. Based on these laws, the authors state that the primary requirement is equipment reliability, whose maintenance practices are the primary determinants. Additional objectives for a lean maintenance process include:

- Plan and schedule the maintenance workload to maintain the maintenance backlog within prescribed limits by providing for forecasted level resource requirements and achievable daily schedules;
- Continually reduce equipment downtime and increase availability through the establishment of a preventive/predictive maintenance program (including failure analysis) that is designed, directed, monitored and continually enhanced by maintenance engineering;
- Ensure that work is performed efficiently through organized planning, level scheduling, optimized material support and coordinated work execution;
- Establish maintenance processes, procedures and best practices to achieve optimal response to emergency and urgent conditions;
- Create and maintain measurements of maintenance performance effectiveness;
- Create and provide meaningful management reports to enhance control of maintenance operations;
- Provide quality, responsive maintenance service in support of operational need.

The challenge is to enable the maintenance organization to achieve the levels of equipment reliability necessary to sustain the lean production goals and objectives. In that sense, a promising strategy is to replace, as much as possible, reactive with proactive maintenance practices. The fundamental objective of TPM is to eliminate accidents, defects and breakdowns. A team-based, proactive maintenance that involves every level and function in the organization, from top executives to the shop floor, TPM addresses the entire production system life cycle and builds a solid, shop floor-based system to prevent losses. Focused on results, one of the fundamental measures of performance used in TPM is the Overall Equipment Effectiveness (OEE), defined as:

OEE = (Equipment Availability) x (Performance Efficiency) x (Rate of Quality)

According to the authors, a world-class OEE level starts at 85% based on the following values:

90% x 95% x 99% = 84.6%

Figure 3.11 shows a model for maintenance as a transformation process in the enterprise system.

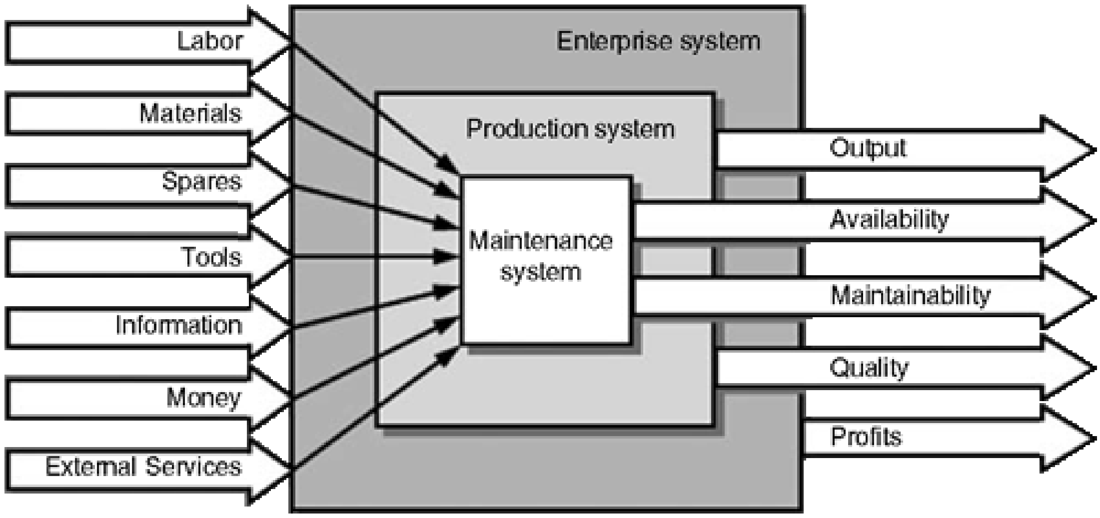


Figure 3.11 – Maintenance as an enterprise hub (Kister and Hawkins, 2006:32)

The maintenance resources include labor, materials, spares, tools, information and money. The way maintenance is performed, that is, the use of the necessary skills to manage these resources, will influence the assets related availability, cost and operational safety, which will determine the enterprise profitability.

According to these authors, the required investment to implement a TPM program is very high with the potential to yield a high return-on-investment (ROI). Through TPM's cooperative effort, job enrichment and pride are created, and from new attitudes, it can increase productivity and quality, beyond equipment life cycle cost optimization and broaden the employee's knowledge and skills. A word of caution, however, is that TPM cannot be applied to unreliable equipment. As a result, the company's first investment in TPM must include the expense of restoring equipment to its proper, reliable condition and then educating personnel in the proper use and care of their equipment.

3.3.6 Condition-based maintenance

Another maintenance approach (i.e., maintenance concept) for a PM program is Condition-Based Maintenance (CBM), which relies on condition monitoring and diagnostics (CM&D) processes. Some authors such as Amari *et al*. (2006) prefer to call it predictive maintenance (PDM). Fundamental concept for most PM programs is condition monitoring which entails data analysis, process monitoring, performance monitoring, inspections and functional testing. According to (IAEA, 2007) **condition monitoring** "*is continuous or periodic tests, inspections, measurement or trending of the performance or physical characteristics of structures, systems and components to indicate current or future performance and the potential for failure.*"

If an asset's condition can be estimated, that is, there is diagnostic data available, the next step is trying to estimate the remaining asset's life in the form of a prognostic. A traditional PDM/CBM cycle is depicted as the flowchart presented in Figure 3.12 .

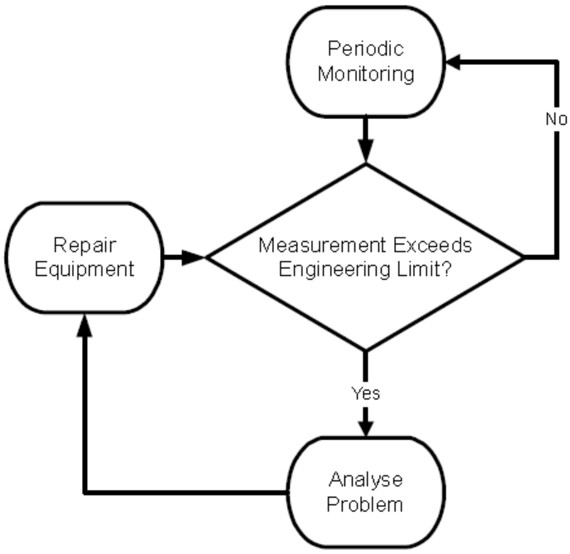


Figure 3.12 – Traditional PDM cycle (Amari *et al*., 2006:465)

According to these authors, in traditional PDM approaches, among the expected benefits are: (i) reduction in the total maintenance program cost; (ii) avoidance of very disruptive equipment outages; and (iii) reduction of costly PM activities when condition assessment shows no need of the scheduled maintenance.

An excellent approach to maintenance decision making in a CBM framework is presented by Utne *et al*. (2012). Among the insights in their article, they recommend the use of root cause analysis (RCA) to complement the FMECA analyzes, on the most critical failure modes identified. The authors provide a structured approach to improve condition monitoring of static equipment. Although it was applied to static equipment, their approach is so structured that it is considered here to be applied also for rotating equipment. Their proposed flow diagram for CBM decision-making is presented in Figure 3.13 .

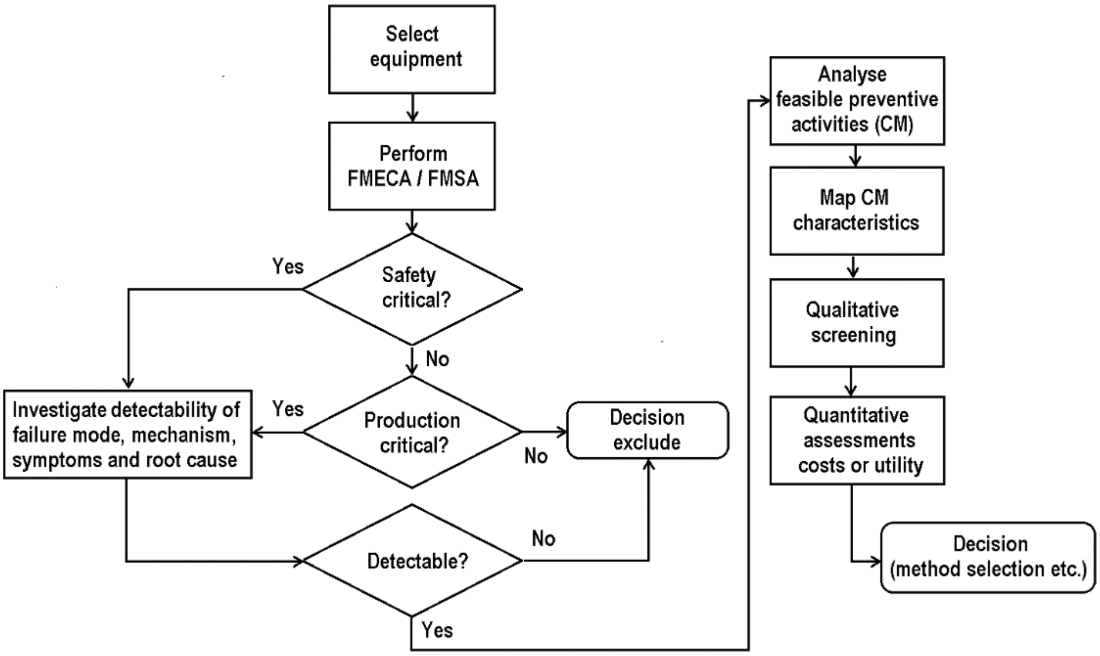


Figure 3.13 – Flow chart for a CBM decision model. Adapted from (Utne *et al.*, 2012)

3.3.7 Condition monitoring and diagnostics of machines

As stated, condition monitoring assessment is a building block of most PM programs. A good start is to obtain some industry consensus which can be found among the related international standards. The ISO 17359 (2015), for example, provides general guidelines and procedures for registration, evaluation and estimation of machine condition assessment. Within the petroleum, natural gas and petrochemical industries on- and off-shore the ISO 14224:2006 provides the basis for the collection and exchange of reliability and maintenance data (RM) for equipment. Also relevant are the reliability handbooks, such as the OREDA (2009) which provides reliability data from a range of equipment used in the oil and gas sector.

Diagnostic procedures should be adjusted according to the potential failures based on their likelihood and severity (ISO 13379:2003). The principle is shown in Figure 3.14 , representing the high-level concerns (maintenance: machine, risk assessment) and the low-level ones (measurements: monitoring, periodical tests, data processing). Each layer consists of a preparatory design phase (left) and a usage phase (right).

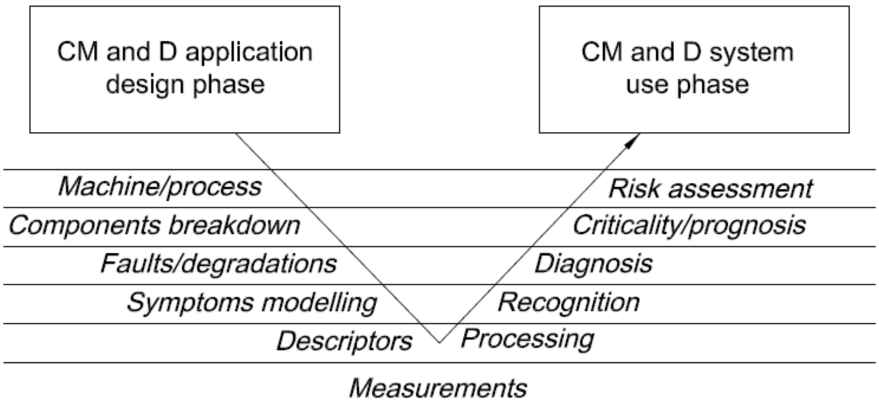


Figure 3.14 – The ISO's "V" analysis (ISO 13379:2003)

Most of the steps in the design phase, left branch in Figure 3.14 , may be followed using FMECA. In (Rausand and Høyland, 2004) there is an excellent description and procedure for this analysis. A primordial reference is the MIL-STD-1629A (1980). ISO standards also include a discussion on symptoms that can be observed in a Failure Mode and Symptoms Analysis (FMSA). The Condition-Monitoring and Diagnostics (CM&D) related activities are the enablers of a CBM program including data collection, data processing and decision. The ISO 13374 provides a data processing scheme as presented in Figure 3.15 .

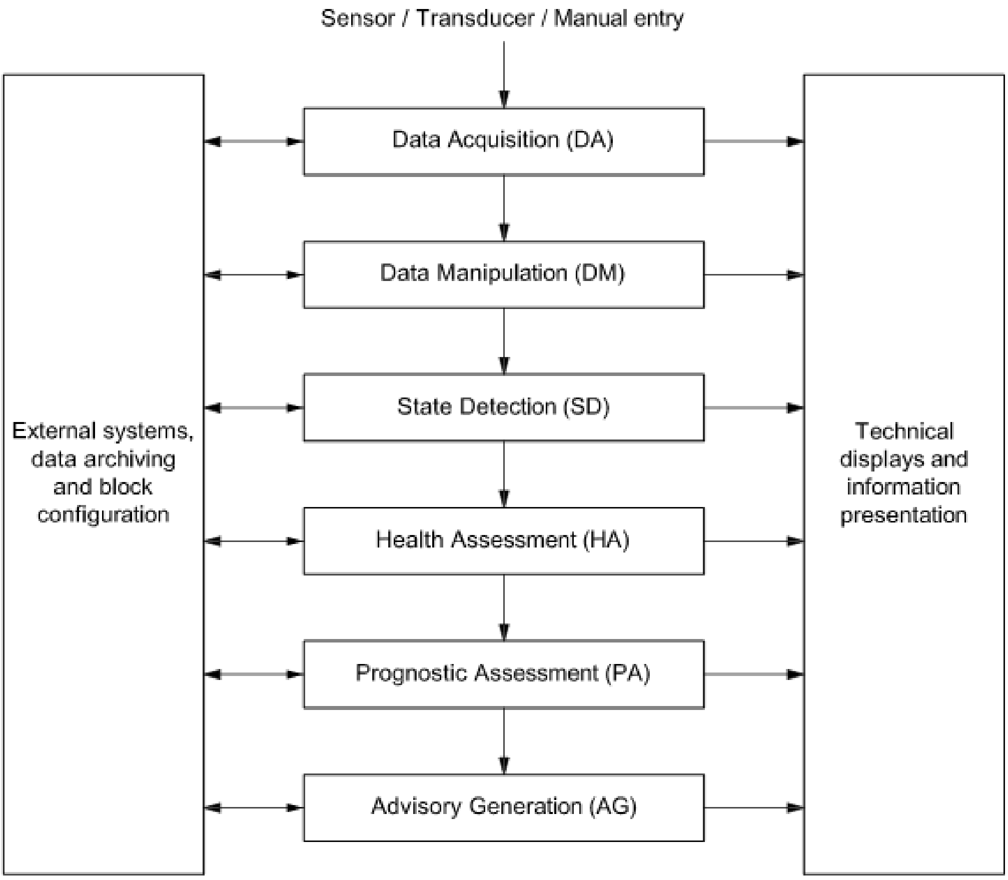


Figure 3.15 – Data processing block diagram (ISO 13374:2003)

As mentioned above, guidelines on using performance parameters can be found in the ISO’s standards. An example with a set of performance parameters for monitoring an aero-derivative gas-turbine engine, for example, is presented in Table 3.4 , which is from the Annex Table C.3 of ISO 13380:2002(E).

Table 3.4 – Faults indicated by performance parameter change (ISO 13380:2002)

Machine type: Aero gas turbine	**Symptom or parameter change**											
Fault	Compressor temperature	Compressor press/ press ratio	Air flow	Fuel pressure/ fuel flow	Speed	Gas generator temperature	Pressure/ pressure ratio	Power turbine temperature	Exhaust temperature	Vibration	Oil debris	Oil leakage/ consumption
Air inlet blockage	•	•	•		•							
Compressor fouled	•	•	•	•	•	•	•	•	•	•	•	
Compressor damaged	•	•		•	•	•	•	•	•	•	•	
Compressor stall					•		•			•		
Fuel filter blockage		•		•	•		•					
Seal leakage						•	•				•	•
Combustion chamber holed				•	•				•			
Burner blocked				•	•		•					
Power turbine dirty	•	•	•		•		•	•		•		
Power turbine damage	•	•	•		•		•			•	•	
Bearing wear/ damage										•	•	•
Gear defects										•	•	
Unbalance										•		
Misalignment										•		
• Indicates symptom may occur or parameter may change if fault occurs.												

To use the information presented in Table 3.4 , it is necessary to check with the experts the symptoms/failure correlations and to establish the decision criteria, i.e. the expected “parameter change” as a fault descriptor[3] or symptom. Additionally, it is necessary to establish, among others: (i) a machine base-line from which the changes (residuals) would be calculated; (ii) operating conditions during measurements; (iii) measurement intervals,

[3] Descriptor: Feature. Data item derived from raw or processed parameters or external observation (ISO 13372:2004)

data acquisition rate; (iv) an inference model for diagnostics and prognostics; and (v) data compression and storage parameters for the historian system.

3.3.7.1 Degradation models and the bathtub curve

For Dekker (1996) maintenance actions will only be efficient if they address the most relevant deterioration and failure mechanisms. Considering degradation (i.e. a reduction in performance, reliability or service life) as a function of factors such as usage, operational environment, aging etc., it can be seen as a stochastic process. In fact, the use of different stochastic processes to represent degradation and thus support decisions is a norm. In the field of water utilities, for example, Jirsak *et al*. (2014) proposed a model using a Hidden Markov Method (HMM) to represent the degradation of Rapid Gravity Filters (RGF). The system condition is presented in five states such as: Excellent; Good; Acceptable; Poor and; Awful. Since the information about condition will not be precise, they specified a belief distribution and algorithm.

Regarding offshore wind turbines, May and McMillan (2014) proposed a model using a Markov chain in a simulation approach to represent the degradation of turbine sub-systems. In the oil and gas sector, a case-study performed by Lundtofte and Solibakke (2014), presents a comparative study considering a Monte Carlo Simulation (MCS) model and the Markov method. This Reliability, Availability and Maintainability (RAM) study focuses on 3 sub-systems of a Floating Production Storage and Offloading oils platform (FPSO). The MCS, in this case, uses a flow network approach in combination with the next-event simulation. It assumes a constant failure rate for all components and the Time-To-Failure is modeled by the exponential distribution.

In the nuclear power sector, a case-study conducted by Saarela *et al*. (2014), presents a Remaining Useful Life (RUL) approach for air filters at a nuclear power plant where the degradation is modeled by the Gamma process taking into account condition monitoring and environmental data. In the space sector, the model proposed presented by Etiene *et al*. (2014) is a study for prognosis and health monitoring (PHM) applied in satellite systems. For the degradation of the phototransistors current drift, the Wiener process associated with an acceleration law is used taken into account the satellite temperature evolution due to the progressive degradation of its radiators.

In a case-study conducted by Welte *et al*. (2006) an integrated approach is developed using a Markov model to optimize maintenance and renewal of hydro-power components. The degradation process is modeled by a Markov chain as a time dependent solution considering imperfect periodic inspection where the length of the inspection interval depends on the system condition revealed by the previous inspection. The approach uses a four levels state definition such as: (1) No indication of degradation; (2) Some indication of degradation; (3) Serious degradation and; (4) Critical. The length of the states has an element of uncertainty and the Gamma distribution is used to model the duration of the main states. In addition, Monte Carlo simulation is carried out to verify results.

In summary, several stochastic processes can be found in model-based applications from different industry sectors. For more on stochastic processes the reader can consult a textbook, e.g., (Ross, 1996). As can be seen from the aforementioned applications, Markov related methods are amongst the most frequent approaches. Regarding degradation scales (i.e. the discrete state-space), several degradation scales and state definitions can be found, and they are usually of the form presented in Table 3.5.

Table 3.5 – Some typical discrete degradation scales

<table>
<tr><td rowspan="2">Ok</td><td rowspan="2">Ok</td><td rowspan="2">No indication of degradation</td><td>Excellent</td></tr>
<tr><td>Good</td></tr>
<tr><td rowspan="3">Failed</td><td rowspan="2">Degraded</td><td>Some indication of degradation</td><td>Acceptable</td></tr>
<tr><td>Serious degradation</td><td>Poor</td></tr>
<tr><td>Failed</td><td>Critical</td><td>Awful</td></tr>
</table>

A common visualization of the aging effect (e.g., the failure/hazard rate) along the life cycle of an asset, is the so-called bathtub curve. According to (Sikorska *et al*., 2011) the classical bathtub curve may be described as a function made up of Weibull distributions (with different values for its shape parameter β), each one representing an associated failure domain.

If a given operator's freedom for maintenance decision-making is analyzed under the classical bathtub curve, for example, see Figure 3.16 , during the *wear-in failures* period, such freedom may be very limited. In this phase, maintenance tasks must follow the recommendations from manufacturers/vendors normally due to warranty considerations.

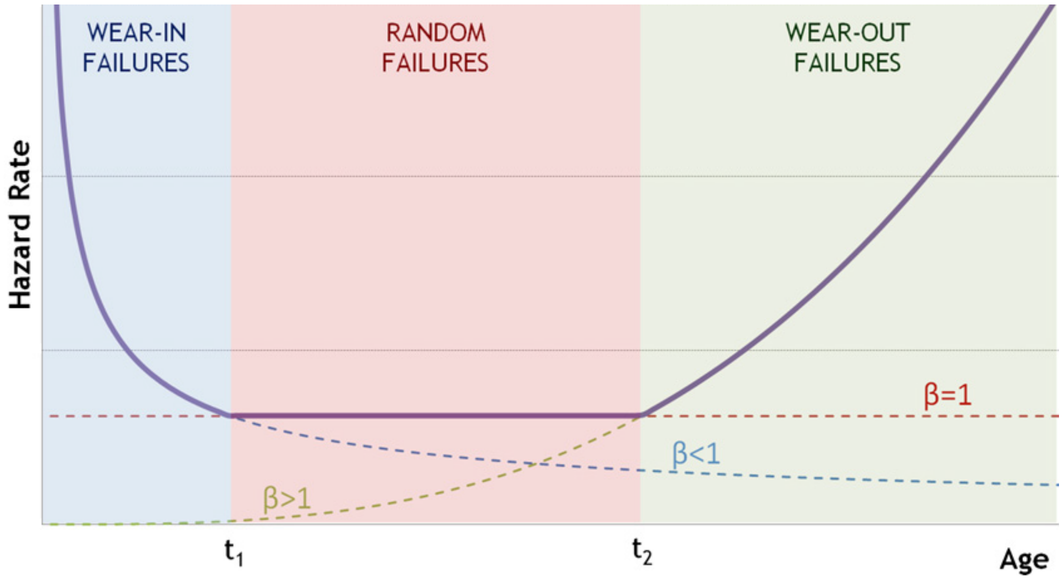


Figure 3.16 – Classical bathtub curve (Sikorska *et al.*, 2011:1817)

During the useful-life phase characterized by *random failures* (between t_1 and t_2), the freedom for maintenance related decisions normally increases with *random failures* and the respective degradation mechanisms introducing uncertainties and risks. In this phase, the use of degradation models becomes necessary for fault detection and diagnostics. In the *wear-out failures* period, beyond degradation models, obsolescence analysis should be included, and decision-making may be even more critical and/or restricted, depending on the alternative outcomes.

3.3.8 Maintenance trade-offs and optimization

As an important decision variable, maintenance costs represent a significant and determinant portion of the total operating costs (TOCs). This is a part of operational expenditure (OPEX), i.e. the expenses required to maintain physical assets in operation, in contrast with CAPEX which stands for capital expenditure. However, according to (Bret-Rouzaut and Favennec, 2011:198) "… the distinction between these terms is often imprecise […]. Some companies, for example, due to legal or fiscal reasons, prefer to rent equipment instead of buying, giving rise to operational costs instead of capital costs."

For decision-making purposes, it is important to consider that the decisions should be taken based on the costs assigned in the managerial accounting scheme only, not on the fiscal scheme. And the quality of these data will be one of the determinants of the decision-making performance.

Traditional maintenance optimization approaches are very often based on cost minimization. However, it is worth noting that, according to the experience described in this thesis (see Section 4.1), it may be very complicated to determine maintenance costs incurred from offshore operations, especially when it comes to discriminating preventive from corrective maintenance costs. Moreover, when it comes to correlate maintenance costs with failure events, for example, the granularity of the available reliability and maintenance data (RM) hides a trade-off between diagnostic model's complexity and its applicability. A balanced solution must be found, that is, a model suitable to the quality of the available data and vice-versa.

An important effect on average maintenance costs is related to the mean time between failures (MTBF). Considering the MTBF as a quality (i.e., reliability) measurement of a given maintenance regime, Van Winden and Dekker (1998) present a case that illustrates a tradeoff between the average maintenance costs and quality related to re-paintings of 500 buildings. For these authors: "*This is typically the kind of graph that strategic decision makers would like to have*." (Van Winden and Dekker, 1998:933).

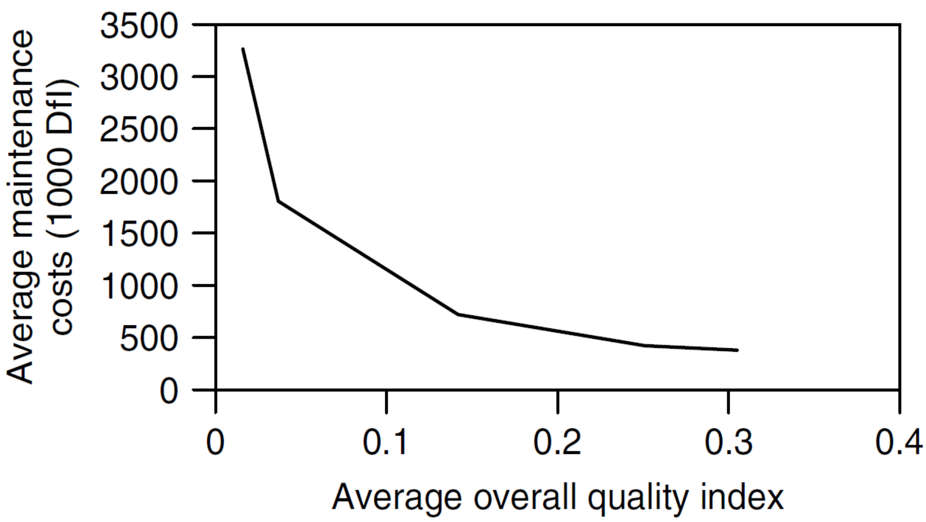


Figure 3.17 – Trade-off between quality and costs (Van Winden and Dekker, 1998)

Regarding the total operating costs of a complex engineering installation, a study provided by NASA (1995), presents the effect of changes in the nominal MTBF on the operating costs of a space station (see Figure 3.18).

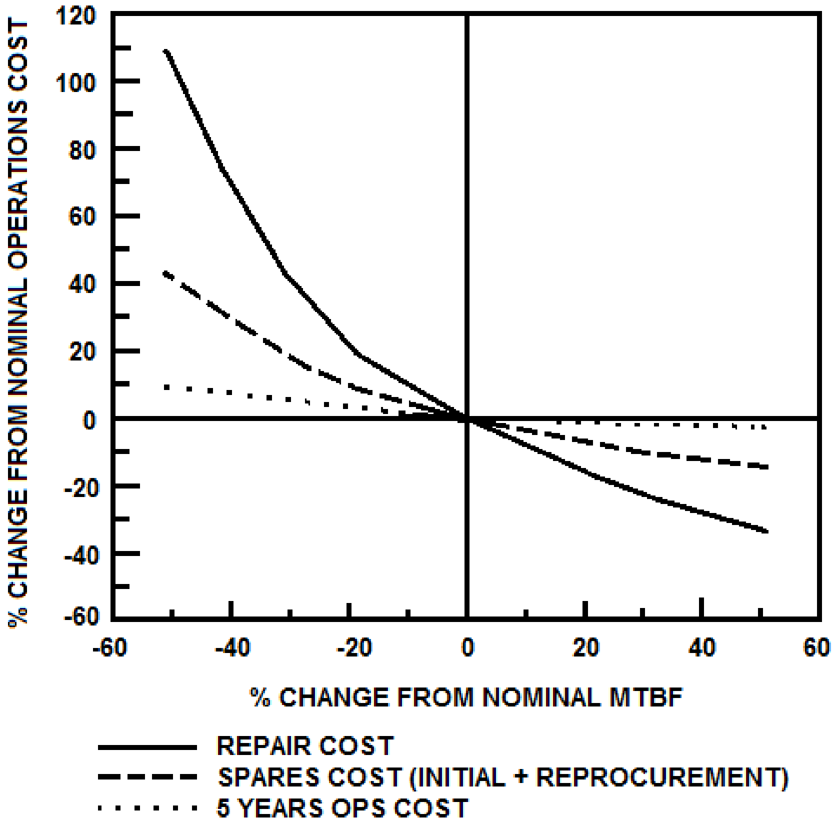


Figure 3.18 – The MTBF influence on operating costs (NASA, 1995)

What can be seen from the above is that, considering a nominal MTBF or MTTF as a threshold, when system reliability is below this threshold, the costs will increase at a much greater rate than it would decrease when it is above this threshold. This effect alone is sufficient to justify and also to adjust a preventive maintenance program.

On the maintenance optimization approaches, according to Dekker (1996), an essential part is the modeling of the deterioration and the occurrence of failures in such a way it is clear how both are influenced by the maintenance regime (i.e., maintenance policy). On the maintenance optimization objectives, they can be summarized under four headings: (i) system function (availability, efficiency and product quality); (ii) system life (asset management); (iii) safety; and (iv) human well-being. Ensuring the system function should be the prime maintenance objective for production equipment and applications of maintenance optimization models usually cover the following aspects: (i) description of a technical system, it functions and importance; (ii) modeling of the system degradation in time and possible consequences for the system; (iii) description of the available information about the system and the actions open to management; and (iv) an objective function and optimization technique that helps finding the best balance.

In summary, according to Welte *et al.* (2006:5) "the objective of maintenance optimization models is to find the maintenance and renewal strategy where the total costs of repair, inspections, production losses and other consequences are minimal."

In a survey into the field of rotating equipment for example, Heng *et al*. (2009) grouped the existing methods for predicting rotating machinery failures into three main categories, as follows: (i) traditional reliability approaches (event-based predictions); (ii) prognostics approaches (condition-based predictions) and; (iii) integrated approaches (predictions based on event and condition data). Traditional approaches to reliability estimations are based on the distribution of event records of a population of identical units and many parametric models, such as Poisson, exponential, Weibull and log-normal distributions have been used to model machine reliability.

In traditional approaches to maintenance optimization, according to Vatn and Aven (2010), the search is for a preventive maintenance interval τ optimizing the object-function $C(\tau)$, expressing the average total cost per unit time. The unit is renewed after time τ. Let PM_{cost} denote the cost of a preventive maintenance action and let $M(\dot{\tau})$ be the total expected cost of corrective maintenance actions.

$$C(\tau) = \frac{PM_{cost}}{\tau} + M(\dot{\tau})/\tau \quad . \qquad (3.1)$$

The cost term $M(\tau)$ depends on the specific model.

Let CbM_{cost} denote the cost of a condition-based maintenance action, triggered by the identification of the degraded state/condition, and CM_{cost} denote the cost of the corrective maintenance action triggered by the identification of a failed state/observed failure. Moreover let U_{cost} denote the unavailability related costs (i.e. loss production), V_d denote the visiting frequency of the degraded state, P_f the steady state probability of the failed state and the relation $\frac{\tau}{MTTF}$ representing the chance to find a failure in respect to the preventive interval.

$$C(\tau) = \frac{PM_{cost}}{\tau} + CbM_{cost} * V_d + CM_{cost} * \frac{\tau}{MTTF} + U_{cost} * P_f \quad . \qquad (3.2)$$

Figure 3.19 presents an example of the results when applying these kinds of approaches.

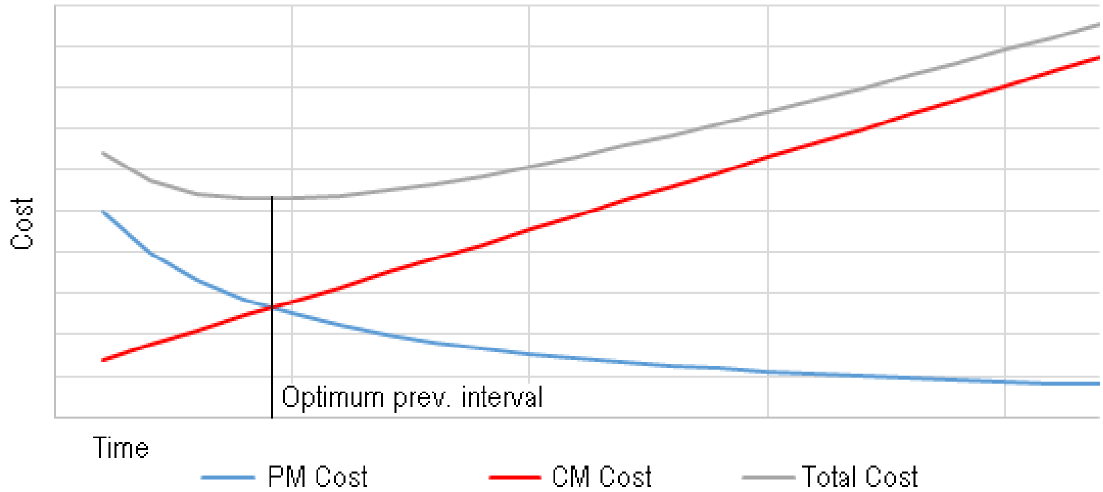


Figure 3.19 – Maintenance costs per preventive interval

3.4 The Markov analysis

According to Machado and Haskins (2016) among the most frequent analysis techniques used in recent maintenance optimization approaches are the Markov approaches. In fact, according to Brémaud (1999) Markov chains are omnipresent in the applied sciences and have found a privileged application domain in OR, reliability and queueing theory.

The Markov chain model was created by the Russian mathematician Andrei Andreyevich Markov, professor at St. Petersburg University. He lived from 1856 to 1922 and made significant contributions to the theory of probability. On the applications, according to Sheskin (2011), a large number of Markov models can be constructed for a wide range of processes including, for example, a waiting line, inventory control, component replacement, machine maintenance and a production line. Excellent literature on Markov chains can be found in (Ross, 1996) and in (Brémaud, 1999) and practical approaches of Markov Decision Processes can be found in (Sheskin, 2011) for example.

Markov models are well suited for deciding reliability characteristics of a system. Especially for small systems with complicated maintenance strategies. The Markov analysis is often chosen to model reliability and availability of a system. Such model allows for computing/estimating the following values (Vatn, 2007): (i) the average time the system is in each state (as basis for economic considerations); (ii) how many times the system in average “visits” the various states (as the need for spare parts, logistics and maintenance personnel); (iii) mean time until the system enters one specific state (e.g., a critical state); and (iv) system failure rate.

Discussion: Among the maintenance related decisions discussed above, it is possible to identify some aspects which are directly correlated with the Markovian approaches. In the classical definition of maintenance (presented in section 3.3), for example, a state-space and respective transitions are defined with desirable state(s) from which failure/degradation represent transitions toward undesirable states/conditions and the maintenance actions aiming to avoid these transitions, or to produce transitions in the opposite direction (restoration). This clearly suggests a Markov chain structure.

3.4.1 The basics of Markov chain

Let X_t denote the state of a process at time t. Assuming X_t as a random variable with $t \in Z_+$ and limiting such a process to visit some states $s \in S$ with $X_t \in S$, we have a *stochastic process* that will be found in one state i at time t if $X_t = i$. Each transition from i to j in one-step has a *transition probability* p_{ij}. If we assume that this process has the Markov property, that is, the probability of moving from i to j being independent of the states visited prior to i, we can now consider a transition matrix P, for which the Markov property holds, i.e.:

$$P_{ij} = P(X_{t+1} = j | X_0 = i_0, X_1 = i_1, \dots, X_t = i) = P(X_{t+1} = j | X_t = i) \qquad (3.3)$$

In other words, the present state provides all relevant information about the future behavior and knowledge about the past is not necessary. Another interpretation is that, *the future is independent of the past, given the present*.

Let p^n_{ij} denote the probability of moving from i to j in n-steps. A state j is said to be *accessible* from a state i if $p^n_{ij} > 0$. When two states are accessible to each other, they are said to *communicate*. Partitions of the process into communicating classes are defined by these probabilities, which implies that each state can only belong to one class. A communication class can be a *closed class*, if the process can only enter states in that class and never leave. If all states communicate, the Markov chain is *irreducible*. Thus, an irreducible chain is one in which it is possible to go from every state to every other state, not necessarily in one step. That is, all states in an irreducible chain communicate. In an irreducible Markov chain, the process can visit every state and some different types of states must be distinguished. A *recurrent* state, for example, is one to which eventual return is certain whilst a *transient* state is one to which the process may not eventually return. Now, assuming that the probability of re-entering state i, while starting in i, is f_{ii}, if $f_{ii} = 1$ that state is recurrent, and if $f_{ii} < 1$ that state is transient.

A transient state *j* will be visited a finite number of times whilst a recurrent state will be visited infinitely many times, provided that the chain has no *absorbing* states, which is a state that only communicates with itself. An absorbing state is a special case of a recurrent state *i* for which $p_{ii} = f_{ii} = 1$ (Sheskin, 2011). A Markov chain that enters an absorbing state will never leave it because the chain will always return to it on every transition. For finite Markov chains, that implies all the states cannot be transient, that is, every Markov chain needs to have at least one recurrent state. Now if the expected time until the process returns to the recurrent state *i* is finite while starting in *i*, then we say that *i* is *positive recurrent*. A state is said *periodic* if the process can return to some state *i*, while starting in *i*, only under some multiple *d(i)* of steps, where *d* is a positive integer $d > 1$. If instead $d = 1$ the state is *aperiodic*. Finally, states that are both aperiodic and positive recurrent are said to be *ergodic* (Lovsjö, 2015).

By applying the first law of total probability and the Markov property we have the so-called Chapman-Kolmogorov (C-K) equation,

$$P_{ij}^{n} = P(X_n = j|X_0 = i)$$
$$= \sum_{k\in K} P(X_n = j, X_r = k|X_0 = i)$$
$$= \sum_{k\in K} P(X_n = j|X_r = k, X_0 = i)\, P(X_r = k|X_0 = i)$$
$$= \sum_{k\in K} P(X_n = j|\, X_r = k) P(X_r = k|X_0 = i)$$
$$p_{ij}^{n} = \sum_{k\epsilon K} p_{ik}^{r} p_{kj}^{n-r} \quad , \tag{3.4}$$

where *K* is the set of all possible states, and *r* is a non-negative integer $r < n$. It means that the probability of moving from some state *i* to another state *j* in *n*-steps is equal to the sum of the probabilities of all the intermediate steps *k* between *i* and *j*. Now we can express the *n*-transition in form of matrix multiplication and if we let $P^{(n)}$ denote the matrix holding the probabilities for *n*-step transitions, eq. 3.4 implies that $P^{(n)} = P^{(n-r)}$. By induction, it can be shown that,

$$P^{(n)} = P^{n} \tag{3.5}$$

i.e., rising the one-step probability matrix to the power of *n* gives the probabilities of moving from state *i* to *j* in *n* steps. If a Markov chain has absorbing states, if it runs sufficiently long, the Markov chain will be absorbed by this state. On the contrary, if all the states are non-absorbing, we can say something about the distribution for a Markov chain as $t \rightarrow \infty$. For an irreducible ergodic Markov chain, letting $v_j = \lim_{n\rightarrow\infty} p_{ij}^n, j \geq 0, v_j$ is the unique non-negative solution of

$$v_j = \sum_{i=0}^{\infty} v_i p_{ij} \; , j \geq 0 \quad , \quad \sum_{i=0}^{\infty} v_i = 1 \quad . \tag{3.6}$$

This is a convenient way of representing Markov chains, since we can solve for the stationary distribution using the set of linear equations in eq. 3.6 instead of using eq. 3.5 with higher powers until we find convergence (Lovsjö, 2015).

3.4.2 The Markov decision process

As Sheskin (2011) states, Markov models can be constructed for a wide range of processes including, for example, a waiting line, inventory control, component replacement, machine maintenance and a production line, see also (Brémaud, 1999). With regards to the Markov decision process, some classical references are Puterman (1994) and Bertsekas (1995). The following exposition is based on Puterman (1994) with ideas derived from (Hernández-Lerma, 1989; Dekker, 2008; Sheskin, 2011).

According to Puterman (1994), Markov decision processes (MDP), also referred to as stochastic dynamic programs or stochastic control problems, can model sequential decision-making problems when outcomes are uncertain. The approach assumes the Markov property (eq. 3.3). The sequential decision problem is to choose, prior to the first decision epoch, a policy to maximize a function of a reward sequence. This function is chosen to reflect the decision maker intertemporal tradeoffs. According to Puterman (1994), possible choices for this function include the expected total discounted reward or the long-run average reward. A Markov decision process is a tuple (*S, A, P, r*), where:

- *S* is a set of states for the process to visit;
- *A* is a set of actions that can be executed at different decision epochs;
- $P: S \times A \times S \rightarrow [0,1]$ is a function that gives the probability of system's transitions to a given state $j \in S$, given that the process was in a state $i \in S$ and the agent decided to execute the action $a \in A$ denoted $P(j|i, a)$;
- $r: S \times A \rightarrow \mathbb{R}$ is a function that gives the cost (or reward) by choosing $a \in A$ when the process is in a state $i \in S$.

The set of decision epochs may be finite or infinite. The sets *S* and A_s may be either arbitrary finite sets or countable infinite sets, and actions may be chosen randomly or deterministically. At each decision epoch the system occupies a state *s* from the state space *S*. At a given decision epoch, the decision maker observes the system in $s \in S$, and may choose an action $a \in A_s$. Let $A = \cup_{s \in S} A_s$ and assume that *S* and A_s do not vary with time *t*. As a result of choosing an action *a* in state *s* in decision epoch *t*, two things happen: (i) the decision maker receives a reward $r(s, a)$; and (ii) the system state at the next decision epoch is determined by the probability distribution $P(.|s, a)$. Let the real-valued function $r(s, a)$ defined for $s \in S$ and $a \in A_s$ denote the value of the reward received in period t. When positive, $r(s, a)$ may be regarded as income, otherwise as a cost. One requirement is that its value or expected value be known before choosing an action, and not affected by future actions.

According to Puterman (1994:22) "A *policy*, contingency plan, plan or strategy specifies the decision rule to be used at all decision epoch. It provides the decision maker with a prescription for action selection under any possible future system state or history." Moreover, decision makers seek policies which are *optimal* in some sense. A policy provides the decision maker with a prescription for choosing actions in any possible state whilst a decision rule prescribes a procedure for action selection in each state in a specific decision epoch, i.e., a policy is a sequence of decision rules and decision makers seek policies which are optimal in some sense.

The goal in a Markov decision model approach is to find the sequence of actions that causes the system to perform optimally with respect to some predetermined performance criterion. Some issues (Dekker, 2008) in applying Markov decision models are: (i) identifying states and establishing the Markov property; and (ii) the state space can become very large, with consequences in the computation time. Indeed, as stated by Sheskin (2011), when an engineer decides to model a system using a Markov chain model, s/he occasionally assumes but cannot prove that such a system possesses the Markov property.

Three classical MDP solution methods are: (i) policy iteration (PI); (ii) value iteration (VI); and (iii) linear programming (LP). According to Dekker (2008), the VI algorithm can be faster than the PI algorithm if the matrix is sparse and only few transitions are possible. Among the most popular algorithms in dynamic programming, according to Hernández-Lerma (1989), the VI algorithm is easy to implement.

In this thesis, according to the discreteness of the solutions, where some structural characteristics that arise from multi-stage decision processes and the return associated with an activity is known only as a stochastic function of the activity level (Dreyfus, 1956), the dynamic programming formulation is considered using the VI algorithm as the solution method (see Section 5.5).

The dynamic programming algorithm induces a stochastic process (Markov process) and finds, by iteratively updating the value of every state in a fixed order, the sequence of actions that establishes the best result of the value function. Its convergence uses the concept of contraction of a Banach space, that is, a linear space with a defined norm. In addition, since the average reward criterion is the choice, i.e., without discount, it is necessary to determine when to stop calculating successive approximations. The convergence criterion is based on the *span semi-norm*, $sp(v^{n+1} - v^n)$, that is, for all $v \in V$, define $sp(v) = \max_{s \in S} v(s) - \min_{s \in S} v(s)$. This is a measure of how close a vector is to being constant. This proof can be found in (Puterman, 1994). In this thesis the Bellman equation is applied in the following form:

$$v^{n+1}(s) = max_{a \in A_s} \left\{ r(s,a) + \sum_{j \in S} p(j|s,a) v^n(j) \right\} \quad , \tag{3.7}$$

where $v^{n+1}(s)$ denotes value at the next state s, $r(s,a)$ is the reward received by choosing action a in state s, and $p(j|s,a)v^n(j)$ is the transition probability related to the action choice multiplied by the value at the previous iteration. The solution may be found by means of the VI algorithm as follows (Puterman, 1994:364).

Input: an MDP $M = (S, A, P, r)$
Output: π^*: an optimal policy
1. Select $v^0 \epsilon V$, specify $\varepsilon > 0$ and set $n=0$.
2. **For** each state $s \epsilon S$ compute $v^{n+1}(s)$ by eq. (3.7) Bellman equation.
3. **If** $sp(v^{n+1} - v^n) < \varepsilon$,
   Go to step 4, otherwise increment n by 1 and return to step 2
4. **For** each $s \epsilon S$ choose

$$d_\varepsilon(s) \epsilon \; argmax_{a \epsilon A_s} = \left\{ r(s,a) + \sum_{j \in S} p(j|s,a) v^n(j) \right\}$$

and stop
Return $\pi^* = (d_\varepsilon(s): s \in S)$

A MDP model development is proposed in this thesis (see Section 5.5).

3.4.3 MDP approaches on maintenance optimization

Among the maintenance related Markov decision models, several are applied to condition-based maintenance (CBM) approaches, where a condition scale is considered with a set of related maintenance actions. Stengos and Thomas (1980), for example, consider a maintenance and overhaul problem of identical blast furnaces and by using MDP techniques, they find the cost-related optimal policy for the case of two units. One of the results is that a specific cycle should be followed to reduce the probability that both items fail together.

Chen and Trivedi (2005) present a semi-Markov decision process (SMDP) approach to optimize condition-based preventive maintenance in terms of optimal policy and preventive intervals, considering three types of decisions: “0” no action is taken; “1” minimal maintenance is performed and; “2” major maintenance is performed.

Chan and Asgarpoor (2006) present a method to find optimum maintenance policy for a component using an 8-state Markov model with two actions: “do nothing” and “do maintenance” in respect to the optimum preventive interval.

Amari *et al*. (2006) provide a generic procedure to obtain optimal inspection schedules and maintenance decisions for *k*-out-of-*n* load-sharing systems in a cost-effective condition-based approach, using a 6-state condition scale and 4 different actions: “no action (NA)”, “minor maintenance (MM)”, “preventive maintenance (PM)” and “corrective maintenance (CM)”.

In the wind power industry, Wu and Zhao (2010) applied a semi Markov decision process (SMDP) to optimize preventive maintenance intervals in a condition-based approach related to wind turbine gear boxes. They represent deterioration in 7 states and considering 4 different actions, aiming to find cost-effective optimal policies, by using the policy iteration (PI) algorithm.

Ossai *et al*. (2016), on the other hand, develop a 6-state Markov maintenance model for components of wind turbines with a survival function, using Weibull distribution to establish the impacts of turbine components maintenance on down time and failure risks. The model is demonstrated using failure rates and downtime information obtained in the literature.

In the field of electrical power systems, Grillo *et al*. (2015) present a method based on MDP to optimally schedule energy storage devices in a power distribution network with renewable generation. Using a 14-state Markov model, optimal scheduling policies minimizing the cost of energy and network losses are obtained and published in tables as decision support documents.

When it comes to integrated production and maintenance approaches, it is worth mentioning the work of Aghezzaf *et al*. (2007). They consider a production system subjected to random failures throughout a specified finite planning horizon. The objective is to find an integrated preventive maintenance strategy that satisfies the demand and minimizes the expected sum of production and maintenance costs. By assuming that any maintenance action reduces, temporarily, the system's available capacity, they formulated and solved a multi-item capacitated lot-sizing problem on a system that is periodically renewed and minimally repaired at failure. An illustrative example shows the steps to obtain an optimal integrated production and maintenance strategy.

Traditionally, Markov models are developed to describe the aging phenomena of a technical component or system by some degradation/condition scale and the optimization is often based on progressive cost functions. Among the similarities of the proposed model with those mentioned above are: (i) it investigates the relations between time-to-failure and time-to-repair as in (Chan and Asgarpoor, 2006); (ii) it aims to generate tables for decision support in different scenarios as in (Grillo *et al*., 2015); (iii) it seeks for integrated production and maintenance policies as in (Aghezzaf *et al*., 2007); and (iv) its action sets comprises 4 different actions as in Wu and Zhao (2010).

In the MDP model development proposed in this thesis, the approach is somewhat simpler. For example, the definition of the state-space, instead of using condition, it follows the observable operational situations (i.e., *k*-out-of-*n*) of the parallel system as a whole, regardless the individual component condition. The planning horizon is infinite, and for the optimization we consider utility in the objective-function which is based on the capacity utilization in respect to a demand range and an adopted *prevention* level. In view of a scenario where it is difficult to determine maintenance costs, such as the offshore operation scenario, the concept of utility is an alternative.

According to Clemen (1996:463) “The whole idea of a utility function is that it should help to choose from among alternatives that have uncertain payoffs. Instead of maximizing expected value, the decision maker should maximize expected utility.”

The case study considered here refers to the same off-shore power generation systems treated by Machado *et al*. (2014) and Perera *et al*. (2015). In Section 5.5 , a prototype is developed by using the Markov decision process to optimize O&M policies of an offshore power plant which is discussed in Section 4.1, as a case study.

4 Field research

This chapter presents the findings from case studies, interviews and survey among experts in the offshore operations and maintenance of the oil and gas industry. The state-of-practices. Interviews were conducted in Norway and in Brazil, with focus on processes related to condition monitoring and diagnostics of machines (CM&D). Interviews' excerpts are presented in boxes coded with the interview sequential number and respective question number, for example, (I3Q4) means that it is from the third interview on question four. The summary of interviews transcripts is available in Appendix C.

4.1 Case I - A remaining useful life approach

Case I was conducted in the period (2010-2014) and is a Remaining Useful Life (RUL) model development approach followed by a reliability-based approach. RUL is a widely used approach for fault prediction, which aims at predicting or estimating how much useful life is left before a failure occurs. Following the definitions discussed in Section 3.3, it consists of a CBM concept. One motivation for this industry project was the fast-growing FPSO fleet of a major operator in the Brazilian continental shelf (BCS) and a need for improvements in the ability to avoid critical failures, mainly of turbomachinery, such as turbo-generators of main power generator systems. The main purpose of this study was to establish a RUL assessment for rotating equipment whilst evaluating the current machine data collection and operating policy of a major offshore operator. The following exposition is based on Machado *et al.*(2014) and Perera *et al.* (2015).

4.1.1 Description of Case I

An operational assessment and data processing and analysis (from field data/information) was performed and a prioritized list of subsystems and machine events was established. Starting from the operator's perspective, models for estimating related time-to-failure were developed and tested. Results, beyond the developed models, included a set of lessons learnt, and respective recommendations, including measures for, e.g., ways to improve data quality and machine event recording practices. The system of interest (SOI) in this approach is located on the main deck of an offshore platform operating in Campos Basin in Rio de Janeiro as presented in Figure 4.1 . This system is an offshore power plant with Turbo-Generators (TG) consisting of 4 aero derivative gas turbine engines connected to electrical generators (turbo-generators – TG) in a FPSO unit.

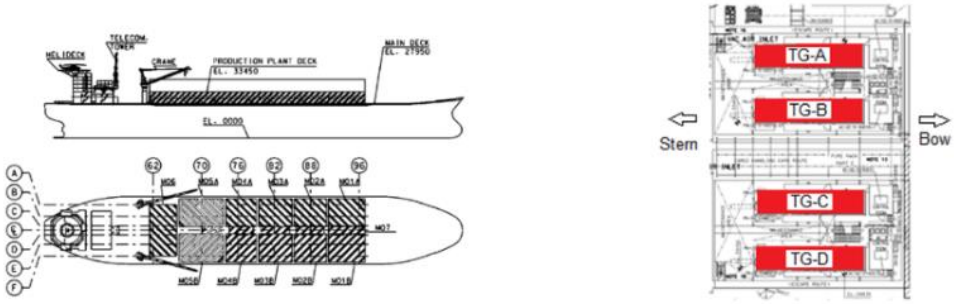


Figure 4.1 – Location of a power generation system in the FPSO

Each TG has a nominal capacity of 25,000 kW and two or more generators must be available, depending on the FPSO's actual demand. In normal operation, considering demands between 35 and 45 MW, for example, each TG's load is about 12 to 15 MW. Different O&M policies can be applied according to the present situation, that is, the relation between availability and demand. The technical characteristics of the system are to be considered, as presented in Table 4.1 and the operational characteristics in Table 4.2.

Table 4.1 – Technical characteristics of the Turbo-Generators

Name	Description	Unit/code
Type of driven unit	Electric generator driven by PT (gas turbine)	PT driven by gas turbine.
Power – design (ISO)	28.337 (38.000 hp) 25.000	kW
Power – operating	13.600 NORMAL CONTINUOUS	kW
Operating profile	Load sharing between TGs	
Speed	Normal - 4.800 / Max. continuum - 5.040	RPM
Number of shafts	2	
Starting system	Motor driven by two pumps of tree installed	Hydraulic
Backup starting system	None	
Fuel	Dual-fuel – operating mostly with gas	Gas or Diesel
Air inlet filtration type	High speed system	
Capacity [Turbine / Generator]	25 / 28750	MW / kVA
FPSO's demand range	35 to 55	MW
Power factor	0,86	MW/mVA

Table 4.2 – Operational characteristics of the power generation system

Operating regime	Basic mission 15 days of continuous operation
Demand profile	1 Off-loading at each 14 days (demand peak)
Utilization factor (average Uptime)	(75 - 81%)
# of operators off-shore	4 (in 12 hours shift)
# of maintainers off-shore	2 (in 12 hours shift)
# of engineers on-shore	2 (office regime)

The high-level analysis consists of the left branch of the ISO's "V" shape (see Figure 3.14) and represents the operator's assessment. In this study, more than 1500 work orders were assessed from the CMMS trying to identify the most critical subsystems of these turbo-machinery and a ranking of the subsystems of the turbo-generators were obtained as presented in Table 4.3.

Table 4.3 – Rankings of TG's subsystems (Machado *et al.*, 2014)

Turbo generators of the FPSO (2008 - 2012) [132.012 operating hours in 170.861 hours calendar time]			
System subdivision based on ISO 14224	**Maint. Costs** Correct.+ prev. [%]	**Interv. frequency** Correct.+prev. [%]	**Down Time** Corrective [%]
COMPRESSOR + HP TURBINE + POWER TURBINE	20	9	24
FUEL SYSTEM	17	13	21
LUBRICATION SYSTEM	13	20	12
EXHAUST	12	19	6
ELECTRIC GENERATOR	11	12	1
AIR INTAKE	9	2	0
MISCELANEOUS	5	8	19
CONTROL AND MONITORING	5	6	11
FIRE AND GAS PROTECTION	5	9	0
STARTING SYSTEM	1	2	5
ACCESSORY DRIVE	1	1	1
COMBUSTION SYSTEM	1	0	0

In summary, the subsystems that demanded more in terms of maintenance cost (registered in the CMMS) were turbine, fuel system and lubrication system. The subsystems that recorded the highest number of maintenance interventions (registered in the CMMS) were lubrication system, exhaust and fuel system. The subsystems that had more failures in the period (registered in the machine-event log) were fuel system, starting system and turbine and the subsystems that demanded more time to repair (registered in the machine-event log) were: turbine, fuel and lubrication.

In this case, by using Support Vector Machine (SVM) and Neural Networks (NN) over the machine event records and data from maintenance work orders, a set of Time-To-Failure (TTF) empirical models were constructed. Figure 4.2 shows the results of an SVM model, where 5% of the full data set was used for modelling, and the remaining 95% for testing. The test results are plotted sorted by days-to-failure so that a clear visual interpretation can be made, where both the actual time-to-failure (the smooth line) and the model estimation are shown. It can be seen that the model follows well the general trend even though it underestimates time-to-failure when there are more than 20 days to the next failure, and overestimates time-to-failure when this is below 20 days. The overall mean absolute error of the time-to-failure estimation over all the test data is about 11 days. The results, using a threshold at {RUL <= 20 days}, were considered promising although not conclusive. Some of the problems were related to overfitting. An example of results obtained with a TTF prediction model is presented in Figure 4.2 where the y-axis shows days to failure and x-axis the sample size.

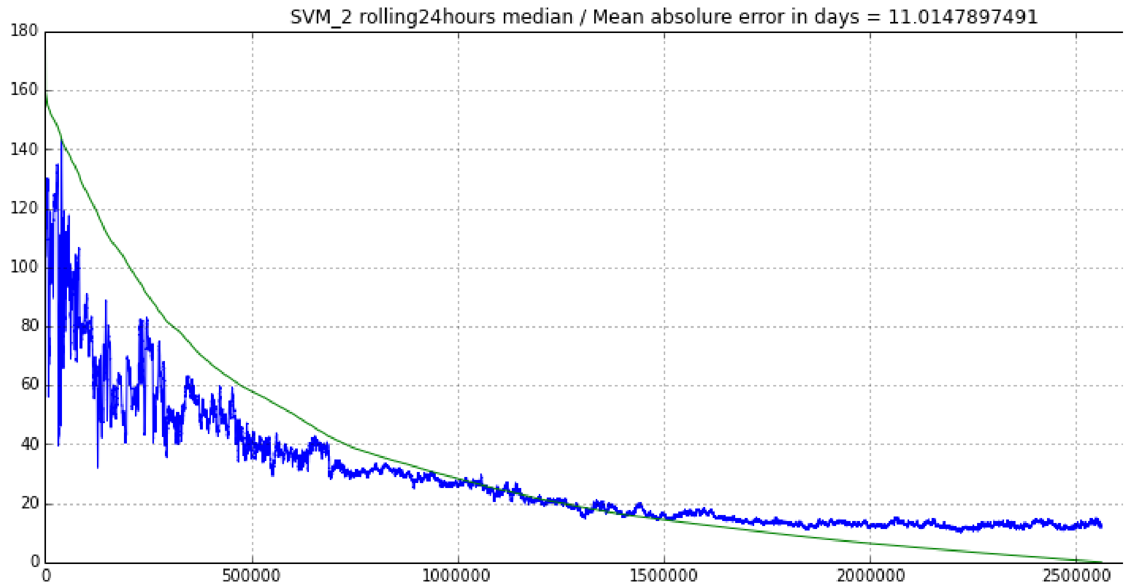


Figure 4.2 – TTF prediction model results (Machado *et al.*, 2014)

A second approach over the same system is presented by Perera *et al.* (2015) through a reliability-based approach using the machine event records and the automated counter of machine operating hours. From the analysis of these time figures for a gas turbine engine (TG-A), the Non-Homogeneous Poisson Process (NHPP) was chosen to represent the failure intensity of a repairable system under minimum repair policy. The approach has resulted in a model to determine the machine relative age. See Figure 4.3 .

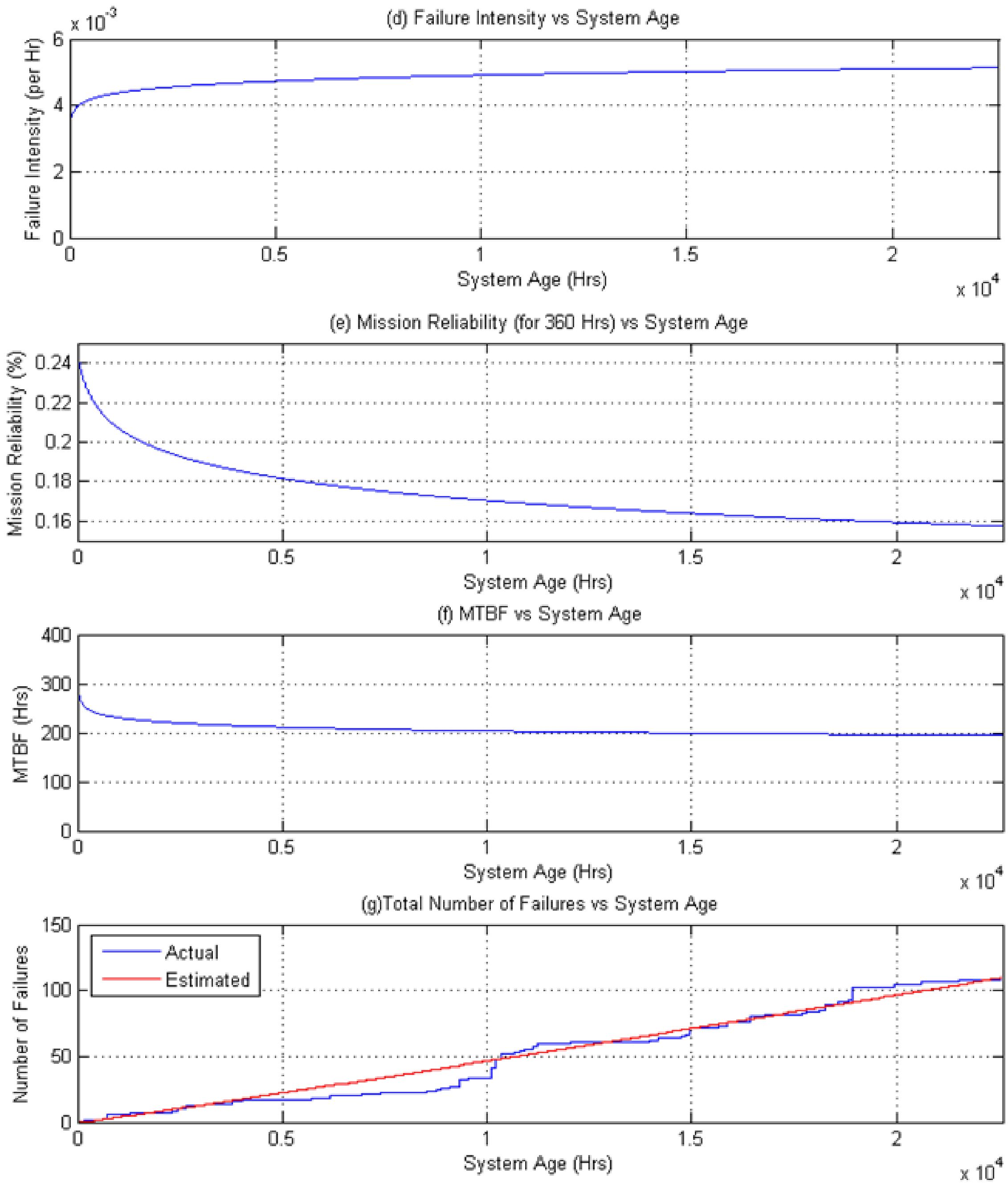


Figure 4.3 – Reliability estimates for TG-A (Perera *et al*., 2015)

4.1.2 Findings from Case I

The study demonstrated that there are some promising alternatives in terms of technical approaches to allow for predictive maintenance regarding critical equipment failure modes. However, the maintenance organization must orient its work and decision-process to diagnostics though a systematic data acquisition, processing and analysis.

Extracting useful information from the records in the CMMS, for example, may be seriously limited due to the inconsistency of the use and recordkeeping related methods.

Particularly in the offshore operational environment, it seems very difficult to discriminate the preventive from corrective maintenance costs and correlate these costs with failure events.

Improvements on data collection and analysis must be considered. It is recommended that the maintenance work orders are classified according to a common system (taxonomy), e.g., ISO 14224, and the same reference should be followed in the machine event's records. A unified taxonomy can facilitate the investigation to understand the failures and degradation mechanisms and correlate them with the respective costs and consequences.

An important aspect of the offshore operation is related to the notification of events. Failure events are observed offshore and must be registered, accordingly, by the operators offshore. Moreover, those records must be checked by the maintenance/reliability engineers onshore and only after this check should this data be archived (or persisted) to form the data-basis for subsequent analysis.

Another point is related to the monitoring sets of the historian and supervisory systems. Some important variables were absent from the historic data base, although that variable was collected by the supervisory systems for alarm purposes. A detailed evaluation should be considered when establishing these systems. PM programs would be well served by establishing common recordkeeping systems and criterion that permits failure events and associated costs to be easily extracted.

4.2 Case II - A lean production approach

This project was conducted in the period (2013-2014) and is a case of lean methodology applied to operations and maintenance management processes in the oil and gas sector in Brazil. Through a composite of lean tools and concepts, such as: process mapping, kaizen, TPM, 5S and root cause analysis, it was possible to achieve significant gains. Established between the E&P organization and a specialized consultancy firm, the effectiveness of this type of approach in the search for the operational efficiency in two gas processing facilities has been demonstrated. The connection between TPM and Lean is discussed in Section 3.3.5.

4.2.1 Description of Case II

The project aimed to increase and/or sustain the availability of critical machinery and thus enable gains in the overall efficiency of the processing plants, by seeking improvements in the work-processes that affect availability, including inventory management. Among the activities envisaged in the work plan were:

- Process mapping with initial diagnostics (AS-IS);
- Identification of improvement opportunities;
- Proposition and design of the future process (TO-BE) through the kaizen methodology and lean concepts;
- Establishment of performance indexes;
- Development of decision support tool (prototype);
- Implementation of the established actions "kaizen newspaper" and;
- Deployment and monitoring.

A visual representation for the relationships between operations, maintenance, materials and the availability is presented in Figure 4.4 .

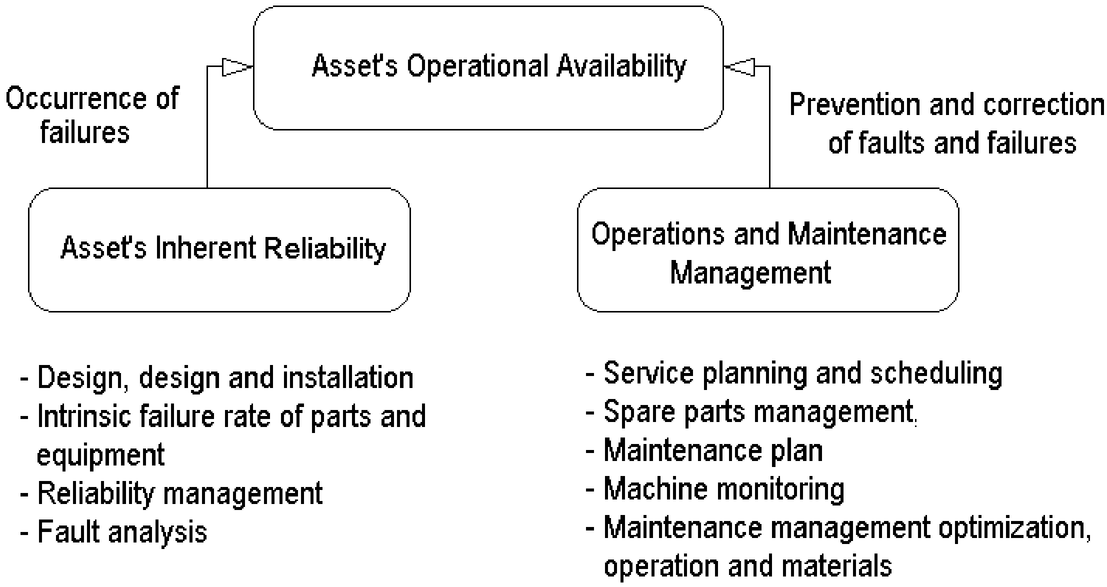


Figure 4.4 – Relationships between O&M management and reliability

4.2.2 Findings from Case II

It was found that lean production practices can help increase operational efficiency in a processes industry, such as the oil and gas. Improvements in machinery availability of 5.6%, spare parts stock availability of 35.0% and the fulfillment of the maintenance schedules of 6.5% were achieved in this project. Among other important improvements are: (i) expanding the planning horizon; (ii) promoting the integration of O&M functions and; (iii) improving the inventory management. The introduction of new organization of turbomachinery maintenance tools and the preparation of kits specific to each type of intervention, and 5S related practices (i.e., Japanese workplace organization method) may help explain some of the significant gains achieved. From the analysis of the work-processes, new practices were proposed and implemented in order to balance the activities among the different professionals involved. For example: the unpacking of parts was transferred to the materials technician, no longer burdening the turbomachinery maintenance team. Another issue that became clear was that it is possible to change the E&P culture in terms of broadening the horizons of planning; integration of functions and; improve materials management. As possible continuity lines: (i) develop a proposed decision support system; (ii) confront the proposed approach with the assumptions of total quality, the Toyota model and the pulled production; and (iii) include quantitative aspects of operations management.

4.3 Interviews and on-line survey

This section presents a summary of the results from interviews and the on-line survey conducted with experts in the field of offshore operations and maintenance. A non-probabilistic, purposive sample approach is used to support this research. Purposive sampling considers the concept of "saturation", or the point at which no new information or themes are observed. According to Guest *et al*. (2006), field-oriented research often uses purposive samples. In their article it is demonstrated that saturation may occur within the first twelve interviews, although basic elements were present as early as six interviews. Variability within the data followed similar patterns.

In this thesis, the interviews were used to validate the on-line survey results. Two mutually exclusive sets of experts have been formed, one for the interviews, with 8 participants, and other for the on-line survey, with 16 participants. The intention is to identify the state-of-practices regarding the maintenance decision-making processes with emphasis on the condition monitoring and diagnostics (CM&D) processes in order to understand how a major maintenance organization deals with the inherent flows of information in the offshore operational environment. From the interviews, the essence of different answers is sought to form a generic answer.

The participants are maintenance engineers, maintenance managers, chief engineers, maintenance specialists, and technicians with operational and/or managerial experience in the oil and gas industry ranging from 8 to 40 years. A summary of the current position of the interviewees is presented in Table 4.4 , with a full background description available in Appendix C. The small set of interviews was considered sufficient for the purpose, especially in light of the many years of experience represented by the participants.

Table 4.4 – Interviewees experience

Interviewee Nr.	**Current Position**	**Experience** [years]
1	Chief Engineer	35
2	Specialist Maintenance Engineer	15
3	Mechanical Engineer	25
4	Maintenance Manager	13
5	Research Manager	35
6	Maintenance Expert	37
7	Maintenance Manager	35
8	Turbomachinery Expert	32

The questionnaires (both for the interviews and the online survey) were prepared under five major headings as follows:

Axis 1 - Roles and responsibilities
Axis 2 - Maturity of the CM&D related processes
Axis 3 - Decision-making and learning
Axis 4 - Key performance indicators
Axis 5 - Barriers encountered and their recommendations

The questionnaires, the interview protocol and a summary of the interview transcripts can be found in Appendixes B and C.

The first question of the on-line survey is about the normative sources used as guidance by the maintenance organizations. Results are presented in Table 4.5.

Table 4.5 – Ranking of normative sources

Standardization organism	**Proportion**
ISO *	12/16
IEC/IEEE	4/16
API	3/16
ABNT, ASME, ASTM, NORMAN, NORSOK, OHSAS and SAE.	1/16

*(with mentions to ISO 14224 and ISO 550000)

On the ISO 14224 specifically, according to the survey:

SURVEY *“Currently ... Working on implementation of ISO 14224 compliant database.”*

This is consistent with interview respondents.

(I4Q11) *"We try as much as possible to stick to the ISO standards."*

4.3.1 Roles and responsibilities

Three questions are concerned with the roles and responsibilities of the agents, of a maintenance organization, in three different processes related to PM programs, such as: (i) data collection; (ii) data analysis; and (iii) technical interface with suppliers. A summary of the roles and responsibilities in the CM&D related processes, according to the interviewees, is presented in Table 4.6. Table 4.7 presents the roles and degree of involvement according to the on-line survey.

About the roles and responsibilities in the CM&D related processes, Interviewee #6 says:

(I6Q3) *"… vibration, temperature etc. So, we monitor if it is … within the right levels.[…] if things pass the different threshold, … Ok, this is for maintenance task. […] So, the measure is an important task that is really the competence of the Reliability Engineer…"*

First of all, a maintenance philosophy is needed for data collection and storage, according to Interviewee#5:

(I5Q1)*"First of all, on data collection, you need to have a philosophy right up the beginning of the concept design as to: "What kind of maintenance strategy you are going to have" And it's that choice of strategy which you will decide: "What kind of data you will need to gather"; "How often you will need to gather it" and "How long you will need to keep it". And a lot of companies haven't understood that.*
Who should be responsible, requires a maintenance philosophy to be established in the concept phase, concept selection. And of course, it has to be operations people who are involved in specifying that philosophy and the engineering team will give assistance on what is possible and what kind of things will be needed.
So, I would say that you need operators (including maintenance operations people) right early on the concept selection phase to work out exactly what kind of data is needed, and how often it is going to be sampled, and how long to keep it for, and what to keep it for.

For Interviewee#1, the IT department should handle the data collection and storage.

(I1Q1) *"Data collection and storage should be handled by the IT department, aiming to check if the system is running OK. That is, if the sensors and data collection and storage devices are operating properly.*

Everyone puts data into the systems, according to Interviewee#4.

(I4Q1) *"In This company everyone puts data into the system. The operators, mechanics, electricians. From the analytical perspective, we are sitting here onshore. We just receive the data from the offshore organization."*

Apparently, the ambiguity of terms remains.

(I6Q1) *"We have reliability engineers then setting up the risks, or let's say… the preventive or predictive maintenance part and the frequencies for that."*

About the disciplines involved in data analysis, the interviewee#5 mentions:

(I5Q1) *"I can see that probably need to be three disciplines involved. So, one would be Reliability specialists. Then, you would need some analysts who are able to handle the data. And it is very important to have the practical maintenance people involved so that they can see what should be done with the data. How realistic it could be and so on. So, I would say: the Reliability people, Data Analysis people and Maintenance people."*

A collaborative work that involves also the vendors, according to Interviewee#1.

(I1Q2)*...Data analysis should be handled by the Operation and Maintenance (O&M) departments working together to analyze data and find out algorithms to predict breakdowns. Vendors with specialized knowledge can only participate in this work."*

Discussing the roles and job descriptions, Interviewee #5 says:

(I5Q1) *"... one of the biggest companies in the world ...to give maintenance a better profile, because the image of maintenance has not been good unfortunately in the past. Top management doesn't really understand maintenance. They just see that it uses a lot of money. So, this company changed the titles of all the Maintenance Engineers and call them Reliability Engineers. And then suddenly it is a positive thing instead of a negative thing, because management associates maintenance with spending money just to keep something going. But they do understand some of them... at least reliability. Ah that's rather important. Uptime and Reliability.*
So, if you call someone a Reliability Engineer and it has a bit more credibility and a bit less baggage than if you call them Maintenance Engineer."

On grouping the key-competences, Interviewee#4 explains:

(I4Q2) *"We have a group in this company called Maintenance Management Analyzers. But, that group consists of a variety of competencies. We don't use the exact term as Reliability Engineer or... but let say... Maintenance Engineers. [...] Not everyone in the group do have the maintenance background either. Some of them are just good at SAP or it could be in automation, for example. But most of the people doing the analysis have a maintenance background."*

On the division of labor, Interviewee #1 says:

(I1Q6) *"Here it is important to establish a division of labor between on- and off-shore personnel. Big interventions/repairs (e.g. two weeks' shutdowns every summer) should be planned and assisted by the on-shore personnel (people on the beach), whilst small importance interventions/repairs should be handled by the off-shore personnel. The platform manager, for example, is involved in the short term and emergency related decisions."*

On the technical interface with suppliers/vendors, according to Interviewee#5:

(I5Q6) *"So the people off-shore. They are not going to deal with the suppliers.... And it's the onshore office who will take contact with vendors if that is needed. But obviously you can't have every onshore office doing its own thing. That is very expensive, so. All companies at their Head Office or from their operations base from the company, at that level HQ – they are going to specify what standards are required and what specifications are required. And they will also, if they are smart, negotiate Frame Agreements with vendors. The HQ works on that level. Setting up Frame Agreements in accordance with the specifications and standards that are required."*

Continuing…

(I5Q6) *"So it all depends on "Where it is, How big they are, What are the competence of their people.[…] so that the standards and frame agreements and specifications are set up by the HQ, the on-shore operations handles any problems or takes up negotiations if the quality isn't up the standards or it's not being delivered in time, and the off-shore people at all simply to execute. And if they can't execute or there is a problem, they report back to their on-shore operations office."*

Based on the interviews, Table 4.6 presents an overview on roles and responsibilities.

Table 4.6 – Roles and responsibilities in the CM&D related processes

Data collection	Data analysis	Interface with suppliers /vendors
• IT department; • Everyone; • Reliability Engineers; • Operations personnel (Offshore); • Headquarters.	• Data analysts (good at SAP-PM); • Maintenance Management Analysts; • Reliability Engineers.	• Onshore (big investments); • Offshore (small investments); • Head Office; land-based org.; • Frame Agreements by the Headquarters managers.

The results presented in Table 4.7 break out the role (professional) who most often was cited for performing a given process. The classification criterion is such that: for 1st place, the option with more votes is selected, followed by a 2nd place only if that option has at least 1/3 of the total votes. The proportions are indicated between brackets.

Table 4.7 – Roles and degree of involvement in three CM&D related processes

Professional Process	Reliability Engineer	Maint. Engineer	Maint. Technician	Maint. Planner	Plant Manager	HQ Manager
Data Collection	C (6/16)	R (6/16) S (6/16)	C (8/16)	S (5/15)	I (7/16)	I (10/15)
Data Analysis	R (13/16)	R (8/15) S (5/15)	C (11/16)	C (6/16)	A (8/16) I (7/16)	I (8/15)
Technical interface with suppliers/vendors	S (6/15) C (5/15)	R (8/16)	C (8/16)	R (7/16)	A (10/16)	I (8/16)

R – Responsible; I – Informed; A – Approval; C – Cooperates; S – Supports.

According to the experts in the on-line survey, the professional responsible for data collection is the maintenance engineer and the process is supported by the maintenance planner. Cooperation is the role of the maintenance technicians and the reliability engineer. Information is provided to the headquarters and plant manager.

On data analysis, according to the experts in the on-line survey, the professional responsibility is shared between the reliability engineer and the maintenance engineer.

Cooperation is the role of the maintenance technicians and the maintenance planner. Information is provided to the headquarters manager and the plant manager, who is in charge of the approvals.

On the interface with suppliers/vendors, according to the experts in the on-line survey, the professional responsibility is shared between the maintenance engineer and the plant manager. Cooperation is the role of the maintenance technicians (again) and the reliability engineer who also supports that, and information is provided to the headquarter manager with approval from the plant manager.

In careful review of the data from Table 4.7, one should consider the claim, from some experts (both from the interviews and the on-line survey), about a lack of management support. Apparently, following the classification criterion, none of the managers fulfill support roles, which can be considered a symptom of a system property that needs attention. Moreover, the role "support" presents a low level of consensus among the experts.

4.3.2 Maturity of the CM&D related processes

On the CM&D related processes, according to Interviewee#1:

> (I1Q3) *"Condition monitoring data are the inputs of our predictive models and it provides information to verify and calculate/estimate the outputs that will provide criteria for decision-making (e.g., Remaining Useful Life). […] The yellow light should turn on when there is e.g., 30 days left until you must stop."*

Some operators are not fully matured on the CM&D processes. As interviewee#4 has declared:

> (I4Q3) *"I wouldn't say that this company has gone very far within condition-based monitoring. We have for rotating machinery. I think that group is one that has come farthest. […] For other purposes, we are more into what I call it the investigating phase. ... trying to investigate how we could utilize CM data to tune our maintenance intervals and so on."*

It is confirmed by Interviewee#2:

> (I2Q3) *"I think one of the reasons why we are not really implementing or having CM implemented broadly across/into the organizations is that the organization is not matured enough to be able to actually utilize the information and have people which are responsible enough and would like to take those decisions."*

On the communication of diagnostics results, survey question 4 asks how the diagnostic results are communicated to the decision-maker. Figure 4.5 presents the results.

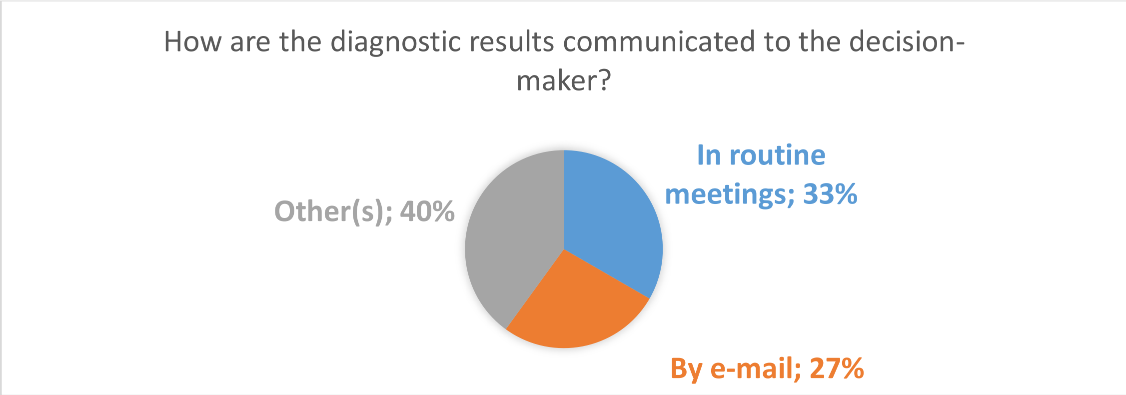


Figure 4.5 – Diagnostics' results communication

According to the experts in the on-line survey, 5 in 15 respondents mentioned routine meetings, 4 in 15 respondents mentioned e-mail/text message and 6 in 15 mentioned others means like: Process Information within DCS; by specialist system; Maintenance plan reports; dashboard, meetings, e-mail, mobile device; ERP SAP - PM module and audits. Another answer is:

SURVEY *"It depends. We have to analyze. If it is a critical failure in a critical equipment maintenance manager is communicated immediately by e-mail and in a meeting. If it is a failure which was detected earlier, engineers usually schedule repairs activities. In last case, managers are communicated in routine meetings."*

On the verification of diagnostics correctness, Survey question 5 is on the follow up of the results of every diagnosis. Figure 4.6 presents the results.

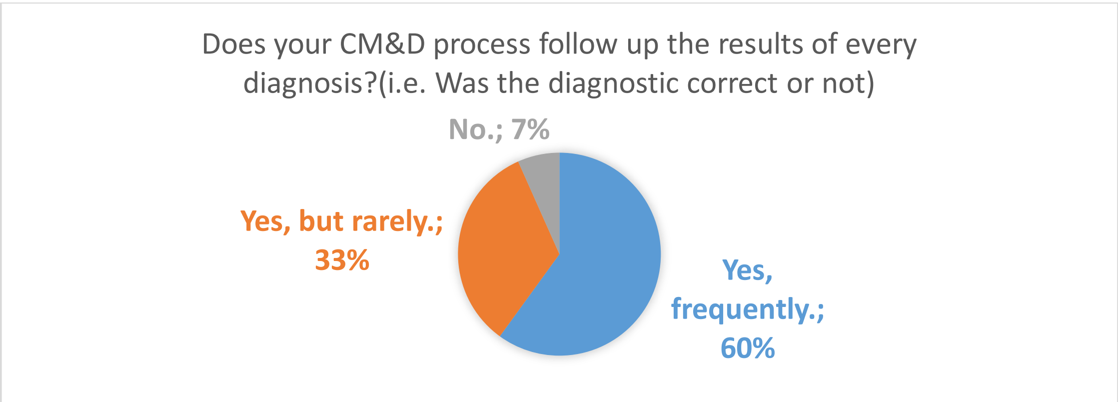


Figure 4.6 – Diagnostics' follow up

According to the experts in the on-line survey, 9 in 15 said "yes, frequently", 5 in 15 "yes but rarely" and 1 in 15 "no", that is, two thirds of the respondents frequently follow up the results of every diagnostics.

On the priority assigned to the maintenance related event's annotations, survey question 8 is on what kind of maintenance related events/issues are recorded for future consultation/analysis in three levels of priority. Figure 4.7 presents the results.

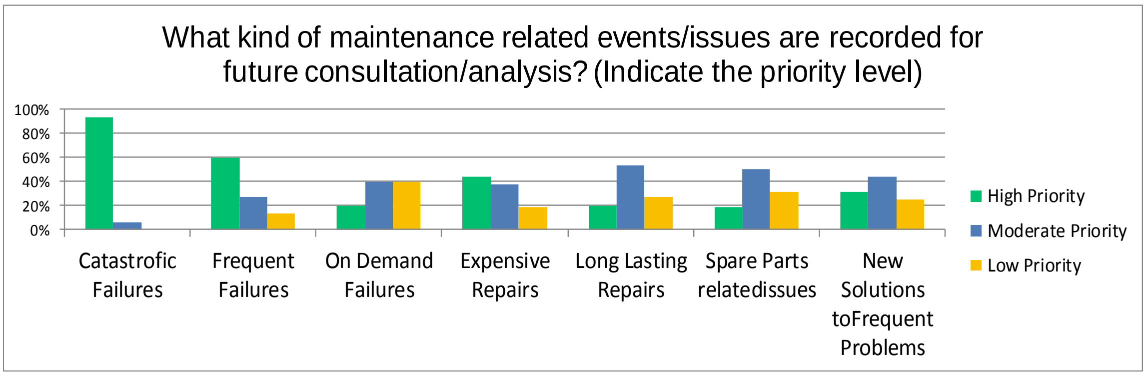


Figure 4.7 – Annotation priority for maintenance related events/issues

As expected, catastrophic and frequent failures are the high priority issues followed by long lasting repairs and spare parts related losses.

4.3.3 Decision-making and learning

Apparently, the first aspect to consider in a decision-making process is its fallibility, as stated by interviewee#2:

> (I2Q4) "*If you have to take many decisions each day, at some point you will miss out on something.*"

On the decision-making horizon and the lessons that can be learned, Interviewee#5 states:

> (I1Q5) "*Depending on the maintenance criteria (e.g. time-based, cycle-based or condition-based) there are, basically, two types of decisions: (i) Short-Term and (ii) Long-Term decisions. Some short-term decisions may be related to continuous monitoring systems, whilst some long-term decisions may be related to periodical monitoring (e.g. subsea equipment). The control room is manned 24/7 and handles short term problems, while the land-based support organisation (manned 8/5) handles more long-term projects. In summary: The process of dealing with these decisions, and its respective combinations, will provide the lessons.*"

About the teams and the silos within the maintenance organization, Interviewee#2 states:

> (I2Q5) "*…what we have seen in many cases is that when we get to the heavy rotating equipment (e.g. compressors, generators etc.) they have dedicated teams, working on that machinery and to some degree, those teams are on the side of the ordinary maintenance organization (maintenance planner and so on). Basically, the company has an organization for handling the maintenance as such, and then they have those small teams siting in their own boxes*"

It is confirmed by Interviewee#4:

> (I4Q4) "*For general maintenance I am afraid I have to admit that we are pretty much stucked within a calendar-based maintenance. Unfortunately, we do not use, at the moment, Condition Based Data at a very large extent.*"

In addition, on sharing information and knowledge, according to Interviewee#5:

(I2Q5) *"But then you handle that equipment in a separate silo, and you don't get that information between the domains, so basically you end up with having... let's say, the Maintenance and the CM domain within the same company. This are, to a limited extent, sharing their knowledge and their approach. That is, or maybe, the most interesting part for the company to see that OK, how are we actually working within those different domains? How can we utilize the skills and the knowledge of the CM silo? That is, the persons siting there having to (i) read info, (ii) interpret information and (iii) make decision from it. And then, how do you take that same thinking over to the maintenance domain?"*

The lack of a process for lessons learning is mentioned by Interviewee#4:

(I4Q5) *"I think we... are describing ...to get there, but we are not there yet. We have started to investigate how could we use Condition Based Data to tune our maintenance or to make decisions but, at the moment, we are not doing it. So, we haven't lessons learned. It is not very present yet. I think that is the Phase 2. We are still on Phase 1."*

On the potential for improvements on the decision-making process, interviewee #5 states:

(I5Q3) *"I think that there is tremendous potential and room for improvement in this role decision-making process. So, at the moment, in the worst cases, and a lot of companies are in the worst case, people who have the data and they work out what they want and...the better people use a Life Cycle Evaluation. So that you can list, in your presentation... you can present of 2 or 3 options, you have to show to the management that you have one preference and that you have considered 2 other things and, in general, managers will always go for the lowest cost solution."*

On the systems for decision traceability, for example, interviewee#1 states:

(I1Q4) *"All of the oil and gas companies have today some kind of system that can provide decision traceability (e.g. CMMS, ERP). Maintenance costs money and needs to be justified somehow."*

When the decision sequence is re-assessed in order to verify performance, Interviewee#5 mentioned:

(I5Q4) *"...some people call that "a Regret Analysis". So, you go back in time and look at the decision that were made and see if they were good or bad. There can be a lot of good learning from doing that."*

According to Interviewee#6 the CMMS (i.e., SAP-PM) data-base is an important component:

(I6Q4) *"... important feature for us is to have everything into the SAP. So, the technician goes on the platforms and finds something that is wrong. Or the reliability engineer looks [...] and something is wrong, and a notification is made that triggers off, depending on the criticality of this equipment ..."*

On the decision-making traceability, survey question 6 is on how the maintenance decisions are registered and made available for traceability. See Figure 4.8.

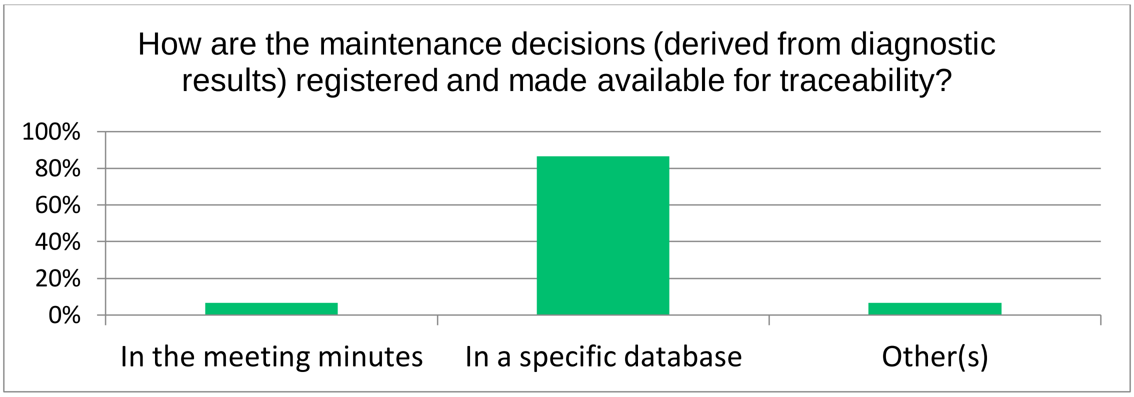


Figure 4.8 – Aspects of maintenance decisions traceability

According to the experts in the on-line survey, 1 in 15 respondents mentioned "meeting minutes", 13 in 15 mentioned a "specific database", and 1 in 15 mentioned "others".

SURVEY – *"The data management system is also the location of the maintenance record and source of the knowledge inventory for the community involved in the Activity; During audits; It should be registered in a specific database. We hope to have that in the future."*

On the presentation and analysis of decision alternatives, one word of caution, according to Interviewee#5 is:

(I5Q3) "*... you can list, in your presentation [...] 2 or 3 options, you have to show to the management that you have one preference and that you have considered 2 other things and, in general, managers will always go for the lowest cost solution. And if you want to propose the one that is the second lowest cost, they will fight that. They will make you justify it. So, you have to present your case based on Life Cycle Costs that even though it might be the more expensive solution at the beginning, the total of the costs of the next years, that maybe the cheapest solution in the first place."*

And another important aspect is related to the necessary skills for the engineers to defend and justify their preferences in the presentation of alternatives to the decision-maker.

(I5Q3) *"Because there seems to be no standard model for presenting this. And so, some engineers [...] it will come down to 2, 3 or 4 slides on a power point presentation. And that is the only thing that the management will have time to look at. [...] There are some few engineers who are very good at that. But the majority of engineers are not good at that. [...] very often the company will not pick the best solution because the decision-making process has not been treated seriously enough."*

4.3.4 Key performance indicators

According to the interviews, the more frequently monitored maintenance KPIs and some related aspects are:

- Planned and unplanned downtime (very important);
- Maintenance backlog (easy to count);

- Vibration and oil analysis (experts only);
- RUL estimates wanted (broadly understood);
- OPEX and NPV (broadly understood).

A discussion on the sets of KPIs and the possible reasons for the choice is provoked by Interviewee#2, as follows:

(I2Q7) *"The most commonly used KPIs are those related to the number of work ordered issues and the number of work orders (WO) completed within due date and so on. I don't think they are used mainly because they are providing a good tool for the organization as such. It gives you an idea of the figures, and... Do we have a backlog? And so on. In that respect, you know if you are coping with the maintenance plans. But, the main reason why I think it is the most commonly used indicators is that it is that data which you have easy access. Basically, if you run a query from your maintenance management system (CMMS), then it is very easy to count"*

And again, the maintenance backlog is an issue, also for Interviewee#4:

(I4Q7) *"Preventive maintenance backlog .... Overall corrective maintenance portfolio and ... failure fraction for safety barriers... But, regarding maintenance it is most on backlog hours in our portfolio."*

On the maintenance KPIs, Interviewee#5 states:

(I5Q7) *"Uptime and Down time. And planned Down time and unplanned Down time. Those are the things that you need to see. To see whether the operation is working in accordance with the plan or if it is just bouncing along from one crisis to another."*

And continuing the discussion on KPIs:

(I5Q7) *"You could probably divide that answer into two different categories of information. So, in any process, there are measurements of pressure and perhaps flow and temperature, in order to control process. So, that is if you like process data, and it is going to be there any way. Even if the design on concept selection was absolutely hopeless ...and the process has to work so they will be specified - pressure measurements and temperature measurements and maybe flow measurements any way. That is a very valuable information. You have that from the process information side. And then on a CM traditionally rotating machines have always specified things like temperature of the bearings and of the lube oil and vibration levels. Temperature and vibration. And on electrical motors you also have the temperature sensors in the motor windings to tell you whether something is normal or if the temperature is increasing."*

And considering machinery performance indicators, interviewee#8 states:

(I8Q7) *MTBF and performance parameters. When an equipment presents an acceptable performance, it is kept in operation and from the moment it falls below an acceptable level you intervene. But we have used other parameters that we have learned over time. One is the number of hours per startup. ... But unfortunately, not all equipment has hour meters and counters. The startup is a critical moment. A machine that is submitted to many startups normally has more frequent failures.*

On specific CM indicators for some critical machines and systems, Interviewee#1 states:

(I1Q7) *"For Compressors and Pumps we frequently monitor performance parameters, for Hydraulic systems – Leakage and fluid consumption; and for Power systems – Insulation resistance."*

A target related to PM compliance for a major operator, according to Interviewee#6, is as follows:

(I6Q7) *"PM compliance and the plan …. this should be according to plan more than 95% of it should be that… then as a part of our goal is to come up as high as possible."*

On the same topic, the on-line survey question 10 asks for the most frequently monitored maintenance key-performance indicators. As result, Figure 4.9 presents a maintenance KPI ranking.

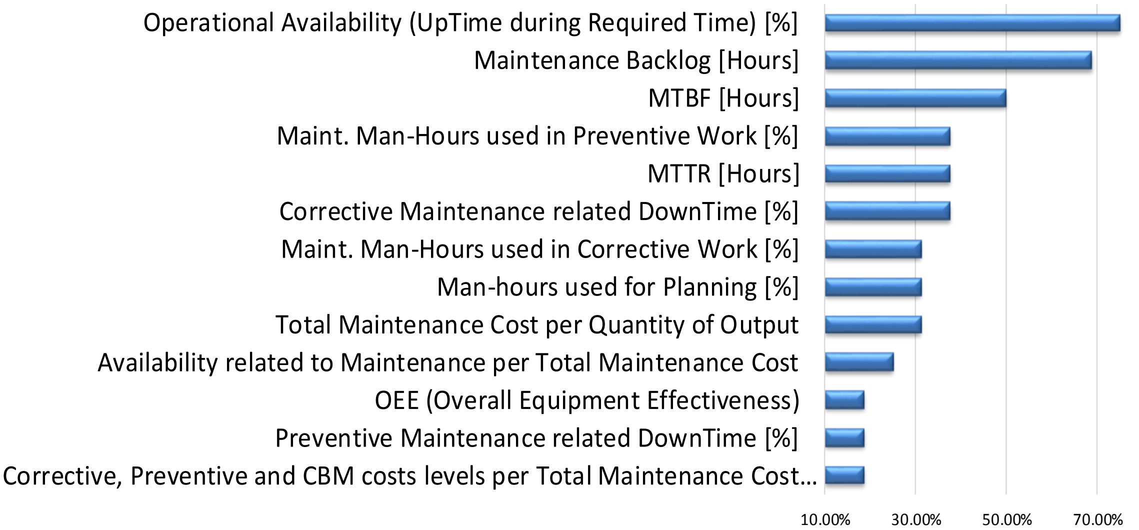


Figure 4.9 – Ranking of maintenance KPIs

Among the emergent aspects revealed in the ranking presented in Figure 4.9, it can be observed that, the Operational Availability, the MTBF and MTTF, which were ranked in 1st, 3rd and 5th positions respectively, are reliability consequences whilst Maintenance Backlog (confirming the interviews) and Maintenance man-hour used in preventive work, which were ranked in 2nd and 4th positions, are actions open to management, i.e., decisions.

Another aspect to observe is the indicator of Man-hour used for planning, which was ranked in 8th position. Moreover, the Overall Equipment Effectiveness (OEE) appears in the 11th position and the Preventive Maintenance related Down Time occupies the 12th position. That may suggest, for example, the need for more planning and prevention.

4.4 Diagnostics summary

This section discusses some of the influencing factors in the CM&D related processes, from the main results of the interviews and the on-line survey.

4.4.1 Factors affecting prevention

The negotiation to obtain room/accommodations offshore for preventive activities is a difficult task, since the production targets may be settled in terms of production volume m^3, that is, apparently, production quality tends to be neglected, in the offshore operational environment.

Some operators assume, without further assessments/discussions, that preventive maintenance plans, if they are proposed by the manufacturers, are over-dimensioned. That assumption may be correct in some cases, but it can also create an atmosphere of conflict among the O&M personnel.

For a maintenance decision-making process to succeed, the huge amount of data available from current industrial equipment, once collected, will require a considerable analytic effort and criteria in the use of models, in turn, widely available in the literature.

One benefit of a CBM approach, frequently mentioned in the literature is the reduction of the amount of preventive maintenance and, if so, the avoidance of maintenance-induced failures. This argument can be used for the good but also for the bad. It may be used as a perfect excuse for doing nothing when it is convenient. “Let us keep monitoring and see what happens.” If the asset survives, it is ok but if not, the maintenance organization is back to the reactive world and the firefighting staff have room again.

4.4.2 Factors against decision analysis

The efforts devoted to decision analysis are, in most of the cases, disproportionately less than those spent on data collection, modeling and analysis. What ends up happening, in those cases, is that the reduced effort dedicated to decision-making (e.g., with 3 or 4 slides and little discussion) often leads to the so-called "greedy solution” (i.e.: the one with the lowest cost in the short term), thus normally providing suboptimal returns in the long run. That situation often results in criticism and dissatisfaction on the part of the decision makers, regarding the validity and applicability of the models and, on the part of the maintenance/reliability engineers, as to the value and support given, from management, to the processes of data collection, modeling and analysis.

At the end of the interviews, question 12 asks if there is anything to add and the Interviewee#5 was the only one to bring an additional discussion, as follows:

(I5Q12) -*"There are clever people in the CMC. I think that is a great deal more that can be done. And my personal belief is that a lot of the problems could be avoided, ... I think often when a field is discovered, and the operator sees how much money can bear under that from that start date. I think there is often a tremendous pressure to just implement, the old-fashioned way of doing things. So, and yes what do we need? Let us put the platform there with the topsides and we have a drilling platform and we will have a production platform, will have a gas separation platform if the water is shallow. And I think, that if… and it requires smart people with a better vision (with a lot of vision) and the terrific ability to sell their case…*

And if those solutions have been rejected and a more ambitions field development concept have been chosen, to keep the development subsea and to go for multiphase, then you can have interchangeable, you can have subsea units that you can pull up and replace as time requires. And you do away with all this nightmare of steel and cables and electricity in a salt water spray environment which is going to cost an absolute fortune to maintain. So, there are so many examples of it. Even now big companies in Norway. I don't have access to data, but I think there were smarter solutions available. Some of the very, very bold decisions that were made, for example.

The T_ gas field is a very good example of this. So, it was very, very close to be a huge Off-shore gas production installation. And one or two people with terrific vision, made themselves very unpopular and said ---No It would be ridiculous to have a full gas processing facility offshore for Troll. All you need is an offshore well-head platform in effect and sending the gas to shore and have all those facilities onshore. And that's what happened. So, the Troll gas platform offshore is a relatively simple platform and you have K_.

And that used to be called a project which is a S_ project, and there was the T_ offshore group that did the offshore platform and there was the Troll onshore group that did the onshore facility. And if you look at the scale of that K_ gas plant onshore on the west coast of Norway… just imagine if that have been offshore on a separate platform or several platforms, just how much more it would have costed to keep that running than it costs presently when it is onshore. That was a very good decision.

And another good decision was O_. Because the O_ gas project could also have been an offshore platform or an offshore complex. But no, the gas is sent from subsea. There is no platform offshore in O_. It is sent directly from the well head through flow lines to shore and treated onshore on A_ at N_ gas plant the O_'s gas plant.

And those are examples of things that would increase the payback of the project dramatically. Even if the numbers don't show it. By avoiding these nightmares of trying to keep old platforms that are rusting and unreliable and then with structure integrity problems. A complete disaster.

So that would be the last point I would than … think much more about subsea and multiphase solutions in the concept phase instead of lumbering ourselves with these old platforms from the steam age. That is what we did in the 50's or 60's. At the end of the steam train era. That is where I put these platforms. And we are still doing it. I am amazed really."

4.4.3 Factors against modelling

The granularity (i.e., quality) of the available reliability and maintenance (RM) data may hide a trade-off between model complexity and applicability. There must be found a balanced solution considering model complexity and of data availability and quality. In summary, on the suitability and use of models, Interviewee#5 says:

(I5Q6) *"Well it's a simplification of life and it could be over simplified and then it is useless. Or, it could need a lot of data, which we don't have. Which makes it useless as well. So … do we have a model which balance those different aspects?*

That seems to be a frequent problem, that is, the reliability and maintenance data (RM) does not match with sophisticated models. Apparently, a staged approach may be appropriate and simple models are to be pursued.

4.4.4 Barriers encountered and recommendations

On the barriers encountered in the implementations of PM programs and CM&D related processes, Interviewee#1 clarifies:

(I1Q8) *"Data collection is the easy part. The analysis to provide the Remaining Useful Life (RUL) estimates, for example, that is the difficult one. The obstacle is to prove that CM/CBM can save money for the oil companies. Once we can prove that we can actually do some good in this area, there will be no obstacles (cost benefit analysis). …We must research more on that in order to improve our analytic and predictive capabilities. That is, looking into the future and finding "How to detect breakdowns in advance?" In addition, Fault Tree Analysis (FTA) and Cost Benefit Analysis (CBA) should be included in that process. We should focus on the most common causes for breakdown, such that we focus on the aspects where there is most to be gained. If you are able to demonstrate clearly, the costs and benefits of the alternatives, it is normally easy to get key support."*

On the commitment to the decision-making process, Interviewee#2 states:

(I2Q8) *"…most of these barriers are on the mental mindsets. To take that fairly easy concept of having a fixed schedule and then turning over to a CBM regime … digging into the data which we gathered from that we might have to issue Work Order where we have uncertainty and we can't give any guarantees. And to have a management which is committed to do that change. I haven't seen that so far. In any of the companies, which I have been involved in.*
Since the CM' guys are sitting in their silos only working within a very limited domain, those people seldomly become the managers of the entire maintenance domain. So, their knowledge won't be at the top and then spread out in the organization. Most of the maintenance roles are covered by personnel which are trained within a traditional PM (Project Management) program set-ups and they are familiar with that and, when

you are familiar with something it is a sort of comfort zone. Having a management, which is eager on doing that change. I haven't seen... frankly"

For Interviewee#8:

(I8Q8) *The biggest barrier is our managers, because we do not have, especially in E & P ..., we have found people who are not from the area. They don't know about maintenance ... firefighters. So that's very clear. ... E & P in this respect, doesn't have a defined policy, then, really, the initiative ends up being, thus, isolated and often discontinued.*
(I8Q5) *In my view ... the problems are associated with the operation and the condition of the installation, i.e., the equipment is being operated outside the operating envelop.*

Other aspects are introduced by Interviewee#4:

(I4Q8) *"One barrier is of course the personnel "Folkforening". The Unions are not too happy with Condition Monitoring because it ...to the last instance, could mean less personnel offshore... And we are a company with many years' experience with calendar-based maintenance and that's why people are used to it. That is a cultural aspect. And thirdly, we are a pretty large company. We have around 34 installations, with a large extent of equipment and the amount in itself is a challenge, because when you try to go to a new regime, from calendar-based to condition monitoring, it requires a lot of efforts and that's also a barrier. You have to get many people to go in the same direction... to succeed. There are obvious some resistance regarding CBM."*

On the potential from using mobile devices, e.g., tablets and iPads, in the offshore operational environment, interviewee #2 says:

(I2Q8) *"So when you go offshore everything, in many cases, still today, things are paper-based. Basically, you have the information in the CMMS, you print out the WO, you take that out to the fields, to the machine or the equipment. And then you have to make notes and then when you get back to the office, you have to get back the information into the system. It takes lots of time and one of most commonly used excuses for having the process like that, is that you are within explosion hazardous area and the EX secure equipment is costly or so on. I don't by that explanation. If you think of all the hours lost. Each hour lost on punching data points, will at least cost you a few thousand NOKs for offshore personnel. On a 14 days shift. If you then use half an hour extra, I think you will use more than that, you have 7 hours 14 thousand NOKs at least, which is loss of productive time. I don't by that excuse. I think it's mainly related to the management not eager on doing the changes as which are all buying."*

About overcoming barriers, Interviewee#2 declares:

(I2Q9) *"We haven't overcome those barriers. We are working on them. Because, as I said earlier. This company is, at the moment, to a large extent, investigating how we could start using more Condition Based Monitoring and we have several projects, at the moment, trying to find... How are we going to do this?"*

In corroboration, Interviewee#4 says:

(I4Q11) *"…we usually think that when you say condition-based monitoring everyone understand what you mean, but they don't. And, as a company to internally agree, what to be as a company… mean by condition-based monitoring and what do we want to put into this aspect. It is relevant. And off course we could lean on some of the standards but again… we have to agree as a company. This is what we mean …this is where we want to go."*

The three main barriers for Interviewee#5:

(I5Q8) *"So I think that my three barriers would be:* *(1) – You have to put enough efforts into the concept stage;* *(2) – You need to have very smart people empowered to use that data and get some smart models developed with clever people (e.g. consultants) so that you can do the prediction bit;* *(3) – Management being unable to appreciate the significance of the decisions they are being asked to make and that the short-term lowest cost is almost never the right solution."*

Asked how the barriers were overcome, Interviewee#8 says:

(I8Q9) *They were not. In fact, it's a matter of luck. When things are aligned, a good manager, a good team of maintenance and operation, you align this, and the thing goes well. When this is not aligned, it is very difficult.*

Among the most challenging difficulties observed in the implementation of CM&D related processes, the following aspects are mentioned by the interviewees:

- Documentation/notification problems in terms of a proper description of the failure event in the computerized maintenance management system (CMMS). "Sometimes we have to waste too much time in order to find out if machine was stopped due to a component failure or not. So, availability indicators are not reliable." Use of systems such as CMMS, ERP require some maturity;
- Difficulties to achieve a uniform information record, although using the ISO standards as a reference, however, each maintenance operator tries to make their own interpretation of the events and failure modes;
- The training of the people's is difficult, the condition monitoring culture is not easy to be implemented (training efforts must be better coordinated).
- A culture change is needed. Some groups are more mature than others;
- Problems to have a vibration or other important variable signature to be used as baseline reference, i.e., a standard procedure to obtain and validate a machine baseline machine;
- Lack of management support;
- Absence of equipment failures database and lack of knowledge of maintenance tools;

- Difficulty in spare parts acquisition;
- Logging of data in the ERP/CMMS system by operation/maintenance, related to events, i.e., faults, failures etc.;
- Difficulties in real-time data transmission;
- Maintenance decisions not taken serious enough;
- Two maintenance groups (specialized and ordinary) operating in silos;
- The hero culture persists (reactive attitude, firefighting).

According to the interview # 2, in many cases, the maintenance organization may be divided in two different groups, the maintenance personnel and the CM experts with limited information sharing of their knowledge and approach. Condition Monitoring silos have dedicated teams – each system has its 'own language' making it difficult to share information:

(I2Q5) "*Basically, the company has an organization for handling the maintenance as such, and then they have those small teams siting in their own boxes.*"

Regarding the heavy rotating equipment (e.g., compressors, generators etc.) there are dedicated teams on the side of the ordinary maintenance organization, that is, two maintenance groups (specialized and ordinary) operating in silos. On the implementation of condition monitoring centers (CMC), Interviewee#4 declares:

(I4Q10) "*Yes, we have one for heavy rotating machinery in City B. I think we have started to look at some valves as well, but in a very early start.*"

On the monitoring services in the CMCs, Interviewee#1 says:

(I1Q9/Q10) *"Some big companies, for example, __ has 25 people in their center in Amsterdam, monitoring about 2.000 compressors, and __ has at least 10 people in their center, monitoring about 200 compressors. Some monitoring services can also be obtained from vendors regarding, for example, electrical devices including intelligent electrical devices (IEDs)… Compressor and pump vendors may also contribute, as they deliver complex equipment. Electric actuators are becoming more common, and subsea processing involves many new types of equipment. Considering the company size, a small operator, for example, may prefer to outsource the monitoring services. Here, again, we should apply the cost benefit analysis."*

If the operator decides to outsource the condition monitoring activities, since some manufacturers and/or vendors also offer these services for some equipment, an important issue that arises then is about what to outsource, whether data collection or analysis, or even both.

(I8Q10) *These centers ... they really do exist, but they are more of a managerial decision, to say, "we have this right now and now we will be able to monitor our equipment from shore." But you go there and see who is monitoring, it's not the people who know the equipment, they're mere data collectors, ... they do not have engineering support behind them ... the participation of the engineering staff in the Center is very small. Because everyone is on firefighting, and so I understand the following: there really is a gain; when you go get information and find a history, but this history is not worked for a future vision ...*

Still on the implementation of CMCs, Interviewwe#2 says:

(I2Q9) *"So these centers are silos which are working within their domain they are very specific on their equipment and domain. That's reasonable but, at the same time, you should have these units interlinked with the overall maintenance organization…. The decisions ought to be made in those centers usually that is made by the maintenance managers in combination with the operations guys. ...there is a need to have clarification on what are the roles? What type of information shall the centers (or these expert groups) provide into the overall organization. There is a need of a better communication between those centers/domains."*

In that sense, Interviewee#5 says:

(I5Q9) *"I think they are doing a very good job there on setting up all these centers they have. So, they have the drilling center, the operations center and there is a condition monitoring center. I think they have identified that is an area they need to focus on. So, the answer is, I fully support that, and I think it is an excellent move in the right direction."*

In summary, Interviewee#1 says:

(I1Q11) *"In discussion with O&M personnel, try to find: (i) what kind of equipment breakdown occur more often and its respective impacts on production; (ii) which algorithms can be used to monitor degradation of these equipment; and (iii) how to predict and avoid those breakdowns."*

On labor division, Interviewee#6 states:

(I6Q10) *Our philosophy is that everything that can be done onshore should be done onshore. And what we have focused on is …to increase the communication between offshore to see each other as value for assets to …with knowledge that can be …tapped into order from onshore to offshore or from offshore to onshore. […]Yes, we have monitoring centers onshore that we also have this discussion with the people offshore when things come up. And you've got to go face-to-face because sometimes the best monitor is the human senses."*

On the recommendations, Interviewee#5 touches the problem of preparing the top management to deal with maintenance decision-making and suggests:

(I5Q9) *"In nearly all oil companies, High people with potential to be top managers. They are very often put first in the HSE and safety, and that is a kind of high profile well regarded and it is an OK experience. I would suggest that the company's policy should be the high-flying people spend 6 or 9 months in commissioning and 6 to 9 months in maintenance as part of their carrier progression because commissioning and maintenance will probably give a better understanding of the complexities and the challenges than anything else."*

A discussion on information sharing is proposed by Interviewee#2:

(I2Q10) *"If you are able to process the information to such a level that you make the information available for more personnel than the domain expert .... When we take the CM systems and the data flows, if you are able to process the information ...that ...gives meaning to more people. That is on the system side. And, then if you have a sort of matured the information ..., to a level where you ... can have these "seen across". Like on the Gjøa platform which you have like 15 expert systems, providing information on different formats and so on, ... if all of these 15 systems deliver the information in such a way that a group of personnel could interpret that information across. Then we are into the RUL part. So basically, if all the systems were providing information in that setting, then we could also share that ... across the organization and have it available for those in the positions of deciding on what to do and when."*

Finally, on the 4th Industry revolution:

(I4Q10) *"OK, today we have predictive maintenance, we have the Internet of Things (IoT) and all those things, in some king of ..., they are linked together, but we haven't sorted our minds on... How to use them together? I think that is a bit of a challenge. A lot of people think that we have come a lot further than we have. The truth is that we are still very stucked within calendar-based, traditional maintenance. And then, to jump from there to the newest ... it is a huge step."*

In fact, if the issues mentioned in this diagnostic are not satisfactorily resolved, it will be difficult to seize the opportunities of the 4th industry revolution.

Talking about the future, in the context of question 11, that is, on how to overcome the barriers, the Interviewee#8, declares:

(I8Q11) *"...as a privileged spectator, in these 32 years of offshore work, I do not have a very optimistic view regarding future scenarios. Because E & P does not yet have a framework for defining maintenance processes ... Although we have heard of Condition-Based Maintenance processes. There is a speech ... but it still does not exist in practice. at least it didn't reach the platforms visibly. There are initiatives, but I haven't seen them come to the offshore operational environment."*

5 Main results and proposals

"So if you understand whole systems and know where to place the trimtab, you can change the course of large systems with minimal effort and energy. You don't really need that long lever; just a properly designed and positioned trimtab."

R. Buckminster Fuller
(1895-1983)

This section presents and discusses the main results of the thesis.

5.1 A concept map for maintenance decisions

In this section, a concept map is proposed to represent the relationships that must be regarded in the maintenance decision-making processes; i.e., a proposed ontology diagram. It provides an essential representation of a shared concept and knowledge and puts focus on the critical elements of, for example, a preventive maintenance program implementation. In Machado and Haskins (2016) a concept map is proposed, adapted from (Bahill *et al.*, 2002). See Figure 5.1.

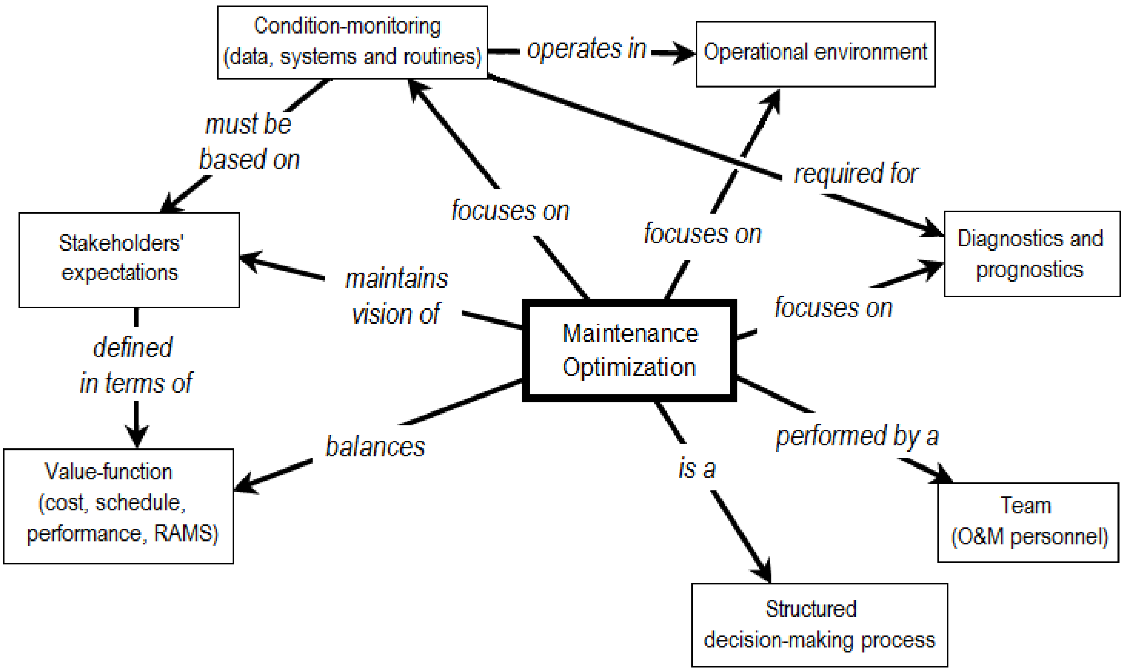


Figure 5.1 – A concept map for maintenance decisions (Machado and Haskins, 2016)

In this concept map, maintenance optimization appears at the center, as the main focal point. The structure and characteristic of this non-planar oriented graph can be subjected to analysis from different perspectives, allowing a broader understanding of the structure and the nature of the relationships, which is fundamental to understand some typical situations and decision contexts and develop, for example, an implementation plan.

5.2 A plan for preventive maintenance program implementations

"With sufficient planning, you can almost eliminate adventure from an expedition."

Roald Amundsen
(1872-1928)

In order to propose a plan for preventive maintenance program implementations (e.g., a CBM program), Machado and Haskins (2016) grouped the recommendations from the literature in the six stages (or steps) of a typical operations research (OR) approach to compose the plan presented in Table 5.1.

Table 5.1 – Plan for PM program implementations (Machado and Haskins, 2016)

Step 1 - Formulation of the problem (Description of the available information about the system and the actions open to management) • Description of a technical system, it functions, importance and boundaries; • Definition of the goals and scope of the analysis (organization's preferences / limitations); • Agreement on terminology; • System's states definition/criteria. (e.g., Excellent; Good; Acceptable; Poor and; Awful);
Step 2 - Construction of a model of the system (Modeling of the system degradation in time and possible consequences for the system) • Modeling of system's functions and the respective failure characteristics (failure modes, criticality, causes and effects); • Definition of the database' structure; • Field data collection and criticality analysis; • Establishment of the condition monitoring routines; • Degradation mechanism identification and modeling (for the most critical system's failure modes).
Step 3 - Definition of the solution through the model (An objective function and optimization/solution techniques); • Diagnostics and prognostics analysis (Applying the model inference rules and labels (e.g., Good, Awful etc.); • Design of experiments; • Selection of the optimization technique (heuristics etc.).
Step 4 - Testing of the model/solutions; • Evaluation of the model parameters and results; • Tuning up the model;
Step 5 - Establishment of controls of the solution; • Assess the system's condition;
Step 6 - Implementation and follow-up. • Decision-making (communication and reasoning); • Maintenance action (planning, scheduling and execution); • Feedback.

These steps are based on the stages of an OR typical approach, as discussed in Section 3.2. The sixth step is probably the most difficult one. Implementation of a PM program, e.g., CBM, requires the involvement of different departments and competences in a collaborative way, aiming to achieve the benefits from a pro-active mindset for decision-making within the organization. Moreover, a common recordkeeping system and criterion that allows failure events and associated costs to be easily extracted from the CMMS are among the crucial aspects.

Attempting to provide an overview of the decision support analyses/tasks and its potential applications, according to the decision level and the life phase of the assets, a proposed framework is presented in Table 5.2.

Table 5.2 – Decision support framework

<table>
<tr><th>Level
Phase</th><th>Early life</th><th>Useful life</th><th>Wear out</th></tr>
<tr><td rowspan="2">Strategic</td><td>Frame Agreements, FMECA / HAZID and Master Minimum Equipment List (MMEL)</td><td>RCM assessments</td><td rowspan="4">Obsolescence and regret Analysis</td></tr>
<tr><td colspan="2" rowspan="2">Life Cycle Cost Analysis (LCCA)
FMECA / FMSA / HAZOP</td></tr>
<tr><td rowspan="2">Tactical</td></tr>
<tr><td>Minimum Equipment List (MEL)
Root Cause Analysis (RCA)</td><td>RCM assessments
(e.g., Markov Analysis)</td></tr>
<tr><td rowspan="3">Operational</td><td colspan="3">MEL use and update (O&M integration)</td></tr>
<tr><td>FMECA / HAZOP
Quantitative Risk Analysis (QRA)</td><td colspan="2" rowspan="2">Review maintenance plans based on RCM assessments
(e.g., FMECA / FTA)</td></tr>
<tr><td>Manufacturers' maintenance plans</td></tr>
</table>

5.3 Minimum Equipment List: a policy and procedures manual

"Creativity comes from applying things you learn in other fields to the field you work in."

Aaron Swartz
(1986-2013)

This is a proposal derived from the air transportation industry for a structured decision-making process at the operational level. It is a cross-sector solution towards the integration of the O&M activities in for the offshore operational environment. The Minimum Equipment List (MEL) provides the criteria and procedures for the O&M personnel to operate a fleet (in this case, similar floating offshore platforms) in the presence of failures while ensuring that the required level of safety and the proper availability is maintained. In other words, it defines the minimum requirements for a complex engineering system under continuous operation.

According to Kinnison (2004) the MEL allows a vehicle to be dispatched into service with certain items inoperative provided that the loss of function does not negatively affect the safety and operation. These items are determined by the manufacturer and sanctioned by the regulatory authority.

Normally, the manufacturer issues a Master Minimum Equipment List (MMEL), which includes all equipment and accessories, relevant for safely operate an aircraft model. It is an approved document created specifically to regulate the dispatch of an aircraft type with inoperative equipment. Establishing the equipment allowed to be inoperative under certain conditions for a specific type of aircraft and still provide an acceptable level of safety.

The MMEL contains the conditions, limitations and procedures required for operating with certain items inoperative, forming the basis for development of an individual operator's Minimum Equipment List (MEL). Result of a careful analysis it provides the criteria and procedures for the O&M personnel to operate in presence of failures while ensuring that the required level of safety is maintained.

A typical statement in the preamble of a MMEL is (ANAC, 2015:9):

> All equipment installed on an airplane in compliance with the airworthiness standards and the operating rules must be operative. However, the rules also permit the publication of a Minimum Equipment List (MEL) where compliance with certain equipment requirements is not necessary in the interests of safety under all operating conditions. Experience has shown that with the various levels of redundancy designed into aircraft, operation of every system or installed component may not be necessary when the remaining operative equipment can provide an acceptable level of safety.

An example of MMEL page is presented in Figure 5.2.

MASTER MINIMUM EQUIPMENT LIST				
Airplane		Revision		Page
System & Sequence Number ITEM	1.	2. Number installed	3. Number required for dispatch	4. Remarks and/or exceptions
24 ELECTRICAL POWER				
42-00 AC External Power System (Continued)				
4) External AC Power Receptacle Shield	C	1	0	(M) May be cracked or damaged provided remaining shield prevents misaligned GPU connection.

Figure 5.2 – Example of a MMEL datasheet. Adapted from (ANAC, 2015)

A Master Minimum Equipment List (MMEL) is developed by the manufacturer and approved by the National Aviation Authority to improve aircraft utilization and thereby provide more convenient and economic air transportation for the public. In Figure 5.2, a part of a MMEL page of an aircraft electrical power system is presented.

In the first column "Item", the equipment, system, component, or function is depicted with the respective "repair category" which means the time allowed for its repair, excluding the day the malfunction was recorded in the maintenance record/logbook. The second column "Number Installed" shows the quantity of instrument and equipment items normally installed, regarding the aircraft configuration. The third column "Number Required for Dispatch" shows the minimum quantity of instrument or equipment items required for operation. The fourth column "Remarks of Exceptions" may include a statement either prohibiting or permitting operation with a specific number of instruments and equipment items inoperative, conditions and limitations for such, and appropriate notes.

A symbol "(M)" in the fourth column indicates a requirement for specific maintenance procedure that must be accomplished prior to operation with the listed item inoperative. The "(O)" indicates a requirement for specific operations procedure which must be accomplished in planning for and/or operating with the listed item inoperative. In certain situations, it is possible to find an "(OM)" which means both. In summary, the MEL concept establishes integrated modus operandi.

Designed by the air transportation industry, it certainly has a potential to be considered for the Oil and Gas industry, since it provides a combined condition/operation-based decision criterion in a standardized policy and procedures manual for O&M integration.

5.4 A Markovian dependability nomogram

This section introduces a nomogram to determine the maximum dependability of a theoretical maintained system. By investigating the relationships between the key-parameters of a renewal process, namely, failure rate, maintainability and availability, through a two-state Markov model and combining some categories of failure and repair rates, the result is a mapping of the feasible solutions (a dependability nomogram).

Regarding *failure rates*, the figures came from Rausand and Høyland (2004:p93), for *repair rates*, the figures were inspired by Bukowski (2006). See Table 5.3.

Table 5.3 – Categories of failure and repair rates

Mean time between failure (MTBF)		
Category	[h]	[1/h]
Frequent (once per month or more often)	730	1.37E-03
Probable (once per year)	8760	1.14E-04
Less Probable (once in three years)	26280	3.81E-05
Occasional (once per 10 years)	87600	1.14E-05
Remote (once per 100 years)	876000	1.14E-06
Mean time to repair (MTTR)		
Category	[h]	[1/h]
Short	8	1.25E-01
Moderate	24	4.17E-02
Large	72	1.39E-02
Very-Large	216	4.63E-03
Ultra-Large	648	1.54E-03

MTTF = Mean time to failure; MTTR = Mean time to repair. Based on (Rausand and Høyland, 2004:p93) and Bukowski (2006)

An implementation of the continuous time Markov chain (CTMC) the so-called Markov process in its steady state solutions is proposed. A transition diagram of a two-state Markov model is presented in Figure 5.3.

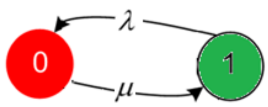


Figure 5.3 – Example of a two state Markov transition diagram

Where $X(t)$ can assume 0 for failed, or 1 for OK state. The transition matrix for the model is: $\Delta = \begin{bmatrix} -\mu & \mu \\ \lambda & -\lambda \end{bmatrix}$ Where: λ = *Failure rate* and μ = *Repair rate*.

Following standard methods, the steady state probabilities P_0 and P_1 can be obtained by $P_0 = \frac{\lambda}{\lambda+\mu}$ and $P_1 = \frac{\mu}{\lambda+\mu}$ and the visiting frequencies by $v_j = -P_j a_{jj}$. The aforementioned categories have been applied and the results can be seen in Table 5.4 .

Table 5.4 – Results

Scenario	MTTF [h]	MTTR [h]	λ/μ	Availability [Prob. OK]	System failure Frequency
1	26280	72.0	2.74E-03	0.997	3.79E-05
2	8760	24.0	2.74E-03	0.997	1.14E-04
3	26280	216.0	8.22E-03	0.992	3.77E-05
4	8760	72.0	8.22E-03	0.992	1.13E-04
5	730	8.0	1.10E-02	0.989	1.36E-03
6	26280	648.0	2.47E-02	0.975	3.71E-05
7	8760	216.0	2.47E-02	0.975	1.13E-04

From Table 5.4 it is possible to observe that the failure/repair ratio is what determines the system availability, similar to Little's famous law, $L=\lambda W$, where L denotes the average number of items in the queueing system, W denotes the average waiting time in the system for an item, and λ denotes the average number of items arriving per unit time. In our simple case, the system average availability, A may be computed by: $A = 1 - \lambda/\mu$ where λ denotes the failure rate and μ denotes the repair rate. From these relations, a dependability nomogram is presented in Figure 5.4.

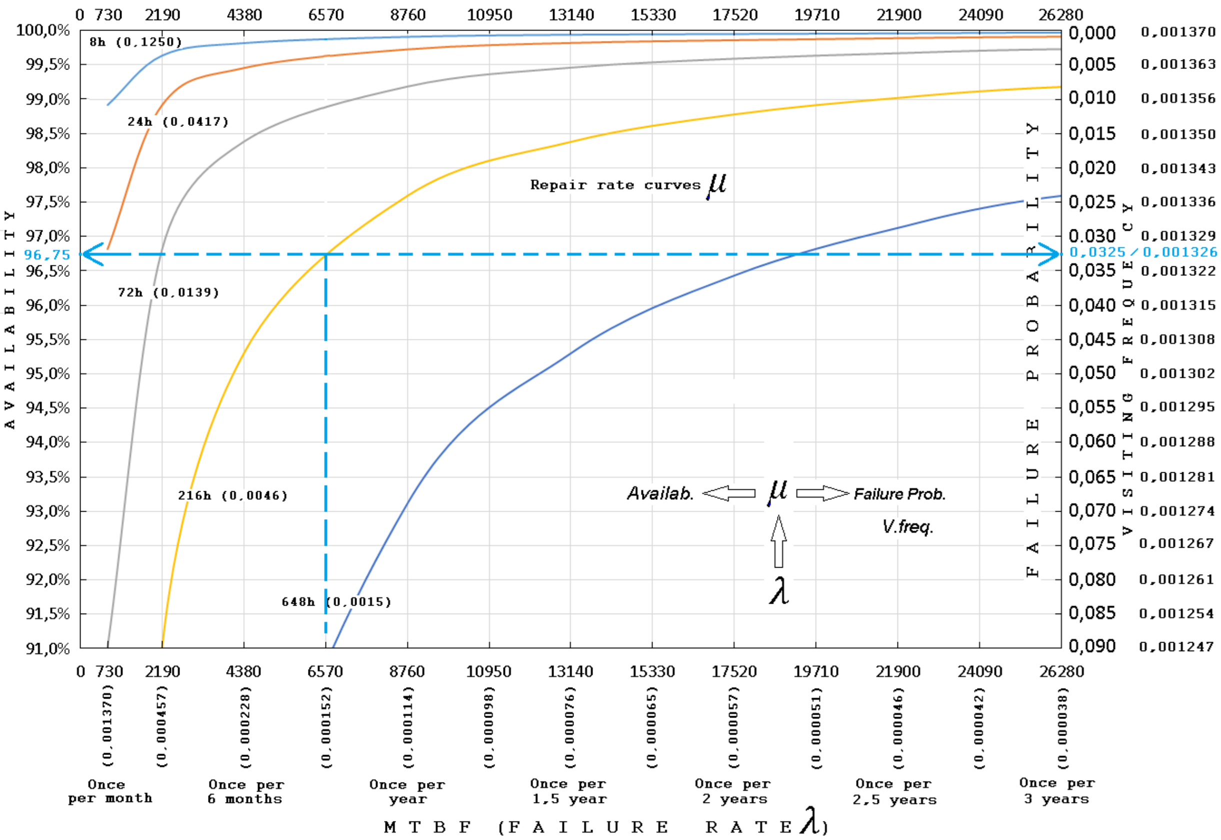


Figure 5.4 – A Dependability Nomogram

Although such nomogram represents a hypothetical system with constant failure rate exponentially distributed and with immediate detection of faults and perfect corrective repair/replacement, it can be thought as a criterion for maximum dependability of a maintained system.

From testing the nomogram in Figure 5.4 for systems that can be represented by a Markov model, it can be argued that, if it is consistent, a decision-maker can check the information reported, from a given asset, regarding its expected overall dependability.

5.5 Using the Markov decision process: the prototype

"Prevention is the daughter of intelligence."

Walter Raleigh
(1554-1618)

This section proposes the use of the Markov decision process to optimize operations and maintenance policies of parallel systems, which application refers to the system described in Section 4.1 (Case I). The approach uses, instead of *costs*, a *utility* function in its optimization. According to Clemen (1996) a utility function can help on the choice among alternatives that have uncertain payoffs, instead of maximizing expected value, the decision maker should maximize expected utility.

For the state-space definition, a set of normal operational situations of the parallel redundant system are considered (e.g., k-out-of-n structures). In this case, a R-out of-O scheme is suggested, where R stands for the number of *required* components for a given operation and O for the number of *operational* components, as *installed* in the MEL approach (See Section 5.3). The current operational situation (or state) and the desired operation (i.e., demand) will determine the dynamic of the system, which will demand, and be influenced by, a sequence of decisions (i.e., operations and maintenance procedures) as depicted in Figure 5.5.

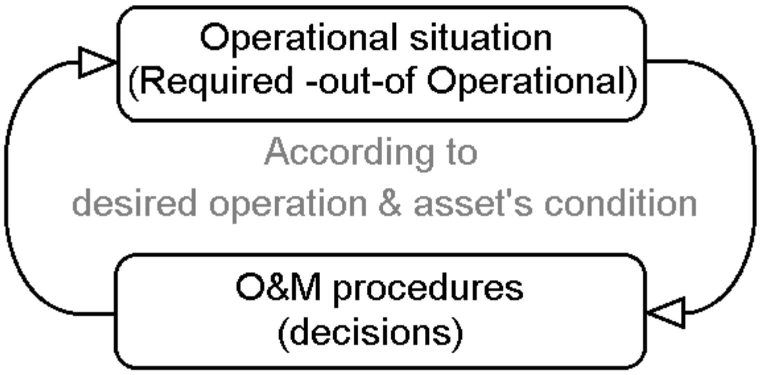


Figure 5.5 – Operational situation R-out of-O

In a kind of game, where the objective is to maximize the sum of rewards in a given period, an agent (player) is subjected to the MDP environment which is composed by decision rules, rewards and restrictions. In summary, by assuming the system's dynamics and using the VI algorithm described in Section 3.4.2 as the solution method, the following approach aims to generate optimal operations and maintenance (O&M) stationary policies.

A case study is carried out from the perspective of an offshore operator/maintainer in search of stationary policies that maximize the system capacity utilization in the long-run whilst identifying maintenance slots for preventive maintenance in a backlog management solution. In addition, the optimal O&M stationary policies are obtained, in respect to a given degree of prevention.

5.5.1 Motivation

In the operation and maintenance of complex production systems, operators must be able to make sequential decisions under uncertainty. Faced with the problem of influencing the behavior of a probabilistic system, a decision-maker must choose a sequence of actions which causes the system to perform optimally with respect to some predetermined performance criteria.

Integrated O&M policies can be very beneficial, especially in scenarios where the logistical aspects have a great impact on total repair times and operating costs, such as in offshore operations. Moreover, according to Vatn (2018), among the important aspects of the so-called Industry 4.0 are the approaches aiming to synchronize and coordinate production and maintenance.

Preventive maintenance actions (e.g., inspections, testing, adjustments, cleaning, lubrication, etc.) are an important part of the maintenance work and can extend a systems useful life and utilization, but may require, in exchange, a price in terms of immediate availability. Depending on the risk aversion of a decision maker (or agent), preventive activities may end up being postponed, generating the so-called *maintenance backlog*.

Experience has shown that with various levels of redundancy designed into an engineered system (e.g., aircrafts, ships, spaceships, etc.), the operation/activation of every installed component may not be necessary as long as the remaining operative equipment can provide an acceptable level of safety (see Section 5.3). In that regard, a solution must provide a preventive operational policy with minimal impact on the operational/production availability.

Many offshore production systems are designed as multi-unit parallel machines and most of them may be operated under different policies, according to the operating scenario (e.g., demand variations, failure and repair rates). These decision options include: (i) maintain the current status and wait for the next decision epoch (i.e., do nothing); (ii) activate a standby component; (iii) deactivate a component and put it in standby mode; and (iv) release a standby component for preventive maintenance.

An optimal O&M policy should maximize production efficiency whilst mitigating degradation and failure mechanisms. In that sense, this study aims to provide the operator/maintainer with optimal long-term policies that focus on the opportunities for preventive maintenance. The underlying assumption is that taking advantage of the best opportunities to carry out preventive actions can safeguard the long-term availability of a production system. Considering prevention as a value to stakeholders, and in light of the fact that testing and inspection constitute an important part of the maintenance work, the purpose of this study is to answer the question: *Under what operating conditions of a parallel system does preventive action belong to an optimal stationary policy?*

In this study, the Markov decision process is chosen as it provides a mathematical framework for modeling sequential decision-making in situations where outcomes are partially random. It considers an infinite horizon problem, with state-space and action-space both finite, and the chosen optimality criterion, following (Puterman, 1994), is the expected average reward.

As a contribution, a metric for prevention is introduced, the *prevention factor* as an additional reward over the preventive action/decision (i.e., an incentive) used to identify the appropriate prevention levels for different operating scenarios, i.e., combinations of failure and repair rates. Some additional/potential benefits of this study are: (i) the development of a utility function (as an alternative to costs), that structures the tacit knowledge of the stakeholders; and (ii) maximizing the capacity utilization rate, such that an associated reduction in CO_2 emissions from these machines (i.e., gas-turbine engines) can be expected. This MDP model approach is somewhat simpler than those described in Section 3.4.3. The definition of the state-space, for example, instead of using condition, simply follows the observable operational situations (i.e., k-out-of-n structures) of the parallel system in continuous operation, regardless the individual component condition. The planning horizon is infinite, and for the optimization it considers utility in the objective-function, which is based on the capacity utilization in respect to a demand range and an adopted prevention level. In view of the offshore operational environment where it may be difficult to properly determine maintenance costs, the concept of utility function is an alternative.

The off-shore power generation system considered here refers to the same described in Section 4.1 (Case I) and treated by Machado *et al*. (2014) and Perera *et al*. (2015).

5.5.2 Problem statement

A major offshore operator is observing a significant increase in the maintenance backlog related to the power generation system of its floating, production, storage and offloading (FPSO) units. Although a condition-monitoring system is available, providing diagnostics and prognostics for each of the parallel component, this information is not integrated with the offshore operations, i.e., the preventive maintenance opportunities are not combined with the varying operational situations (k-out-of-n) of the parallel system. In this application, let k denote the number of required components for a given operation and n denote the number of current operational components.

After a series of meetings, it was decided that "standard" O&M policies should be prescribed by the turbomachinery experts from the company's headquarters, with the intention to coordinate and synchronize production with the preventive maintenance of these assets. Considering the typical operating scenarios, optimal opportunities for preventive maintenance should be identified according to variations in demand, and the appropriate prevention levels should be recommended. In summary, the solution should connect the condition-monitoring information with the system control actions. In that respect, the maintenance and reliability engineers were asked to develop such a decision support tool, capable of generating optimal O&M policies to help improve the maintenance backlog management.

The system is operated according with a cold standby strategy, assuming that the redundant components are protected from the operational stress associated with operation so that no component fails before its activation (Peiravi *et al.*, 2019). Regarding the switching system, the probability of starting failure is considered as a constant value (β). Considering the system normal continuous operation, the offshore machinery operator takes the control actions empirically. However, what the operators cannot know for certain is which action, among the available actions in a given situation, is optimal in a long-run perspective. More specifically, in which situation a standby machine should be released for preventive maintenance.

5.5.3 The MDP model development

An offshore power generation system operating in the Campos Basin, Brazil is the case subject. The system contains 4 turbo-generators (TG) consisting of aero-derivative gas turbine engines with normal capacity of 25000 (kW) coupled with electric generators with normal capacity of 28750 (kVA). The range of required grid load of the platform is from 35 to 55 MW which dictates the operation of 2 or 3 generators, allowing the adoption of different operating policies. Historical data from the turbo-machinery event records is collected and analyzed to estimate the failure and repair rates. Aiming at a generic model to be used as a standard, other references were also considered to form a set of baseline scenarios. A summary of estimates and references is presented in Table 5.5 . Figure 5.6 presents the states and transitions at component level.

Table 5.5 – Estimates and base-line references for the model

Failure rate references [1/h]	
Average failure rate estimate TG-A (Perera *et al.*, 2015)	0.004807
Ref.1 - Average failure rate (OREDA, 2009)	0.002212
Ref.2 - Frequent failure (Rausand and Høyland, 2004)	0.001369
Repair rate estimates [1/h]	
Average repair rate (minor repair - preventive)	0.0453
Average repair rate (major repair - corrective)	0.0251

Calendar time 21432 [h] - Operating time 15845 [h]. The references are for aero-derivative gas turbines (all failure modes) Source: Petrobras (2010), (OREDA, 2009), (Rausand and Høyland, 2004) and (Perera *et al.*, 2015)

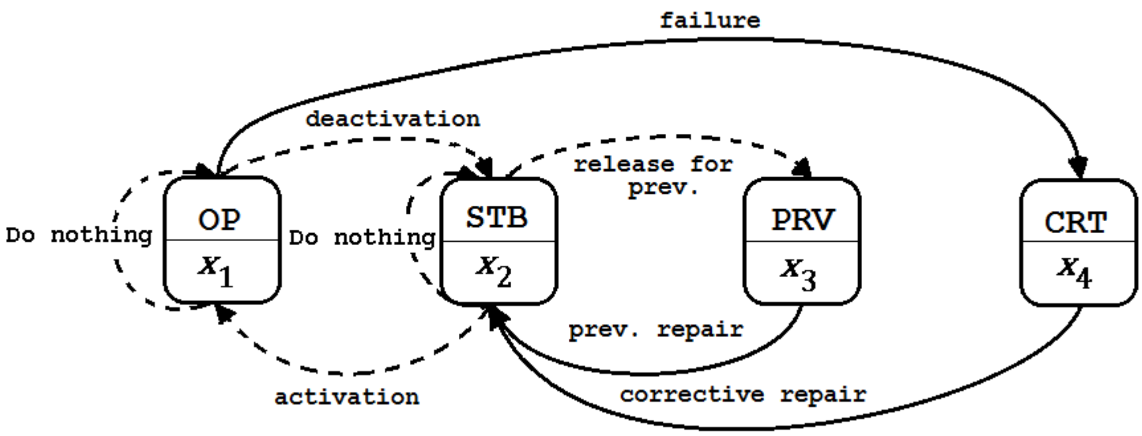


Figure 5.6 – States and transitions at component-level

In Figure 5.6 solid arrows represent the transitions due to events (e.g., failures and repair completions) and dotted arrows represent the transitions governed by control actions which are coded as: (1) “Do nothing”; (2) “Activate”; (3) “Deactivate” and (4) “Release for preventive maintenance”.

Although stochastic, the system state is observable by means of a state $s_t = (x_1, x_2, x_3, x_4)$ containing the number of components (TG) in each of the possible positions of Figure 5.6, where $x_1$denotes the number of components in “Operating” (OP), x_2 denotes the number of components in “Standby” (STB), x_3 denotes the number of components in “Preventive maintenance” (PRV) and x_4 denotes the number of components in “Corrective maintenance” (CRT). When the agent decides to do nothing and wait for the next decision epoch, transitions may occur by chance, due either to a failure or a repair completion. Failure of a component causes a transition from (OP) to (CRT) and a repair brings the respective unit to (STB). By choosing to deactivate a unit, a transition from (OP) to (STB) occurs. Start-up failures are also considered, and the action of special interest is action (4), namely “Release for preventive”, that causes a transition from (STB) to (PRV).

In order to consider only the relevant states and transitions that represent the continuous and normal operation of the system, a procedure has been adopted in the construction of the model as follows:

(i) define, with the stakeholders, the normal operating conditions/situations, preferences, decision rules and limits;
(ii) from the full operative state (i.e., all components operating) towards the least operative states add connections and states such that a strongly connected graph is obtained (i.e., an irreducible Markov chain);
(iii) simulate all the transitions, adding new states and transitions, if necessary, according to the plausible failures and the respective repair completion events;
(iv) collect data and estimate the transition probabilities;
(v) check the chain with the decision rules and define the action sets available in each state (action sets).

From step (iii), the third consecutive fault (from independent causes) is considered infeasible, due to its very low probability and the hypothesis that, at least one repair completion happens previously. As a result of applying the above procedure, a 16-state Markov chain evolved as presented in Figure 5.7. States are labeled with roman numerals and coded according to the scheme explained in Figure 5.6, with the first number representing x_1 and so on. This prescribe a stat-space $S = \{I, II, III, \ldots, XVI\}$. The coding scheme can be verified also in Table 5.7.

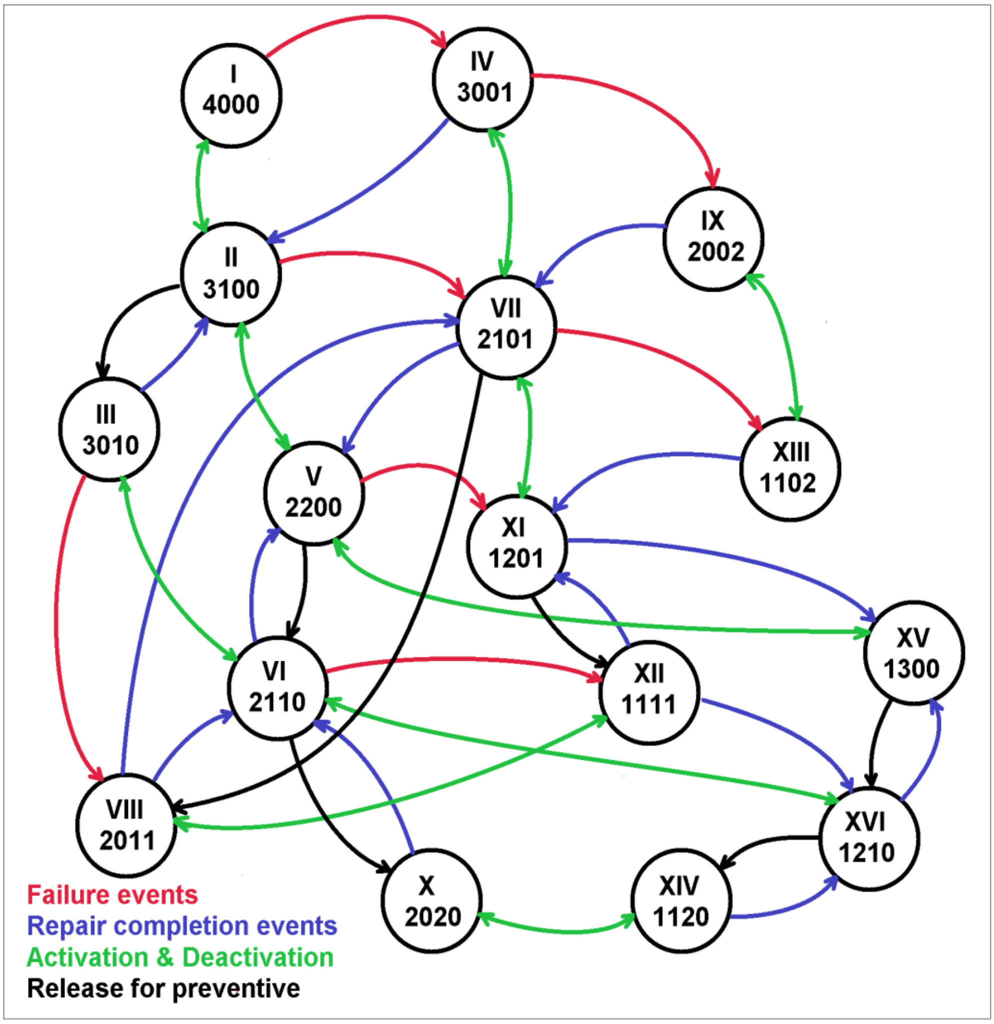


Figure 5.7 – Transition diagram for the 4-component parallel system

In Figure 5.7, the failure events are represented by red unidirectional arrows, whereas activations and deactivations are represented by green bidirectional arrows. Repair completion events are represented by blue unidirectional arrows, and the release for preventive maintenance appears in black unidirectional arrows. Loops are omitted for simplicity. From a state with all components in operation (I-4000), for example, when a failure occurs the next system state will be (IV-3001) and a corrective repair starts. The repair completion at state (IV-3001) causes a transition to state (II-3100) and so on.

In this case, since the operational decisions are taken frequently, and the system performance is to be measured in average terms, the expected average reward is chosen as the recommended optimality criterion, according to Puterman (1994). The MDP is solved as an infinite horizon problem with decisions taken at every system transition. Among the model assumptions are: (i) discrete state and action spaces; (ii) rewards and transition probabilities are stationary and bounded, i.e., $r(s,a) \leq M \leq \infty \forall a \in A_s, s \in S$; (iii) failure and repair rates are constant and equal for all components; (iv) the component's time-to-failure follows an exponential distribution; (v) failures are independent; (vi) system is maintained such that repair does not change failure intensity; (vii) maintenance starts immediately after failure. This implies the existence of an optimal stationary policy consisting of decision rules $\pi = (d_1, \dots, d_\infty)$.

5.5.3.1 Transition probabilities

The probabilities of moving from state s to a state j given that action a is chosen, $p(j|s,a)$, are obtained from the estimates presented in Table 5.5. When action (1) "Do nothing" is chosen, the transitions occur according to the most probable event, while by choosing actions (2) "Activate", (3) "Deactivate" or (4) "release to preventive", result in deterministic transitions. Action (2) "Activate" can become probabilistic, by assigning a value β denoting the on-demand failure probability (ODF), which represents the unreliability of the switching system. Considering exponentially distributed failure and repair rates, the transition probabilities are computed in different cases. From the states (I-4000), (II-3100) and (V-2200), and under action (1), the first event is inevitably a failure, since we choose to do nothing until a failure occurs. Hence, we have:

Failure (states I, II and V) $\quad p(j|s,1) = 1, \;\; j = (x_1 - 1, x_2, x_3, x_4 + 1).$ (5.1)

From states where there are components under repair, i.e., $x_3 \; and/or \;\; x_4 \neq 0$, there are three options with transition probabilities satisfying:

Failure
or
Preventive repair completion
or
Corrective repair completion.

$$\begin{aligned} p(j|s,1) &= \frac{x_1\lambda}{x_1\lambda + x_3\mu1 + x_4\mu2}, \; j = (x_1 - 1, x_2, x_3, x_4 + 1); \\ &= \frac{x_3\mu1}{x_1\lambda + x_3\mu1 + x_4\mu2}, \; j = (x_1, x_2 + 1, x_3 - 1, x_4); \\ &= \frac{x_4\mu2}{x_1\lambda + x_3\mu1 + x_4\mu2}, \; j = (x_1, x_2 + 1, x_3, x_4 - 1). \end{aligned} \tag{5.2}$$

And when actions 2, 3 and 4 are chosen, the transition probabilities satisfy:

Activation	$p(j\|s,2) = 1-\beta,\ j = (x_1+1, x_2-1, x_3, x_4);$	
Starting failure ($\beta \neq 0$)	$j = (x_1, x_2, x_3, x_4);$	(5.3)
or Deactivation	$p(j\|s,3) = 1, j = (x_1-1, x_2+1, x_3, x_4);$	
or Release for prev.	$p(j\|s,4) = 1, j = (x_1, x_2-1, x_3+1, x_4);$	

where β denotes the probability of a starting failure (on demand failure).

5.5.3.2 Rewards

The FPSO's power demand L is the main factor in the composition of the decision rules and rewards. In this application the rewards are amounts of utility, as a currency. Each state is rated in this currency, which depends on the operational situations experienced by the system. Let u_s denote the state utility which is computed by:

$$u_s = \frac{L}{ltx_1} + \alpha x_2, \qquad \forall s \in S. \tag{5.4}$$

where the first term in (4.4) represents the current capacity utilization ($\leq 1{,}00$), and let lt denotes the *target load* for a component. The second term represents the decision freedom provided by the presence of standby components, with $\alpha \epsilon (0.04, \ldots, 0.1)$ denoting the standby utility factor. Since the machines share the load equally, the target load is the desired load for the component (according to a prescribed load factor), preferably the best efficient point (BEP) is to be considered. Moreover, let $E(s)$ denote the expected sojourn time in the current state which is computed by:

$$E(s) = \left(\frac{1}{\lambda x_1 + \mu 1 x_3 + \mu 2 x_4}\right), \qquad \forall s \in S. \tag{5.5}$$

The expected sojourn time is a function of the state and action choice and from (4.4) and (4.5) the scenario dependent rewards are defined in Table 5.6. Let l_s denotes the component load at state s; $lact$ denotes the activation load; $lmin$ denotes the component minimum load; lt denotes the component's target load; and $Prev$ denotes the prevention factor.

Table 5.6 – Scenario dependent rewards

Action Utility		Restriction	Zone
1 – Do nothing	$r(s,1) = \begin{cases} u_s E(s) \\ 0 \end{cases}$	$lmin < l_s \leq lt$ otherwise	Equilibrium
2 – Activate	$r(s,2) = \begin{cases} u_s \\ 0 \end{cases}$	$x_2 > 0$ and $l_s \geq lact$ Otherwise	Standby availability
3 – Deactivate	$r(s,3) = \begin{cases} u_s \\ 0 \end{cases}$	$(lact - l_s) \geq 0$ otherwise	Deactivation
4 – Release for prev.	$r(s,4) = \begin{cases} u_s Prev/m \\ 0 \end{cases}$	$x_2 \geq 1$and $x_3 + x_4 < 2$ Otherwise	Preventive

$m = \lambda/\mu 1$ Denoting the scenario's severity

As can be seen from Table 5.6 when action (1) "Do nothing" is chosen, transition may occur by chance and a sojourn time is multiplied by the state utility. Actions (2) "Activate" and (3) "Deactivate" are rewarded by the current state utility. Action (4) "Release for preventive" is rewarded considering also the *prevention factor*, Prev. The prevention factor changes the MDP's environment, allowing the windows for preventive opportunities to emerge.

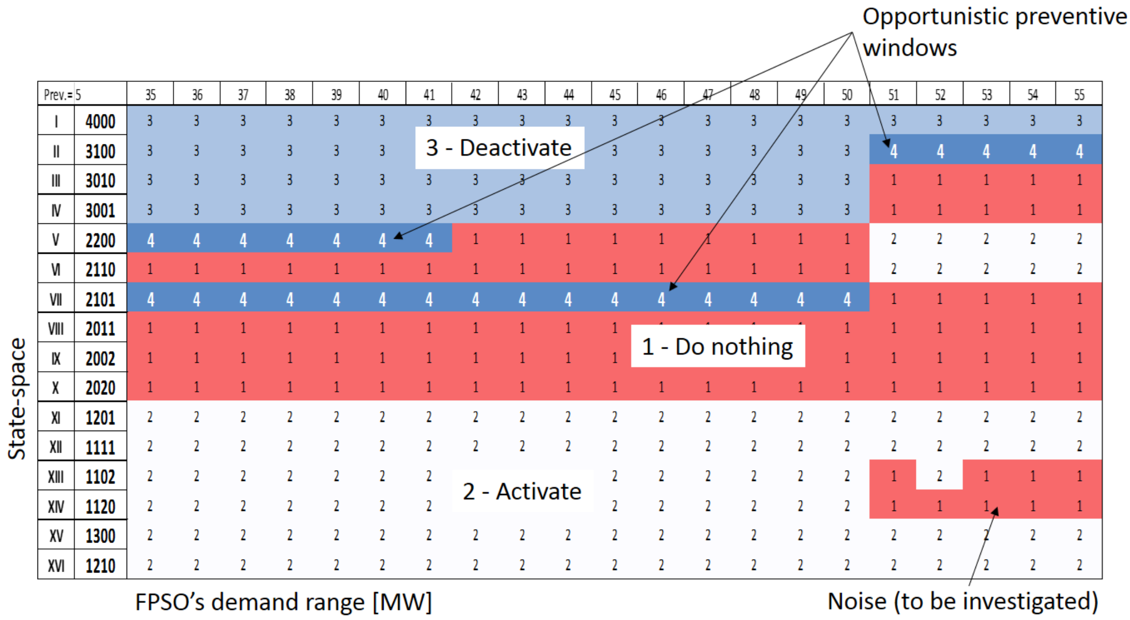
The objective is to find the policy that maximizes the sum of rewards which is computed recursively by Bellman equation subject to: (i) the 16-state Markov chain topology and dynamic properties; (ii) the decision rules and respective action sets; and (iii) the error tolerance ε. Once the VI algorithm converges, the ε-optimal policy π^* can be obtained, that is, a utility-based optimal stationary policy.

It worth noting that, if the modelling considers maximizing the availability or capacity utilization alone, the chance of the preventive action to become optimal is minimal or null. In fact, according to the experiments results, only from extreme scenarios with very high failure rates, action (4) becomes optimal without any preventive incentive (i.e., *Prev* = 1). It is worth noting that the preventive action is only available in 7 of the 16 states. The action sets are presented in Table 5.7 . In this application, in each run, the problem is solved for all demand levels from [35, 36, 37,…, 55] MW forming an output with 21 optimal policies (columns) as presented in Figure 5.8.

Table 5.7 – Action sets and zones

States	I 4000	II 3100	III 3010	IV 3001	V 2200	VI 2110	VII 2101	VIII 2011	IX 2002	X 2020	XI 1201	XII 1111	XIII 1102	XIV 1120	XV 1300	XVI 1210
1 Do nothing	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2 Activate	0	1	0	0	1	1	1	0	0	0	1	1	1	1	1	1
3 Deactivate	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
4 Rel.f/Prev.	0	1	0	0	1	1	1	0	0	0	1	0	0	0	1	1

"0" denotes a non-feasible action



Prev.= 5		35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55
I	4000	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
II	3100	3	3	3	3	3	3					3	3	3	3	3	3	4	4	4	4	4
III	3010	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
IV	3001	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
V	2200	4	4	4	4	4	4	4	1	1	1	1	1	1	1	1	1	2	2	2	2	2
VI	2110	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2
VII	2101	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	1	1	1	1	1
VIII	2011	1	1	1	1	1	1	1	1	1	1	1					1	1	1	1	1	1
IX	2002	1	1	1	1	1	1	1	1	1	1	1					1	1	1	1	1	1
X	2020	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
XI	1201	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
XII	1111	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
XIII	1102	2	2	2	2	2	2	2				2	2	2	2	2	2	1	2	1	1	1
XIV	1120	2	2	2	2	2	2	2				2	2	2	2	2	2	1	1	1	1	1
XV	1300	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
XVI	1210	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

(1) “Do nothing” in red, (2) “Activate” white, (3) “Deactivate” white blue and (4) “Release for preventive” in dark blue.

Figure 5.8 – Optimal policies output (example)

In this example, the opportunistic windows for preventive maintenance (in dark blue) can be identified in state (V-2200) from 35 to 41MW, in state (VII-2011) from 35 to 50 MW and state (II-3100) from 51 to 55MW. It is worth noting that, for decision purposes, only the first ten states should be considered, since with only one machine in operation, the system does not fulfill its function. It's like a four-engine aircraft that needs at least two engines running to keep the flight going.

This MDP model has been submitted as an article entitled “Using the Markov decision process to optimize operations and maintenance policies of parallel systems: applications to an offshore power plant” (see Articles).

5.5.4 Experiments

To demonstrate the application of the MDP model, experiments are prepared using a data set of 9 conceived scenarios, including data from the case study. The experiments consider a set of default parameters as follows: Activation load, *lact* = 15MW; Target load per component (TG), *lt* = 25MW; Minimum load per component (TG), *lmin* = 12MW; Power range, Load = [35:55]; Standby utility, α = 0.9; On demand failure (ODF) probability, β = 0.05; and Error tolerance, ε = 0.05. And by varying the prevention factor in a range from 1 to 10 for the conceived scenarios, a progressive emergence of the preventive opportunity windows (within the optimal policies) are observed, allowing to identify the corresponding prevention levels (prevention ranges) for each scenario. From the point from where no changes are observed in the preventive opportunity windows as the prevention factor increases, the maximal *Prevention level* is assumed. Combinations of the failure and repair rates presented in Table 5.3, form the 9 conceived scenarios as presented in Table 5.8.

Table 5.8 – Scenarios

Scenario	**Failure rate scenarios**		**Minor repair rate**	**Major repair rate**
1	Probable failure	0.000114 [8760h]	0.041666 [24h]	0.013888 [72h]
2			0.013888 [72h]	0.004629 [216h]
3	Frequent failure	0.001369 [730h]	0.125000 [8h]	0.041666 [24h]
4				0.013888 [72h]
5			0.041666 [24h]	0.013888 [72h]
6				0.004629 [216h]
7			0.0453 [22.1h]	0.0251 [39.8h]
8	Case study	0.002212 [452h]		
9		0.004807 [208h]		

The computational experiments were implemented in Matlab running in a 2.90 GHz CPU with processor Intel Core i5-2310 with 4.00 GB of RAM in a 64-bit operating system. The scenarios were explored with some fixed parameters and a preliminary sensitivity analysis was performed, whose results are summarized in Table 5.9. Table 5.10 present the experimental results for the parallel system described above. An example of the output with the sets of policies is presented in Table 5.11 for the scenario 8 (Case study) and Table 5.12 summarizes the results for the scenarios 7, 8 and 9 where the unique difference is the failure rate.

Table 5.9 – Parameter values, ranges and effects

Parameter, symbol	**Default value/range**	**Effect on the set of policies**
Activation load, ($lact$)	15MW – [10 - 17]	No changes on preventive windows.
Target load p/component, (lt)	25MW – [22 - 27]	It moves the windows accordingly (left < 25 > right).
Min. load p/component, ($lmin$)	12MW – [10 - 25]	No changes on preventive windows.
Standby utility, (α)	0.09 – [0.05 - 0.15]	Increased α anticipates (mainly in State V) the preventive windows' openings in relation to the load.
Preventive factor, ($Prev$)	[1 - 20]	Increased $Prev$ enlarges the preventive windows.
On-demand failure prob., (β)	0.05 – [0 - 0.15]	Increased β eventually reduces the activation region.

Load range [35 to 55 MW]; Error tolerance, ε = 0.05

Table 5.10 – Summary of results

Scenario	MTBF [h]	$MTTR_{(Prev.\ \&\ Corr.)}$ [h]		Prevention range Min. – Max.	Processing time [sec.]	N. of iterations [@55MW]
1	8760	24	72	5 – 7	107.19	1493
2		72	216	6 – 6	77.72	1058
3	730	8	24	2 – 3	37.72	328
4		8	72	1 – 3	34.05	381
5		24	72	2 – 5	27.07	297
6		24	216	1 – 4	76.91	851
7		22.1	39.8	3 – 5	19.02	179
8	452	22.1	39.8	3 – 6	14.74	166
9	208	22.1	39.8	1 – 6	13.28	136

Table 5.11 – Optimal preventive opportunities and prevention factors (Scenario 8)

Failure rate category, λ 0.002212 [452.0h]	Minor repair rate, μ_1 0.0453 [22.1h]	Major repair rate, μ_2 0.0251 [39.8h]	Prevent. factor

Prev=	4	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55
I	4000	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
II	3100	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	4
III	3010	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
IV	3001	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
V	2200	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2
VI	2110	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2
VII	2101	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	1	1	1	1	1
VIII	2011	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IX	2002	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
X	2020	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
XI	1201	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

State II from 51 to 55MW and State VII from 35 to 50MW

Prevent. factor: **4**

Prev=	5	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55
I	4000	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
II	3100	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	4
III	3010	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
IV	3001	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
V	2200	4	4	4	4	4	4	4	4	4	4	4	1	1	1	1	1	2	2	2	2	2
VI	2110	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
VII	2101	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	1	1	1	1	1
VIII	2011	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IX	2002	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
X	2020	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
XI	1201	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

State II from 51 to 55MW, State V from 35 to 45MW and State VII from 35 to 50MW

Prevent. factor: **5**

Prev=	6	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55
I	4000	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
II	3100	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	4
III	3010	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
IV	3001	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1
V	2200	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	2	2	2	2
VI	2110	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
VII	2101	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	1	1	1	1	1
VIII	2011	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IX	2002	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
X	2020	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
XI	1201	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

State II from 51 to 55MW and States V and VII from 35 to 50MW

Prevent. factor: **6**

Activation level, *Iact* = 15MW; Target Load per TG, *It* = 25MW; Minimum Load per TG, *Imin* = 12MW;
Power range, *Load* = [35:55]; ODF probability, β = 0.05; Standby utility, α = 0.9; Error tolerance, ε = 0.05.

For each scenario the MDP model generates different sets of policies within the range of power demand from 35 to 55MW, indicating the corresponding prevention levels which are proportional to the severity of the scenarios. To observe that, maintaining the same repair rates and increasing only the failure rate, the required prevention levels increases as presented in Table 5.12 and depicted in Figure 5.9.

Table 5.12 – Effect of varying MTBF on the prevention levels

Input (scenario)	Scenario 7	Scenario 8	Scenario 9
MTBF [h]	730.0	452.0	208.0
MTTR 1 [h]	22.1	22.1	22.1
MTTR 2 [h]	39.8	39.8	39.8
Arbitrary prevention levels	**Output (preventive windows' size, i.e., # of cells filled with "4")**		
1	0.0%	0.0%	15.6%
2	0.0%	0.0%	17.7%
3	3.4%	14.3%	21.1%
4	3.4%	14.3%	21.1%
5	25.2%	21.8%	21.1%
6	25.2%	25.2%	32.0%
7	25.2%	25.2%	32.0%

Window opening (%) in relation to 147 cells where action "4" is allowed (7 states x 21 power levels)

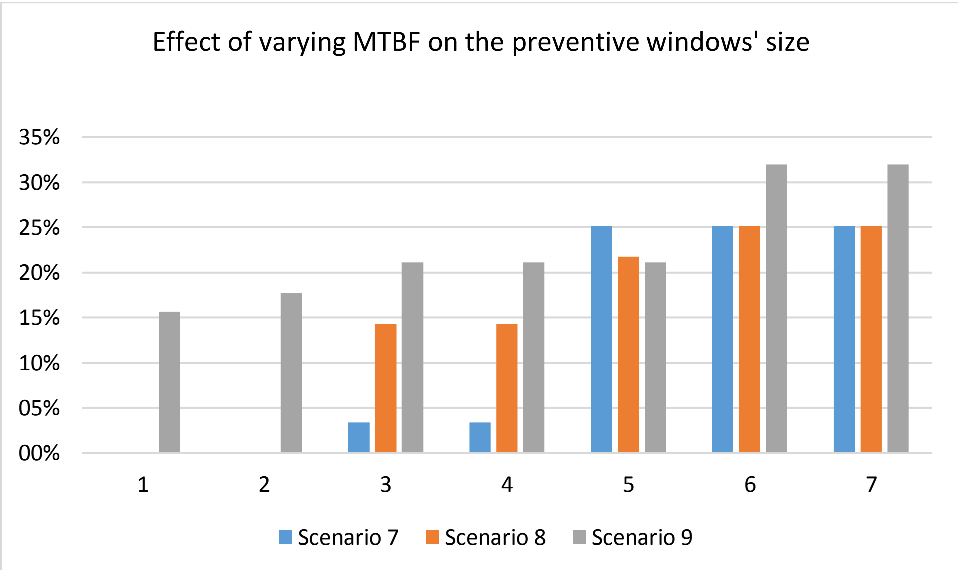


Figure 5.9 – Effect of varying MTBF on the prevention levels

5.5.5 Discussion on the experimental results

An optimized O&M policy should have an associated prevention level, which can be interpreted as the importance given, by the decision-maker, to preventive in relation to the other available actions/decisions. Considering availability maximization alone, for example, the chance of the preventive action to be optimally chosen is minimal or even null, according to a given operating scenario.

The MDP model has generated different policies, prescribing the prevention levels (ranges) for each of the conceived scenarios. These results can be used for decision purposes by a maintenance planner or coordinator, as long as a demand profile can be foreseen, e.g., a scheduled offloading. From Table 5.12 it is possible to observe that an increase in the prevention factor causes an increase in the windows for preventive maintenance. As expected, two clearly defined thresholds appeared in all policies. A deactivation one at the top, in light blue with “3”, and an activation one at the bottom, in white, filed with “2”. Between these two thresholds, where no action is needed, in red filled with “1”, this is where the preventive windows normally emerge. Table 5.11 can be seen as a page of a policy and procedures manual to guide decision making at the operational level of the entire FPSO’s fleet.

In summary, by incrementing the prevention factor, different and progressive windows for preventive maintenance were identified. According to the experiments, the preventive windows involved states (II-3100), (V-2200) and (VII-2101). However, no preventive windows appeared in state (VI-2110). Apparently, state (VI-2110) is not a good situation for preventive actions, although that action is available and with assigned utility (see appendix). It can be an effect of the system topology (i.e., an emergent property of the system) that deserves further investigation. Additional experiments with on-demand failure probability also demonstrated coherence on the resulting policies.

The results can be useful for decision purposes by a maintenance planner or maintenance coordinator, as long as a demand profile can be foreseen, e.g., a scheduled offloading. An optimized O&M policy have an associated prevention level/range, which can be interpreted as the relative importance that should be given to the preventive action in relation to the other available actions.

The MDP model solves the problem of finding opportunistic slots for preventive maintenance in a reduced computation time (from 13 to 107 seconds) for the conceived scenario, maybe due to its low dimensionality (discrete and small state space and actions). The experiments results showed that the optimal policies generated by the MDP model may be non-intuitive.

The proposed model is simple and possesses “what if” analysis capabilities, which are important for customizations and may promote useful discussions and learning regarding the operation and maintenance of parallel systems. In combination with condition-monitoring tools, the solution can promote O&M integration since tables with the stationary optimal policies can be published, as a decision support almanac, promoting standardization and regularity for the related decision process.

The model can be useful for integrated planning purposes and its applicability is promising since many offshore production systems are designed as a 4-component system with 33% redundancy. Among the next steps in the development of the model are: (i) perform a complete sensitivity analysis and investigate, for example, the effect of a given preventive stationary policy on the long-run availability performance and associated costs; (ii) include demand curves in the optimization algorithm and provide policies for a pre-defined planning horizon; and (iii) extend the model and test different value-functions.

6 Final considerations and conclusions

This section concludes the thesis concerning the maintenance decision-making processes in the oil and gas industry and presents some continuing lines for this research.

6.1 Thesis contributions

The Systems Engineering based approach proved useful in the understanding of the maintenance decision-making processes and contexts in the offshore operational environment of the oil and gas industry (the big picture). In summary, the thesis described the relationships among the agents and discusses the requirements for cultural change towards prevention (i.e., PM programs) in the maintenance organization, and provides a systemic understanding of the related decision-making processes. The concept map for maintenance decision making ontology presented in Section 5.1, for example, which is adapted from a SE perspective is a contribution that summarizes the relationships that must be regarded in a maintenance decision-making process development.

Through a discussion on the decision analysis tools with focus on the dynamics of maintenance decision-making, including the Markovian approach, the thesis identifies consequences of maintenance decisions, considering the complexities and boundaries of the offshore operations, as in Section 3.2 and Section 3.4.

Moreover, the thesis suggests a cross-sector solution for operations and maintenance integration such as the minimum equipment list (MEL), that is, a policy and procedures manual presented in Section 5.3, which is derived from the air transportation industry. It is an effective way to integrate O&M work processes and may be an opportunity to regulate the offshore operations considering, for example, a fleet of similar installations such as the fast-growing fleet of FPSOs in the Brazilian Continental Shelf, mainly on the pre-salt layer fields, and abroad.

Based on the interviews, the on-line survey and case studies, the discussions conducted in this thesis allowed for a state-of-the-practices diagnostic of the maintenance decision-making processes, with focus on the condition-monitoring and diagnostics of machines in the offshore operational environment.

Among the thesis constructs, the Markov dependability nomogram presented in Section 5.4, for example, is an innovative and didactical way that describes availability performance and its influencing factors. It represents, in a Markovian framework, the maximum dependability of a maintained system.

Finally, this thesis proposes a development of a decision support tool, as a maintenance backlog management solution, using dynamic programming in a tailored Markov decision model application, which is capable of generating optimal O&M policies for parallel systems in continuous operation. That solution can be used for condition-based maintenance programs in a practical approach as system level allowing the use of utility functions and decision logic. In summary, this investigation has provided:

- An ontological scheme;
- An alternative optimization approach for backlog management using dynamic programming;
- A diagnostic of the current practices on maintenance decision-making;
- A comprehensive decision support framework for PM program implementations;
- A cross-sector solution for O&M integration.

6.2 Conclusions

- Issues on data collection & analysis persists, especially in the offshore environment;
- Prevention culture must be encouraged;
- Suitable models are to be pursued (parsimonious modeling);
- O&M integration is opportune in the Industry 4.0 context;
- The SE approach proved useful to provide the "big picture" of the research scope and in the search for alternative solutions.

As consequences of the above, some recommended practices are:

- Set production and quality-based objectives (MOE and FOM) e.g., OEE, RAMS, learning from data (operational availability = system utilization);
- Set focus on a decision process with traceability (e.g., decision trees, MDP, regret analysis, common recordkeeping system);
- Promote:
    - a prevention culture and extend planning horizons (use RUL estimates);

    - O&M&IT integration (e.g., MEL, work-process mapping and redesign, Kaizen).
- Improve management support (e.g., TPM, training);
- Combine maintenance concepts in the PM program (e.g., RCM, LEAN, CBM).

6.3 Continuing lines for this research

The following topics are considered as continuing lines for this research:

1. The questionnaires may be extended to assess the maintenance support performance of a given organization.
2. The survey may be extended to collect data from additional sources and additional interviews may be considered.
3. The text from the interviews may be further explored via the use of computer-aided qualitative data analysis software (CAQDAS).
4. The concept map for Maintenance decision-making ontology could be tested and matured in a pilot project.
5. Integrated O&M protocols and checklists may be developed based on the thesis constructs.
6. The effectiveness of: (i) the MEL approach; and (ii) of the plan for PM program implementations could be verified in the offshore industry (in a pilot project).
7. The MDP model (proposition) may be verified and extended to allow for different component's failure rates and planning horizons. Optimal policies may support O&M scheduling.
8. Making a series of nomograms that match real-world situations.

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Appendix A – Articles

Submitted articles

MACHADO, M.M, HASKINS, C., VIDAL, M.C.R. *The Markov Approach and a Dependability Nomogram* – Submitted in 21/11/18 to the IEEE – Latin America Transactions – Submission #6998.

MACHADO, M.M, SILVA, T.L., ARRUDA, E.F., CAMPONOGARA, E., FERREIRA-FILHO, V.J.M. *Using the Markov decision process to optimize operations and maintenance policies of parallel systems: applications to an offshore power plant* – Submitted in 30/01/19 to the Reliability Engineering & System Safety – Submission #115.

Published articles

MACHADO, M.M., HASKINS, C., *Maintenance Optimization Approaches for Condition Based Maintenance: a review and analysis*. Proceedings of 26th annual INCOSE (IS 2016) Edinburg, Scotland, UK, July 18-21, 2016.

MACHADO, M.M., MANGUINHO D.A.P.M., VALLAND A., USHAKOV S., ROVERSO D. & BEERE H.A. 2014. *RUL modeling for turbo generators of a FPSO: Challenges and opportunities*. Proceedings of Rio Oil & Gas Expo and Conference.

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Submitted articles

The Markov approach and a dependability nomogram

Abstract

This article discusses some of the basic concepts of Markov chain theory and the reasons for the importance and wide applicability of such models in the field of maintenance optimization. Following the discussion of some definitions, maintenance compensations, visualization tools and experimentation with a simple explanatory model, the article explores the relationships between the key parameters of a renewal process. As a result, a visualization of the Markov process is proposed in the form of a nomogram to determine the reliability of a theoretical reparable system.

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Using the Markov decision process to optimize operations and maintenance policies of parallel systems: applications to an offshore power plant

Abstract

A key problem in the operation of complex systems is to synchronize long-term production and maintenance, particularly in adverse operational environments where logistical aspects have a major impact on total repair time and operational costs such as oil field operations. An important issue in these contexts is the deferred preventive maintenance (i.e., *maintenance backlog*). This work is concerned with the continuous operation of multi-unit parallel systems, namely a sequential decision problem, and aims to find optimal operations and maintenance stationary policies for such systems. Markov decision process is used to develop a solution capable of generating optimal policies to support backlog management. A case study is provided from the perspective of an off-shore operator/maintainer in search of policies that maximize a utility function, whilst identifying maintenance slots with respect to the operating scenarios and suitable prevention levels. Beyond the proposal of a simple and effective model, a contribution of this work is the introduction of the *prevention factor*, as a decision support metric.

Published article – 1

26th Annual INCOSE International Symposium (IS 2016)
Edinburgh, Scotland, UK, July 18-21, 2016

Maintenance Optimization Approaches for Condition Based Maintenance: a review and analysis

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Abstract. This study contains a preliminary review of recent maintenance optimization applications, collected from different industries. The idea is to meet and discuss promising approaches, implementation aspects and critical elements, in order to provide guidance for further research. Starting from a set of applications, analyzed under a systems engineering approach, the study proposes a conceptual map to represent the ontology of condition-based maintenance programs and suggests some guidelines for developing an implementation plan.

Keywords: Maintenance optimization, condition monitoring, degradation modeling, condition-based maintenance.

Introduction

In search of high levels of assets' availability, efficiency and safety, among the operator's main concerns are certainly, maintenance optimization aspects. Especially when logistic costs are imperative (e.g. offshore production environment), the ability to find an optimal balance between costs and benefits of maintenance decisions to avoid critical failures emerges as a key factor for the industry.

According to (Machado et al, 2014) significant benefits can be achieved, for instance, when major maintenance interventions (e.g. equipment overhaul) can be postponed based on conclusions from the use of degradation models. Such an approach can be complex but its implementation results may reduce maintenance and logistic costs while keeping availability within required levels. It should be noted that a given system's campaign would not be always extendable as desired. Knowledge gained of the system's state or condition (past and actual) facilitates the ability to detect failures at an early stage. However, there is always a possibility that an intervention could be required earlier than initially expected or planned. In such cases, the main advantage has been avoiding random failure disorders.

According to Dekker (1996: 233) "the problems in applied maintenance optimization models frequently concern data collection and analysis. Application of models requires a good formulation of the problem, which is not easy since most concepts used (such as failure), allows various interpretations. Furthermore, many models are not robust against violations of assumptions or misinterpretation of their concepts." In accordance with Welte, Vatn and Heggset (2006: 1), "…in spite of the great number of methods, mathematical models for maintenance optimization are hardly used in practice. One reason can be that there are often difficulties in providing the proper amount of data."

The set of maintenance optimization applications reviewed herein, involved a variety of tasks and organizational pre-conditions such as: (i) expert's judgment methods, (ii) strong notification culture, (iii) routines for machine event's recording, data collection and analysis, (iv) aspects of information technology (e.g. data infrastructure and analytic capacity), and (v) thorough operational experience. In that sense the authors agree with Vatn and others (1996) that the need for such diverse expertise may be one of the reasons why it has been so hard to implement model based maintenance approaches.

In order to coordinate the activities in a maintenance optimization application, a robust communication framework oriented to analysis, synthesis and decision must be available with a proper analytical capacity and expertize. Such framework can be conceived, among others, by the use of Systems Engineering approach, principles of Operations Research and by managing communication, coordination and collaboration in a sociotechnical system that emerges from the technical assets (e.g., a condition-based maintenance program). This normally involves hardware, software and humans in many different roles.

A proposed optimization approach should be well communicated to reliability engineers, maintenance engineers, technicians and the plant manager. According to Bertalanffy (1968), one of the main goals of General Systems Theory was to promote interdisciplinary cooperation by improving the communication between specialists.

The present collection and analysis has been conducted with the intention of teasing out common attributes that might provide some insight into the real work of maintenance optimization approaches. Starting from a set of applications, analyzed under a systems engineering approach, the main objective of this study is to propose a conceptual model to represent the ontology of the so-called condition-based maintenance and develop an implementation plan for the offshore operator in the oil and gas industry.

Maintenance strategy: development and context

According to Rausand and Høyland (2004) maintenance tasks and resources have traditionally been allocated based on (i) requirements in legislation, (ii) company standards, (iii) recommendations from manufacturers and vendors, and (iv) in-house maintenance experience. See Fig. 1. Many companies are faced with laws and regulations that set requirements to their maintenance strategies. Recommendations from manufacturer are not always based on real experience data. Many manufacturers get very little feedback from the users of their equipment after the guarantee period is over. Also, it is claimed sometimes that manufacturers' recommendations may be more slanted toward maximizing the sales of consumable spares rather than minimizing the downtime for the user. Fear of products liability claims may also influence the manufactures' recommendations.

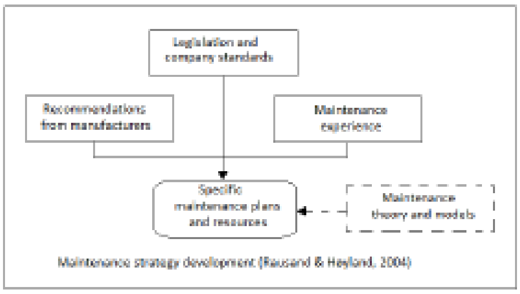

Fig. 1 - Maintenance strategy development

In the following sections, according to the author's experience and from the analysis of maintenance optimization applications, the study examines some aspects of maintenance theory and models.

Main actors and their roles

The maintenance organization should certainly count on cooperative work. The Reliability Engineer, for instance, will consider the system's functions and its respective failure characteristics while the Maintenance Engineer will be focused on maintenance schedules and its logistical aspects. According to Rausand and Røyland (2004) the main concern of a Reliability Engineer is to identify potential failures (regarding a functional block) and to prevent these failures from occurring. It is therefore necessary for the reliability engineer to identify all relevant functions and the performance criteria related to each function.

From a typical Maintenance Engineer's job description, the main concern is as follows: to keep the system in a continuous and smoothly running operation by using routines of monitoring and inspection, to perform maintenance planning and execution, to sustain the production plan, reduce the incidence of costly breakdowns and develop strategies to improve overall reliability and safety of plant, personnel and production processes at minimum costs. (Adapted from a job description available in http://www.prospects.ac.uk/maintenance_engineer_job_description.htm).

The Operational Technician should be oriented to the situation awareness and troubleshooting whilst maintaining routine support activities such as data collection and machine-event' recording.

In the work-processes, operational and maintenance teams should work in a coordinated manner in order to provide an adequate decision support for the plant manager, who has the final word. The recommendations based on the assessments must be well discussed and decisions implemented in a collaborative way under the assumption that, every action may affect the final overall plant's results. Finally, the plant manager should be the one who considers the costs and benefits of a decision while influencing the sociotechnical system to produce efficiently.

Among the Plant Manager's primary responsibilities are: leading the operation and maintenance staff, coordination of plant operations including production, logistics and maintenance while ensuring compliance with all labor, safety, environmental and corporate policies and regulations. In order to maximize daily production, the plant manager should be able to develop and manage the strategies, production planning, stock management, instrumentation calibration, plant modifications and develop innovative systems and processes utilizing all available technology. In summary, the plant manager should ensure that the assets are maintained, supported and available as measured by KPIs such as OEE%. (Adapted from a job description available in http://lagancement.com/getmedia/LCP-Plant-Manager.pdf).

Afterwards, the results and findings must be subject to some analysis, in order to give feedback for the decision-process in the form of lessons learned in troubleshooting.

In the course of this study, it was clear that the systems engineering approach could help better understand this variety of viewpoints. The authors started with the assumption that, by identifying the main actors, their roles and by discussing the most relevant elements mentioned in recent applications, it will be possible to prepare a plan to pave the way for future implementations of condition-based maintenance systems.

Key-definitions and concepts

Most of the following definitions were extracted from Rausand and Høyland (2004).

Maintenance – The combination of all technical and corresponding administrative actions, including supervision actions, intended to retain an entity in, or restore it to, a state in which it can perform its required function [(IEC50(191)].

Maintenance support performance – The ability of a maintenance organization, under given conditions, to provide upon demand, the resources required to maintain an entity, under a given maintenance policy [IEC 50(191)].

Reliability – The ability of an item to perform a required function, under given environment and operational conditions and for a stated period of time (ISO 8402).

Quality – The totality of features and characteristics of a product or service that bears on its ability to satisfy stated or implied needs (ISO 8402).

Availability – The ability of an item (under combined aspects of its reliability, maintainability, and maintenance support) to perform its required function at a stated instant of time or over a stated period of time (BS 4778).

Maintainability – The ability of an item (under stated conditions of use, to be retained in, or restored to, a state in which it can perform its required functions, when maintenance is performed under stated conditions and using prescribed procedures and resources (BS 4778).

Dependability – The collective term used to describe the availability performance and its influencing factors: reliability performance, maintainability performance, and maintenance support performance (IEC 60300).

Failure (event) – The termination of its ability to perform a required function (BS 4778).
2- An unacceptable deviation from the design tolerance or in the anticipated delivered service, an incorrect output, the incapacity to perform a desired function (NASA 2002).
3- A cessation of proper function or performance; inability to meet a standard, non-performance of what is requested or expected (NASA 2000).

Failure symptom – An identifiable physical condition by which a potential failure can be recognized [(MIL-STD-2173(A)].

Normal operating condition - operating condition that represents as closely as possible the range of normal use that can reasonably be expected. [IEC 62368-1:2010, 3.3.7.4].

Maintenance optimization models overview

According to Dekker (1996), the first operations research models for maintenance appeared in the 1960's, attempting to optimize preventive maintenance programs. In the

1970's condition-monitoring came forward focusing on techniques which predict failures using information on the actual state of equipment allowing for condition-based maintenance programs. This approach has proven to be more effective than the typical time-based preventive maintenance.

Another important approach is the reliability-centered maintenance (RCM), which was founded in the sixties initially oriented towards the airplane maintenance (Rausand & Høyland, 2004). This reliability concept emerged just after World War I and was then used in connection with comparing operational safety of one-, two-, and four-engine airplanes. Reliability was measured as the number of accidents per hour of flight time. Among the optimization methods there are linear and non-linear programming, dynamic programming, Markov decision methods, decision analysis techniques, search techniques and heuristic approaches. In general, applications of maintenance optimization models cover the following aspects (Dekker, 1996):

- Description of a technical system, it function and importance;
- Modeling of the system degradation in time and possible consequences for the system;
- Description of the available information about the system and the actions open to management;
- An objective function and optimization technique that helps in finding the best balance.

In their survey, Heng and others (2009) grouped the existing methods for predicting rotating machinery failures into three main categories, as follows:

- Traditional reliability approaches – event-based predictions;
- Prognostics approaches – condition-based predictions;
- Integrated approaches – predictions based on event and condition data.

According to (Heng et al, 2009) traditional approaches to reliability estimations are based on the distribution of event records of a population of identical units. Many parametric models, such as Poisson, Exponential, Weibull and Log-Normal distributions have been used to model machine reliability. The most popular among them is the Weibull distribution due to its ability to accommodate various types of behavior including infant mortality in the "bath tub" curve.

According to Rausand and Røyland (2004) the approaches to reliability analysis can be distinguished in three branches: (i) hardware reliability (regarding technical components and systems), (ii) software reliability, and (iii) human reliability. Within hardware reliability, we have the physical and the actuarial approach. In the physical approach (often called structural reliability analysis) the strength S of a technical item and the load L that the item is exposed to, are modeled as random variables and the failure will occur as soon as the load is higher than the strength. The load will vary with time and so the strength, since the item will deteriorate with time due to failure mechanisms, (e.g.: corrosion, erosion and fatigue). Therefore, strength and load can be considered as time-dependent variables. In the actuarial approach all our information about the operating loads and the strength of the component are described in the probability distribution function $F(t)$ of the time to failure T. No explicit modeling of the loads and strength is carried out and reliability characteristics like *failure rate* and *mean time to failure* are deduced directly from the probabilistic distribution function. The traditional system reliability analysis is well explored in many books, e.g.: (Rausand & Røyland, 2004). As an extension to the traditional system reliability approach, another concept such as *symptom-based reliability*, which is based on symptoms of the operating systems, has been proposed by Natke and Cempel (1997) (see Cempel et al. 2000). This symptom-dependent reliability is quite different from the commonly known lifetime-based reliability.

Maintenance objectives

Based on Dekker (1996) maintenance optimization models are those mathematical models whose aim to find the optimum balance between the costs and benefits of maintenance decisions, while taking all kinds of constraints into account. In most of cases, maintenance benefits consist of savings on costs which would be incurred otherwise. Maintenance optimization objectives can be summarized under four headings:

- System function (availability, efficiency and product quality);
- System life (asset management);
- Safety and;
- Human well-being.

Ensuring the system function should be the prime maintenance objective for production equipment. Here maintenance have to provide the right (but not the maximum) reliability, availability, efficiency and capability (i.e. producing at the right quality) of production systems in accordance with the needs. In principle, it is possible to give an economic value to the maintenance results, and a cost-balance can be done. According to (Welte et al., 2006) the objective of scheduling and optimization of maintenance models is to find the maintenance and renewal strategy where the total costs of repair, inspections, production losses and other consequences are minimal.

Maintenance decisions

According to Vatn (2007), there are many kinds of decisions regarding maintenance optimization and some of them are:

- Deciding the amount of preventive maintenance;
- Deciding whether to do first line maintenance (on site or at the workshop);
- Choosing the right number of spare parts in stock;
- Preparedness for corrective maintenance;
- Time of renewal and;
- Grouping of maintenance activities.

According to Ferreira Filho (2014) the set of methods to formulate and solve problems is what is usually called operations research (OR), which is a scientific method for decision-making. Broadly consists in the description of a system with the aid of a model, and through experimenting with the model, discovering the best way to operate the system. The operations research as we know arose during World War II as result of studies carried out by interdisciplinary teams of scientists, hired to solve military problems of strategic and tactical order. An OR study typically involves six stages, as follows: Formulation of the problem; Construction of a model of the system; Calculation of solution through the model; Testing of model/solutions; Establishment of controls of the solution;

Implementation and follow-up. Furthermore, elements of graph theory, simulation, fuzzy logic and some heuristics are often used in optimization approaches.

An overall reference model

Rausand and Røyland (2004) mentioned in their book a promising approach proposed by (Vatn et al, 1996). In this approach, influence diagrams were used in the conception and for the communication of the model between the persons involved i.e., plant manager, maintenance engineers and reliability engineers. An influence diagram is a directed graph, $G = (N, E)$ where N is a set of nodes, and E is a set of arcs (edges) connecting the nodes. See Figure 2.

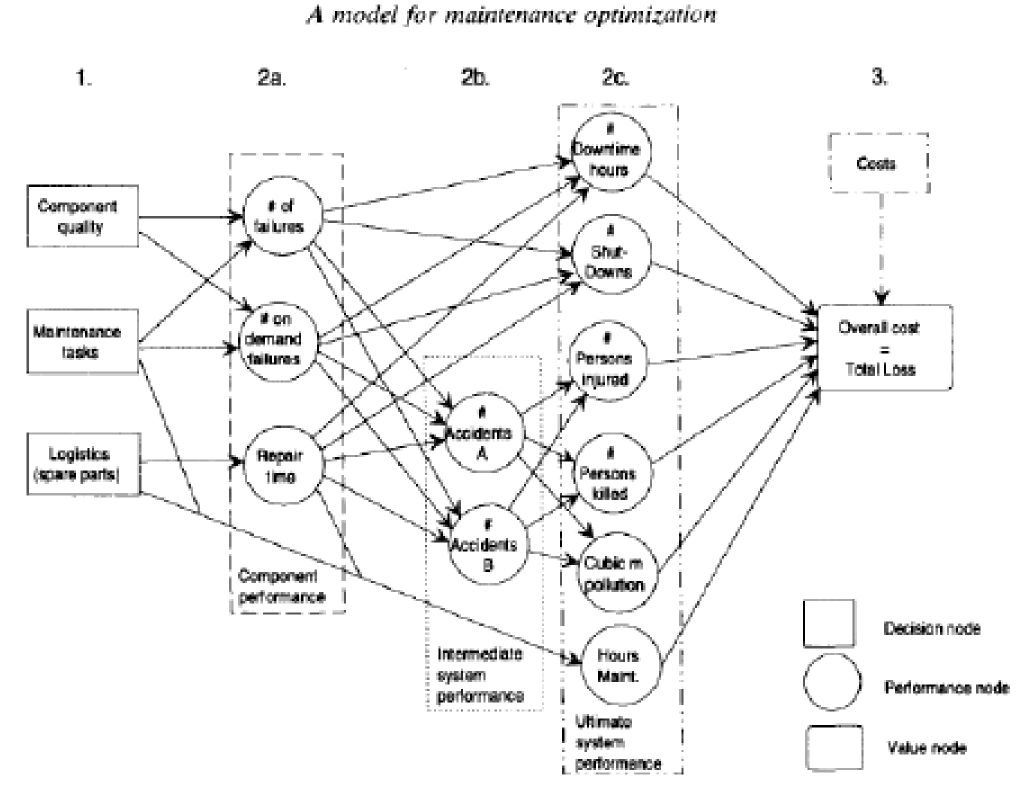

Fig. 1. Influence diagram showing effect of maintenance.
(Vatn, Hokstad and Bodsberg, 1996)

Figure 2 – Influence diagram for a maintenance optimization model

In the summary of their paper, Vatn et al. (1996) concluded that decision theory, data analysis and expert judgement methods are essential to establish credible input data to the analysis and a thorough operational experience is required to establish optimal methods. The need for this diverse expertise may be one of the reasons why it has been so hard to implement model based maintenance approaches in practice. As extensions, they mentioned, among others: (i) to include models of on condition based maintenance; (ii) present a practical approach for large systems; (iii) allow for use of true utility functions in situations where the effect of the alternatives on the attributes are unknown in advance;

(iv) more explicit use of decision logic; (v) compiling the results into maintenance schedules.

Degradation processes modeling: a brief overview

An essential part of a maintenance optimization approach is the modeling of the system's degradation and the occurrence of failures in such a way that is clear how both are influenced by the maintenance regime. Maintenance actions will only be effective if they address the most relevant degradation mechanisms. Sheriff and Smith (see Dekker 1996, p. 232) classified these mathematical models as: Deterministic models; Stochastic models: (i) under risk, and (ii) under uncertainty. Considering degradation as a reduction in performance, reliability or life expectancy, for most systems and components it is typical to think of degradation as a function of factors such as usage, environment, ageing etc. (Jirsak et al., 2014). Hence, it seems reasonable to consider degradation as a stochastic process and as such, it has been modeled in many different ways according to Kharoufeh and Cox (see Jirsak et al. 2014, p. 736).

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Condition monitoring and diagnostics of machines

In order to implement a condition-based maintenance program, criticality analysis must be performed, monitoring routines, data collection and analysis must be scheduled through optimized work-processes within the organization. In that sense, basic guidance can be found among the related standards. From the ISO - International Organization for Standardization, for example, the ISO 17359 (2011) provides general guidelines and procedures for registration, evaluation and estimation of machine condition meanwhile the ISO 13379 (2003) presents guidelines for data interpretation and diagnostics techniques. The ISO 13372 (2004), for instance, provides a vocabulary. The ISO 13381 (2004) provides some guidelines for prognostics. The ISO 13373 (2002) is devoted to vibration condition monitoring. The ISO 18436 (2008) for requirements for qualification and assessment of personnel and the ISO 13374 (2003) is about data processing, communication and presentation. Another relevant ISO standard for the oil/gas industry is the ISO 14224 (2006) which is devoted to the collection and exchange of reliability and maintenance data for equipment. Also important is the reliability database OREDA (2009) which provides reliability data from a wide range of equipment used in the oil and gas industry. Problems of machinery diagnostics and prognostics using condition-based maintenance approaches are well addressed in literature for both data acquisition, data processing and maintenance decision support, e.g.: (Jardine et al., 2006). Despite the absence of consensus on the terminology related to diagnostics, according to Vachtsevanos and others (see Machado et al, 2014, p.2), "*it can be described as a procedure of reasoning to interpret the health condition of machinery equipment using data acquired during its operation. It has a vital role in decision-making, both in aspects of operation and maintenance tasks*". In addition, diagnostic procedures should be adjusted according to the potential failures (based on their likelihood and severity) that can occur in a machine ISO 13379 (2003). The principle is shown in Figure 3. The V-shape represents the high-level concerns (maintenance: machine, risk assessment) and the low-level ones (measurements: monitoring, periodical tests, data processing). Each layer consists of a preparatory design phase (left) and a usage phase (right).

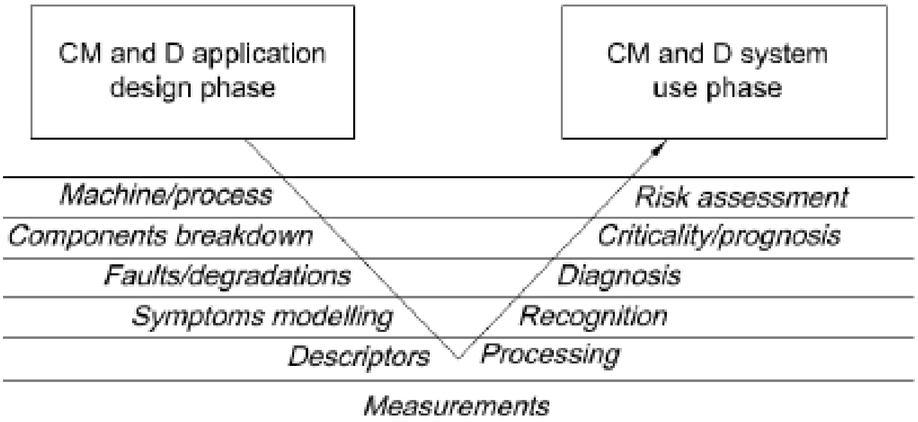

Figure 3 – Condition monitoring and diagnostics (CM&D) (ISO 13379:2003)

Analysis

Dekker (1996) presents a complete survey based on searching the ISPEC database and asking a number of leading experts about their applications. As result, he founded a set of 112 applications, which he composed and classified as follows:

- 48 Proposed models (PM) – a new model is put central, but in which indications are given about applications of the model;
- 42 Case studies (CS) – the optimization model has been used with real data to provide advice to management on a real problem;
- 14 Application tools (AT) – the focus is on an application tool, like a decision support system or expert system and which mention applications of the tool;
- 8 Discussion papers (DP) – gives some overview and discussion of case studies or comparison of applied methods and concepts.

Most of studies were written in cooperation with academic reliability researchers (68 of 112). Few originate from industry and if they do, often from an industrial research institution. The year of publication of all 112 papers are presented in Table 1.

Table 1a – Sample 1

Year	Publications [n.]
-1969	1
1970 – 1974	4
1975 – 1979	17
1980 – 1984	20
1985 – 1989	45
1990 -	25
Total	112

Source: (Dekker, 1996)

Table 1b – Sample 2

Year	Publications [n.]
1995 - 1999	2
2000 - 2004	0
2005 - 2009	2
2010 - 2014	8
Total	12

From Table 1, one can notice an increasing number of publications in the surveyed period. According to Dekker (1996), among the models applied, the age and block replacement models score high, but they are often applied in somewhat different form. Other popular models are Markov decision models and the so-called delay time model introduced by Christer and Waller (see Dekker 1996, p. 233). Equipment overhaul comprises the largest group of applications (about thirty). Another fruitful area is vehicle replacement (ten papers). In order to trace as many references on applications as possible, a problem encountered was that the practitioners more often publish in proceedings than in regular scientific journals, so this category is far more difficult to trace and is not covered by regular databases. The problems in applied maintenance optimization models frequently concern data collection and analysis. Application of models requires a good formulation of the problem, which is not easy since most concepts used (such as failure), allows various interpretations. Furthermore, many models are not robust against violations of assumptions or misinterpretation of their concepts (Dekker, 1996).

Results of preliminary review and analysis

Following the guidelines proposed by Dekker (1996) and the aforementioned sources, the authors started from a collection of maintenance optimization applications in the ESREL-2014 database, by using the same search keywords used by Dekker (1996). As the data from the articles was gathered it was coded (labeled and categorized), analyzed and interpreted. Regarding classification, following the same criteria adopted by Dekker (1996), the new set were composed of 4 case studies, 4 proposed models, 2 application tool and 2 discussion papers. Findings and analysis of these articles are given in Table 3, provided at the end of this paper. Markov decision methods, Monte Carlo Simulation and Gamma process were the most frequent approaches followed by Weibull distribution and Wienner process. See Table 2.

Table 2 – Methods and techniques

Methods and/or techniques	Cases	Freq.
Empirical modeling	(3), (4), (5) and (6)	4
Markov decision methods	(3) and (4)	2
Simulation	(7) and (9)	2
Gamma process	(1) and (7)	2
Weibull distribution	(2)	1
Wiener process	(5)	1
	Total	12

A Conceptual Model for Condition-based Maintenance Program

In order to put focus on the critical elements of a CBM program by the use of a Systems Engineering approach, a conceptual map is proposed in Figure 5 as a representation of a CBM program's ontology.

In this proposed concept map, maintenance optimization appears at the center, as the main focal point. The structure and characteristic of this non-planar oriented graph can be subjected to analysis from different perspectives, allowing a broader understanding of the structure and the nature of the relationships, which is fundamental for the development of an implementation plan.

One advantage of such a mapping over the traditional views is that the temptation to visualize the system as a set of linear processes is avoided and the reader can focus on the relationships as shown. Perhaps the most significant contribution of the ontology is the definition of the CBM program as a structured decision-making process, as seen on the lower right corner of the concept map.

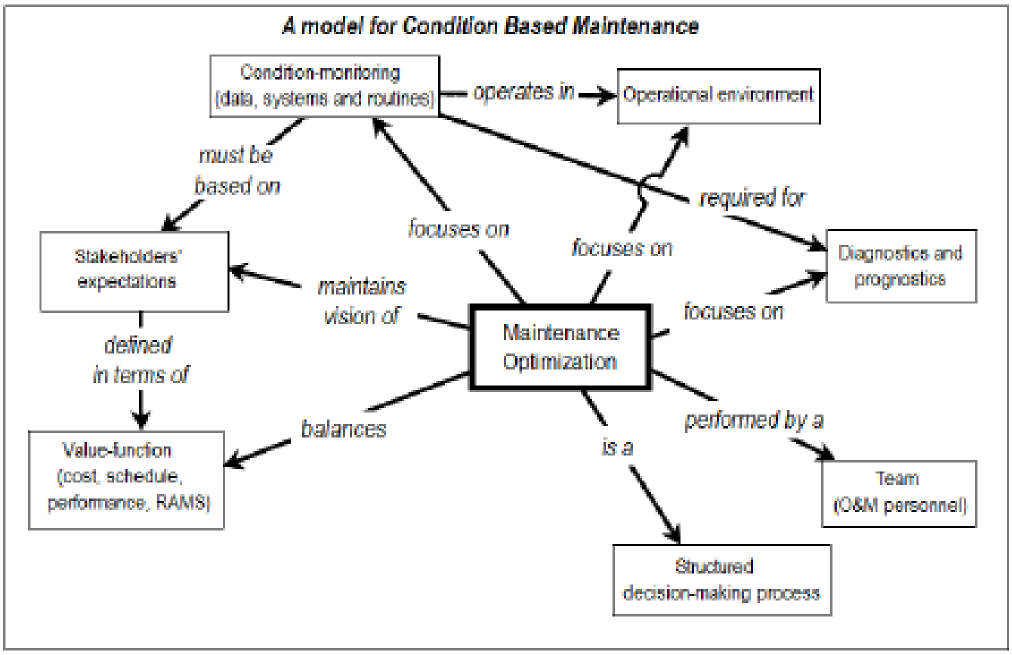

Figure 5 – Concept map the CBM ontology, inspired by Bahill et al, 2002.

A proposed CBM implementation plan

Applying a typical approach of an Operations Research study, the six steps of a CBM program implementation are as follows.

Step 1 - Formulation of the problem (Description of the available information about the system and the actions open to management)

- Description of a technical system, it functions, importance and boundaries;
- Definition of the goals and scope of the analysis (organization's preferences / limitations);
- Agreement on terminology;
- System's states definition/criteria. (e.g.: Excellent; Good; Acceptable; Poor and; Awful);

Step 2 - Construction of a model of the system (Modeling of the system degradation in time and possible consequences for the system)

- Modeling of system's functions and the respective failure characteristics (failure modes, criticality, causes and effects);
- Definition of the database' structure;
- Field data collection and criticality analysis;
- Establishment of the condition monitoring routines;
- Degradation mechanism identification and modeling (for the most critical system's failure modes).

Step 3 - Calculation of solution through the model (An objective function and optimization technique);

- Diagnostics and prognostics analysis (Applying the model inference rules and labels (e.g.: Good, Bad etc.);
- Design of experiments;
- Selection of the optimization technique (heuristics etc.).

Step 4 - Testing of the model/solutions;

- Evaluation of the model parameters and results;
- Tuning up the model;

Step 5 - Establishment of controls of the solution;

- Assess the system's condition;

Step 6 - Implementation and follow-up.

- Decision-making (communication and reasoning);
- Maintenance action (planning, scheduling and execution);
- Feedback.

The sixth step is probably the most difficult one. Implementation of a CBM program requires the involvement of different departments and competences in a collaborative way, to achieve the benefits from a pro-active mindset for decision within the organization.

Final considerations

Among the approaches and techniques available in the literature, Markov decision methods, Monte Carlo Simulation and Gamma process are still the most frequent approaches followed by Weibull distribution and Wienner process. Proposed models and case studies are the majority among the increasing number of applications. The problems faced by the applicants frequently concern data collection and analysis. This suggests that the actions to design and operate an optimized maintenance program have the following preconditions: (i) improve the quality usage of data (condition monitoring and reliability data); (ii) perform criticality analysis (equipment, components and degradation mechanisms); (iii) establish monitoring and feed-back routines; (iv) improve, if necessary, the related work-processes and; (v) install an appropriate analytical capacity (human and technological).

Furthermore, in order to develop fruitful discussions towards maintenance optimized applications and programs implementations, the authors argue that the operators should consider the industry consensus from the international standards, apply the Systems Engineering approach and the principles of Operations Research, identify in-company expertizes and, challenge the academia, as much as possible, with consistent historical databases key-questions.

In summary, considering the oil and gas industry, system's operation (i.e. availability) should be one of the most important maintenance optimization headings. Decisions should lead to the maintenance and renewal strategy where the total costs of repair, inspections and production losses are minimal. Maintenance actions should address the most relevant degradation mechanisms. The procedures of reasoning to interpret machine condition should form the basis for decision-making, both in aspects of operation and maintenance tasks.

As further research lines, in order to acquire the benefits of a robust and holistic approach, a promising opportunity to innovate in maintenance optimization can be starting from the operator's perspective and continuously strive to find a balanced combination of experienced-based and data-driven modeling. Finally, the authors considered that operators (and maintainers) should be able to select the appropriate set of tools and methods for modeling and simulation in order to allow extracting relevant information and knowledge from field data for learning and for decision purposes.

Acknowledgements

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Appendix - Preliminary review

Table 3 – Applications of maintenance optimization (Dec. 2014)

N.- Publication category / Characteristics	1-CS	2-AT	3-PM	4-PM	5-PM	6-CS	7-CS	8-AT	9-CS	10-DP	11-DP	12-PM
Author / Year	Saarela et al, 2014	Hidalgo & Souza, 2014	May and Mcmillan, 2014	Jirsak et al, 2014	Etienne et al, 2014	Machado et al, 2014.	Welte, Vatn and Heggset, 2006.	Medina-Oliva et al, 2014	Lundtofte and Solibakke, 2014	Dekker, 1996	Heng et al, 2009	Vatn, Hokstad and Bodsberg, 1996
Industry-sector / application level (unit or system) / equipment type	Nuclear power generation / unit / Air Filters	Hydro power generation / unit / Speed regulators of Hidro generators	Wind power generation / system / Offshore Wind turbines	Water utility / unit / Rapid Gravity Filter	Space / system / Satellite	Oil & Gas / system / Power generation (Gas turbine engines of a FPSO)	Hydro power generation / system / Hydro power components	Maritime transportation / system / Fuel engines	Oil & Gas / system / (FPSO - Power generation; Recompression and; Water injection)	All / NA / NA	All / NA / NA	Processing plant (generic) / unit / components of a processing plant
Maint. Optimization problem / Approach type (problem statement) / Obs.	Predictive maint. / RUL Modeling	Predictive maint. / Reliability / multicriteria	Scheduled maint. - Probabilistic	Scheduled maint. Probabilistic / Hidden Markov model	Scheduled maint. PHM - Prognosis and Health Monitoring	Predictive maint. / RUL Modeling (Empirical TTF modeling for gas metering valve related faults)	Scheduled maint. Optimization / Probabilistic (Markov chain model / Gamma distribution)	Predictive maint. / PHM - Prognosis and Health Monitoring - application in KASEM e-maintenance	RAM analysis model using MCS and Markov method	Discussion paper	Discussion paper	Scheduled maint, optimization / Multi-objective linear optimization model
Objective/value-function / Method(s)	TTF estimations	PM intervals by using decision's preference (min cost or maximiza reliability/ PROMETHEE	Min. Costs of CBM under system detection rates and False alarms	Condition-monitoring / Markov process	Health monitoring and prognostics	Data driven TTF estimations	Condition-monitoring / Markov	Minimize the effects of unexpected system failures / predictive diagnostics	RAM analysis and comparison between MCS and Markov method.	Survey / Search on the ISPEC database	Survey	Min. Cost by optimal maint. schedule for components of a system according to performance measures.
Decision figures (criteria) / Performance variables	Dif. Pressure etc.	Reliability and costs	Costs, detection rates, false alarms	Performance Data	Cond. Monitoring data	Exhaust temperature spread	Cond. Monit. data, costs and discount rate	Cond. Monit. data	Time to failure	NA	NA	RAMS and costs
Model used (Stochastic process) / Constrains taken into account	Gamma process	PROMETEE method / Exponential	Hiden Markov Model/Chain	Hiden Markov Model	Wiener process	Regression-based model	Markov chain model / Gamma distribution and MCS	Software KASEN e-maintenance	Markov method and MCS	Survey	Survey	Weibull law

Published article – 2

IBP 1802 14

RUL MODELING FOR TURBO GENERATORS OF A FPSO: ALTERNATIVES AND CHALLENGES

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Abstract

Maintenance planning of critical equipment is always among the operator's concerns mainly when the assets are located offshore. Thus, the ability to predict failures emerges as a factor to improve operational efficiency of offshore installations. In this scenario, data quality issues and the ability to use technical information are becoming important objectives for the business. Far from a simple task, to estimate the Remaining Useful Life (RUL) is one of activities that demand involvement of different disciplines and skills in a collaborative way. This article presents and initiates a discussion about some of the relevant emerging aspects in the development of practical Remaining Useful Life approach for offshore machinery. The research is conducted using data sample from turbo generators providing power for one FPSO and includes data acquisition, processing and filtering; data analysis; degradation mechanism identification and; recommendations for further work. The approach is developed under the guidance of ISO standards for condition monitoring and diagnostic of machines counting also with the collaboration of experts in the field.

Keywords: Remaining useful life, condition monitoring, maintenance decision-making, production system, production facilities.

1 - Introduction

Let us start with the core question: Why and how should the operator dedicate his/her efforts in estimating the remaining useful life (RUL) of the considered critical assets? In our case, the main reason is a need to adopt a predictive approach devoted to critical equipment installed offshore particularly onboard of floating production storage and offloading units (FPSOs) in a scenario of great logistical challenges as for the Brazilian pre-salt layer production.

Experience has shown that in most cases certain major maintenance interventions (overhauls) which are performed periodically can be postponed, based on conclusions from the use of degradation models and remaining useful life estimations enabling significant benefits. Such an approach is complex for analysis, but at the same time, its implementation results may reduce maintenance and logistic costs while keeping availability within required levels. The relevance of this study is based on that Petrobras will have a significant increase in the number of turbo-generators of equal design in the next few years. Thus, it is very important to assure that the company is collecting the most relevant data to cover the most significant failure modes. Since turbo-generators are very critical and likely the most expensive part of equipment installed on FPSO, such modeling will also become relevant for other oil companies.

One good starting point is a failure mode, effects and criticality analysis (FMECA), which typically highlights the failure modes with the highest probability of occurrence and the most severe consequences. Maintenance policies, which involve maintenance plans revision, definition of performance and integrity indicators, constitution and population of machine events databases, should be efficiently utilized in order to make a successful condition monitoring program. The main idea of this study is to establish a RUL assessment for rotating equipment whilst evaluating the actual machine data collection and policy. According to (Moura et al., 2007), a widely used method for fault prediction is the model of Remaining Useful Life (RUL) whose idea is to predict or estimate how much time (life) is left before a failure occurs given an estimation of the current state of the machine and the history of their operational profile.

Before starting the discussion of the methods used herein, it should be stated that the problems of machinery diagnostics and prognostics using condition-based maintenance approaches are well addressed in literature for both data acquisition, data processing and maintenance decision support (Jardine et al., 2006), as well as the modeling methods (e.g. Sikorska et al., 2011; Li and Nikitsaranont, 2009).

It is also important to note that the machine campaign cannot always be extended. Due to increased knowledge of the condition of the equipment and, therefore, having the ability to detect faults at an early stage, there is always a possibility that an intervention could be required before what was initially expected. In such cases, the main advantage has been avoiding random failure disorders.

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The present project is conducted under the guidance of the Center for Integrated Operations in the Petroleum Industry - IO Center.

2 - Methods used

As a starting point, the operator can find good guidance in the ISO standards for condition monitoring and diagnostic of machines. The ISO 17359 (2011) provides general procedures for registration, evaluation and estimation of machine condition, and the ISO 13379-1 (2012) presents the main aspects for data interpretation and diagnostics techniques. Despite the absence of consensus on the terminology related to diagnostics (Vachtsevanos et al., 2006), it can be described as a procedure of reasoning to interpret the health condition of machinery equipment using data acquired during its operation. It has a vital role in decision-making, both in aspects of operation and maintenance tasks. In addition, diagnostic procedures should be adjusted according to the potential failures (based on their likelihood and severity) that could occur in a machine (ISO 13379-1, 2012). The principle is shown in Figure 1. The V-shape represents the high-level concerns (maintenance: machine, risk assessment) and the low-level ones (measurements: monitoring, periodical tests, data processing).

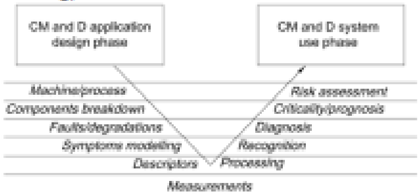

Figure 1 – Condition monitoring and diagnostics (CM&D) cycle (From ISO 13379-1: 2012)

Condition monitoring for offshore installations is certainly a challenge, not least when it comes to data quality and analysis. Having identified the critical functions it would be possible to identify the critical components, failure modes and degradation mechanisms. Occurrences of critical failure modes will make it necessary to shut down the turbo generators, and this will represent a point in time where maintenance has to be performed. It is the period from the current situation until the point in time when maintenance becomes necessary that will be estimated by RUL modeling. By estimating the remaining useful life for one degradation mechanism and failure mode, it will also be possible to identify, one at a time, the components that should be maintained. This can be illustrated by Figure 2.

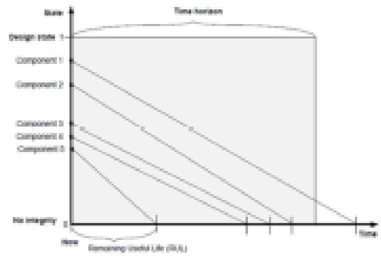

Figure 2 - RUL of critical components for determination of next maintenance action

As a starting point the examples of matching faults to measured parameters and techniques for aero gas turbine and electric generator were adopted, as much as possible and not limited to, ISO 13380 (2002), i.e. Table C.3 and Table C.8 respectively. Eventually there should be a number of critical functions, provided by a number of considered components with associated failure modes for which RUL analysis can be performed. Due to complexity of the analysis, it is suggested to look at one failure mode at a time. The failure mode with the shortest RUL for the chosen component will represent a point in time associated with the earliest required maintenance action.

2.1 - Machine/process

The system under study belongs to the main power generation system of an FPSO unit operating in the Campos Basin - Rio de Janeiro. It has 4 turbo-generators each consisting of an aero derivative gas turbine with nominal capacity of 25000 kW driving an electric generator. The main emphasis is given to the gas turbine and some technical characteristics of the machines under study are shown in Table 1:

Table 1 – Technical characteristics of the system under the study (Based on Table A.19 of the ISO 14224)

Name	Description	Unit/code
Type of driven unit	Electric generator driven by PT	PT driven thermodynamically by gas turbine.
Power – design (ISO)	28.337 (38.000 hp)	kW
Power – operating	13.600	kW
Operating profile	Load sharing between three Turbo Generators (TGs)	
De-rating	No	
Speed	4.800 / Maximum continuum 5.040 / Control 4.560 to 5.040	RPM
Number of shafts	2	
Starting system	Motor driven by two pumps of tree installed	Hydraulic

Backup starting system	None	
Fuel	Dual-fuel – operating mostly with gas	Gas or Diesel
NOxebatement	None	
Air inlet filtration type	High speed system	

2.2 - Components breakdown, faults/degradations

From a maintenance perspective, it is of interest for the operator to have a functional tree of the machine. This tree should be composed mostly of the maintainable parts. For the purposes of this study, we assume as a guideline, the ISO14224 (2006) (refer to Table A.18 and Figure A.5 in ISO 14224).

From the component breakdown, one should list all possible failure modes and their respective causes and degradation mechanisms. Then the criticality of each of the failure modes should be assessed by the expert judgment or from historian data based on significance (safety, availability, maintenance costs, etc.) and the probability of occurrence (refer to Tables 2 and 3). Since even for single components there is a large number of potential failures (a gas turbine can have up to 20000 components/subsystems and more), it might be reasonable to decide at this stage which faults should be covered by the diagnostics. Both the operating conditions best suitable for identifying the chosen faults as well as the reference conditions should be defined.

2.3 - Symptoms modeling, descriptors and measurements

In the modeling of symptoms, the operator must count on the expertise within the organization with respect to a particular asset (equipment). In view of the growing importance of these machines in the production chain, we believe there is a place for collaboration between manufacturers of machines and condition monitoring systems, experts (internal and external) as well as cooperation with research institutions. It is important to state that the operator does not necessarily have enough information for RUL modeling (e.g. a revised failure tree and/or a revised FMEA).

According to ISO 13379-1, descriptors can be obtained from condition monitoring systems, either directly or after the processing of the measurements. The diagnostics becomes easier when descriptors that are more selective are chosen and hence more selective symptoms. Descriptors has one big advantage over the measurements – their selectivity helps to increase the accuracy of the diagnostics quite significantly.

Data from sensors were stored, processed and analyzed in order to identify: 1) correlations between parameters that best explain the events (e.g. principal component analysis etc.); 2) patterns of behavior (symptoms) related to the major occurrences; 3) if there were variables that should be included in the monitoring set and; 4) what more can be considered (according to what is available in the historian data-bases) in the correlation of variables with their failure modes or critical components/subsystems.

The process of collecting and storing relevant information (data) from the monitored physical assets for the purpose of condition-based maintenance (CBM) is considered in the current case as a data acquisition process (or simply the measurements). In general, all the collected data can be subdivided into two groups (Davies and Greenough, 2000): 1) event data (includes information on what actually happened, what caused the event and what was done); 2) condition monitoring (CM) data (measurements related to the health state of the machine (i.e. vibration data, temperature, pressure, oil debris analysis data, etc.). Typically, the event data collection requires manual data entry, while CM data nowadays is collected with the help of sensors and is done automatically. One thing that we would like to draw the readers' attention to is that both the event data and the condition monitoring data are equally important for successful CBM and overlooking of one type of data can result in limited efficiency of data use and overall problems with CBM (Jardine et al., 2006).

2.4 - Processing and recognition

Data processing should be started with data filtration/cleaning, since the collected data (especially those entered manually) may contain errors. The most common types of errors include the human factor and sensors fault/malfunctioning. In general all CM data can be divided into 3 categories: 1) value type data (single value collected at a specific time (i.e. temperature, pressure, oil debris analysis data, etc.)); 2) waveform type data (time series data collected at a specific time (for example, vibration and acoustic data)); 3) multidimensional type data (multidimensional data collected at a specific time (i.e. different images like X-ray, thermographs, etc.).

2.5 - Diagnostics, prognostics and RUL

The final step in all condition based maintenance approaches is making decisions. Diagnostic of machine failures is basically a procedure of mapping the information obtained in the measurement space and/or features in the feature space to machine failures in the failure mode space (definition is according Jardine et al., 2006). Different statistical methods are available for machinery failure diagnostics. Here we will list only some of them. Hypothesis testing has been applied to failure detection (Kim et al., 2001; Sohn et al., 2002) as well as statistical process control (SPC; Fugate et al., 2001). Another method is cluster analysis (Artes et al., 2003). It looks for minimum within-group variance while maximizing between-group variance. Typically, different distance measures/functions are used for pattern recognition. For more details on this topic, the reader can refer to the literature (e.g. Gourmas et al., 2002; Lou and Loparo, 2004). Another method that can be used for failure diagnosis is the so-called hidden Markov model (HMM; Elliott et al., 1995). Another fast expanding group of methods is called artificial intelligence (AI) techniques. In literature, two groups of AI techniques for machine diagnostics are popular among the researchers: artificial neural networks (ANNs) and expert systems (ESs). In addition, such techniques as fuzzy logic systems, fuzzy-neural networks (FNNs) and evolutionary algorithms (EAs) can be highlighted (Jardine et al., 2006).

Prognostics are a complex task (comparing to diagnostics; (Sikorska et al., 2011). In general, two main types of prognostics can be shown. The first includes a prediction of the time that is left before machine (component) failure occurs and is called remaining useful life (RUL). The second one is used to predict the time that the machine would operate without a failure (important for nuclear power plants) up to some time in future. RUL can be defined as the conditional random variable with the help of the following formula:

$$T - t | T > t, Z(t) \qquad (2.1)$$

where T denotes the random variable of time before failure occur, t is the current age of machine (component) and $Z(t)$ is the past condition profile (history) up to the current time (Jardine et al., 2006).

3 – Preliminary results

From the high-level analysis, according to the available records, the magnitude of the maintenance costs of the power generation system represents 6.5% of the total maintenance costs of the related FPSO for the period considered (2008–2012) and Table 2 presents the relative impacts of each main turbo-generator's subsystem on maintenance costs, number of intervention and down time respectively.

Table 2 – Subsystems' importance for turbo generators

Turbo generators of the FPSO (2008 - 2012) [132.012 operating hours in 170.861 hours calendar time]			
System subdivision based on ISO 14224	Maint. Costs Correct.+prev. [%]	Interv. frequency Correct.+prev. [%]	Down Time Corrective [%]
COMPRESSOR + HP TURBINE + POWER TURBINE	20%	9%	24%
FUEL SYSTEM	17%	13%	21%
LUBRICATION SYSTEM	13%	20%	12%
EXHAUST	12%	19%	6%
ELECTRIC GENERATOR*	11%	12%	1%
AIR INTAKE	9%	2%	0%
MISCELLANEOUS	5%	8%	19%
CONTROL AND MONITORING	5%	6%	11%
FIRE AND GAS PROTECTION	5%	9%	0%
STARTING SYSTEM	1%	2%	5%
ACCESSORY DRIVE	1%	1%	1%
COMBUSTION SYSTEM	1%	0%	0%
*Subsystem representing the generator			

What can be seen at the top of the table, for instance, is a set of subsystems (COMPRESSOR + HP TURBINE + POWER TURBINE) previously grouped with different criteria than ISO14224(2006). FUEL SYSTEM and LUBRICATION SYSTEM also comes up with important negative impacts on production. Other consideration should be given to MISCELLANEOUS as a subsystem that comes in 3rd place in terms of corrective down time.

After that, the prioritized machine events were obtained directly from the Human Machine Interface as presented in Table 3.

Table 3–Event type (prioritized)

Event type
FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN
FC: GAS DOWNSTREAM PRESSURE FAULT SHUTDOWN
FC: GAS UPSTREAM PRESSURE FAULT SHUTDOWN
FC: LIQ UPSTREAM PRESSURE FAULT SHUTDOWN
FC: IGNITION FAILURE SHUTDOWN
GG EXHAUST AVERAGE TEMPERATURE HIGH SHUTDOWN
IS-SD: MAIN LO RUNDOWN TANK FILL TIMEOUT
WHRU INLET/BYPASS DAMPER LINKAGE FAILURE
FC: LVDT VIGV 2/3 POSITION ERROR SHUTDOWN

In the following sections we intend to perform, as much as possible, the required steps from measurements up to risk assessment, passing through: data processing; failure recognition; diagnosis and; criticality/prognosis.

3.1 - Findings from data analysis

In the following, we report the preliminary findings of four stages of data analysis:

1) Fault recognition/classification - Analysis of occurrences of one selected fault type (FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN) in the operation of one selected turbo generator (TGC), and classification model to recognize turbo generator 'runs' leading to this fault (see Section 3.1.1);

2) Model based diagnostics - Analysis of occurrences of one selected fault type (FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN) and its correlation with a model of turbo generator efficiency (see Section 3.1.2);

3) Data processing – Analysis of turbo generator exhaust temperature distribution and its relation to selected fault types (see Section 3.1.3) and;

4) Prognostics – Construction of empirical time-to-failure models for the aggregated set of fault types related to gas metering valve (see Section 3.1.4).

3.1.1 - Fault recognition/classification of FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN

The first approach pursued in this project was directed at exploring whether turbo generator 'runs' (i.e. periods of operation from start to stop) immediately preceding a fault could be distinguished from 'runs' not followed by a fault. Given the large amount of operational data available (over 100 measurements for each turbo generator, sampled for the most part at 1 minute intervals, and collected for 4 years (one year was left for future testing)), the first analysis was focused on one fault type, one turbo generator, and two years of operation. The fault selected was the one given highest priority by the operator, i.e. FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN, the turbo generator selected was the one with most faults of this type, i.e. TGC, and the years selected were the ones with most occurrences of this fault type, i.e. 2010-2011. Data was then collected, time aligned, and aggregated in one table, which then included 92 separate measurements and 1,035,507 time samples, for a total exceeding 95 million data values. The FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN fault is triggered whenever the pressure downstream of the GFMV (gas fuel metering valve) exceeds the value of 68.95 kPa before ignition is detected (i.e. the exhaust temperature is above 65 °C and rising at a rate higher than 12 °C/s). In short, this is a protection against gas accumulating in the manifold without ignition, with the risk of a spark and subsequent explosion within the combustion chamber.

One immediate challenge with analysing this type of fault was the unavailability of logged data for the most relevant measurements near the GFMV, i.e. the ones triggering this event. In particular both gas pressures upstream and downstream of the GFMV were not available, as well as the GFMV opening position and the gas temperature upstream of the GFMV.

Of the 92 collected measurements, a subset of 7 was selected which were deemed to potentially include the most relevant information for this particular fault type. The selected measurements were: Fuel gas supply pressure; Fuel gas manifold temperature; Gas generator P1 pressure; Gas generator combustion inlet pressure; Gas generator exhaust pressure; Gas fuel flow and; Inlet air filter differential pressure. Individual turbo generator 'runs' were then identified, for a total of 102 in the selected two years of operation. Of these, 9 runs were followed by a FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN fault, of which 7 were gas fueled runs, and 2 were diesel fueled runs. We focused on the 7 gas runs in this analysis.

The next step involved the definition of which features to use to describe turbo generator 'runs' which could then be used as input to classification algorithms that would generate models that would distinguish 'bad runs' (i.e. runs followed by an FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN event) from 'good runs'.

A combination of standard statistics (e.g. mean, median, standard deviation, slope), ad hoc statistics (e.g. recent slope, outlier proportion, level discontinuities), and cluster analysis features (cluster memberships from k-means clustering (Hartigan, 1975) in the space of the 7 selected measurements) were computed and used in input to a Gradient Boosting Classifier algorithm (Friedman, 2001) to obtain a model that would identify runs followed by FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN events.

Given the limited number of examples available of runs followed by FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN events, all were used in the modeling, while only about half of the 'good runs' were used, i.e. 47 of 93. The results obtained seemed promising at first but cross validation tests however, gave inconsistent results as shown in the following figures (where FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN is coded as Fault-1, and the numbers represent numbers of 'runs'). The cross validation runs show poor performance (i.e. wrong predictions) on the separate test data. On the left side of Figure 3, the test data contains 23 good runs and 4 bad ones. On the right side, the test data contains 24 good runs and 3 bad ones.

		Predicted Class	
		Good	Fault 1
Actual Class	Good	20	3
	Fault 1	3	1

		Predicted Class	
		Good	Fault 1
Actual Class	Good	16	8
	Fault 1	3	0

Figure 3 - Cross validation results on test data

It is important to consider that some discussion on false positive results can be taken if a price is assigned for verification tests or interventions, but it is out of the scope of this study.

The conclusion from this first study was that we had too few examples of FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN events to be able to conclude whether the proposed method and computed feature were adequate to generate reliable fault detection models from data. This might be improved by including data from other turbo generators and the remaining years.

3.1.2 - Model based diagnostics – PCA analysis of turbo generator efficiency and its relation to FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN

As a next step, it was decided to investigate the use of turbo generator efficiency models to try to identify more physical indicators that could relate to the faults. An initial look at the data available led to the following questions: Are there any observable differences in the time period leading to an ignition failure? (Short term (during purge), longer term (previous ignition), over time (normal operation prior to ignition failure)); Are there any observable differences between turbines with many failure and those with few? The first question investigates if there is a degradation process which will be observable in the process measurements. The second looks for significantly different behaviour of the machines prior to failure, thus giving clues to what degradation mechanisms are active.

The data available allows for a good analysis of the general running of the turbo generators. The data is collected continuously over a long operating period with varying external conditions and internal loads. This variation is essential for the use of an empirical technique such as principal component analysis (PCA; Abdi and Williams, 2010). This analysis technique is very useful when: The system is expected to follow physical laws; the relationships between system measurements can be approximated by linear relationships and; Data for a wide range of external and internal operating conditions are available. These criteria are generally fulfilled for the case of the turbo generators. However, in order to fully comply with these criteria certain filters were applied to the data. These filters have been selected to remove sections of the turbo generators behaviour which does not fit to these criteria.

Given the focus of this analysis on the turbine efficiency, from around 100 measurements available, only 15 were selected which are relevant for the heat and mass balance of the turbine.

Table 4 – Initial list of measurements

GG Input Pressure (atmospheric)	Active Power
GG Combustion Inlet Pressure	GG Exhaust Average Temperature
GG Exhaust Pressure	WHRU Inlet Temperature
Fuel Gas Supply Pressure	WHRU Outlet Temperature
GG NL Speed	Ambient Temperature
GG NH Speed	Gas Supply Temperature
PT N3 Speed	Gas Supply Flow
Exhaust Gas Temperature	

The first stage of filtering is to remove any measurements which are out of range. These are measurement values which are not physical and are associated with malfunction of the measurement instrument or the recording of the measured value. In addition, filters on single values are added to confine the data to the steady state region. For this set of data this is also the region with the majority of data. The main consideration here is that the turbine is in operation, i.e. it is rotating and pressures, temperature are reasonable. However, this filtering should not remove points of poor operation.

This initial filtered data was used for principal component analysis of data from 2010 for turbo generator TGC. The resulting co-variances and principal components were determined and the noise associated with each measurement was assessed. This gave a good indication of the applicability of the technique, and led to a further selection of measurements to be used, as listed in the following table.

Table 5 – Final list of measurements

GG Input Pressure (atmospheric)	Exhaust Gas Temperature
GG Combustion Inlet Pressure	Active Power
GG Exhaust Pressure	GG Exhaust Average Temperature
GG NL Speed	Ambient Temperature
GG NH Speed	Gas Supply Flow

The remaining measurements correlations could be adequately described by just 3 principal components. From a closer inspection, the first principal component reflects the system response to changes in power, while the next two reflect the system response to changes in atmospheric pressure and temperature. Using these 3 major principal components a reconciled set of measurements could then be reproduced. It was then decided to use the residual of the power (difference between measured and reconciled power) as an indication of the efficiency (health) of the turbine.

To be able to better trend efficiency, data was further filtered to cases where the power exceeds 12.5 MW. The following figure plots the residual trend of the gas generator power.

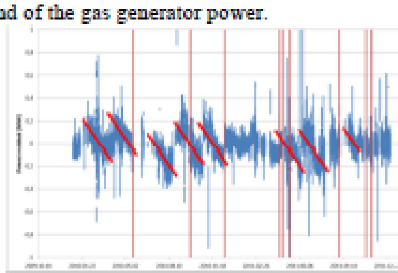

Figure 4 - Trend of power residual for turbo generator TGC and fault occurrences

What can be seen are some clear indications of short-term trends lasting about 2 months. These trends show a gradual reduction in turbine efficiency followed by a sharp recovery. It would be interesting to see if these trends coincided with periodic maintenance (such as turbine wash) conducted on these turbines.

As for the faults, of the 9 FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN events, a few of them appear to be when the turbines efficiency is at its lowest. This is not always the absolute lowest but at a point just before efficiency recovery. This gives some indication of a connection between ignition faults and turbine efficiency. However, this is far from conclusive.

An example of behaviour in the power residual which possibly shows a precursor to a fault is seen in the fault during May 2010. The following figure shows a clear drop in the efficiency in the days preceding the ignition fault.

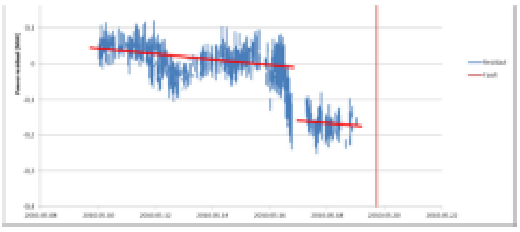

Figure 5 - Power residual before ignition fault

The same analysis was then performed for data from 2011 for turbo generator TGD. This period is of interest as there it contains two ignition failure faults. The noise in the associated signals is comparable to that for TGC.

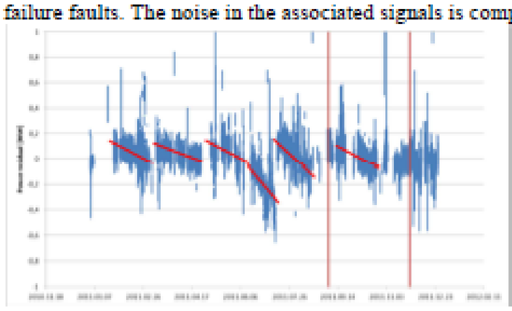

Figure 6 - Trend of power residual for turbo generator TGD and fault occurrences

What can be seen are again indications of short-term trends lasting about 2 months. As for the faults, they appear to be somewhat related the lowered turbine efficiency; however this is again not conclusive evidence.

A conclusion that can be drawn at this early stage is that the ability to determine turbine efficiency changes is a clear benefit of the proposed technique. Although there was no conclusive connection between turbine efficiency and ignition faults this method may still prove useful for general monitoring of these turbines.

3.1.3 Data processing – Analysis of turbo generator exhaust temperature distribution

Given that several of the faults being considered are related to the gas fuel system, and given the fact that several relevant measurements in proximity to the GFMV are not available in the historical data (see Section 3.1.1), an attempt was made to investigate whether gas fuel system problems could be observed in the exhaust temperature, and in particular in the exhaust temperature spread.

This is an alternative analysis, since we are performing a kind of forensic investigation according with what is available in the historian databases. According to Table C.3 in the ISO13380 (2002), exhaust temperature observations can provide descriptors for faults related to the compressor, which is assigned as important subsystem by the operator (see Table 2).

Exhaust gas temperature is among the most critical parameters in a gas turbine. The quality of the measured temperature is related to the number of thermocouple probes, their position, and their sensitivity. Since the temperature profile of the exhaust of a gas turbine is not uniform, the greater the number of probes, the better is a representation of both the average exhaust temperature and its profile (Gianpaolo, 2013).

The turbo generators considered in this study are equipped with 17 annular thermocouples. In order to analyse the spread and variability of the exhaust temperature, an analysis had to be performed to identify a baseline that takes into account possible miscalibrations of the instrumentation. Looking for example at the median temperatures recorded by the 17 thermocouples of turbo generator TGC over one year period, one can observe significant differences of up to 60°C, as shown in the following radar plot.

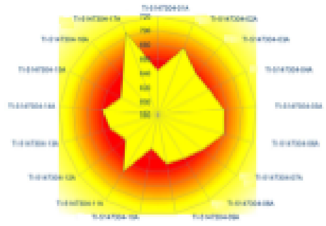

Figure 7 - Median temperature distribution

It was then decided to individually normalize the temperature measurements (to their median) and then calculate their deviation from the current median value. This gave us the possibility of clearly visualizing temperature deviations (dT) in time, as in the following figure, where we have plotted a heat-map (see the heat colour scale to the right) of the 17 thermocouples on the y axis, and time samples on the x axis.

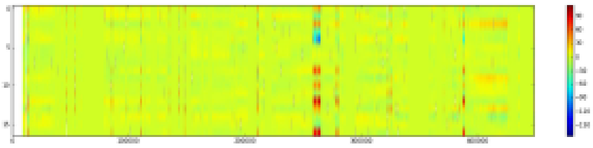

Figure 8 - Normalized exhaust temperature deviations

The next step was to try to identify features of these temperature deviations (dT) that would correlate with the faults of interest. The following figure overlays the time of the faults (shown as blur vertical lines) to the heat-map.

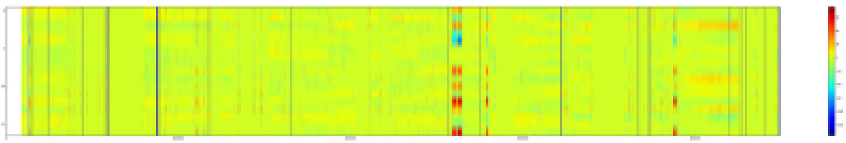

Figure 9 - Faults overlaid on heat-map

Features that were then computed were simple statistics such as standard deviation, mean, min, and max of dT, and rolling statistics of these features with varying windows (e.g. rolling mean of dT_std over 60 minutes). The next section discusses how these and other features can be used in modelling time-to-failure.

3.1.4 - Prognostics – Empirical time-to-failure modelling for gas metering valve related faults

The last stage of this preliminary analysis has involved attempts to construct prognostics models that would estimate time-to-failure given in input a selection of the available measurements and additional features computed as described in the previous sections.

The first step was to simply perform a visual inspection to identify any obvious relationship between individual features/measurements and time-to-failure. The faults included in this study are the 5 fault types related to the FGMV, i.e. FC: OVERFUEL TO IGNITION FAILURE SHUTDOWN, FC: IGNITION FAILURE SHUTDOWN, FC: GAS UPSTREAM PRESSURE FAULT SHUTDOWN, FC: GAS DOWNSTREAM PRESSURE FAULT SHUTDOWN, and GG EXHAUST AVERAGE TEMPERATURE HIGH SHUTDOWN).

As an example, we show in the following figure a plot of time-to-failure (here expressed as days to next fault) against the standard deviation of temperature differences between the 17 exhaust temperature sensors (i.e. dT_std, see Section 3.1.3). The plot includes data from all 4 turbo-generators (TGA, TGB, TGC, and TGD) for the period 2010-2012, for a total of 3,933,925 data points.

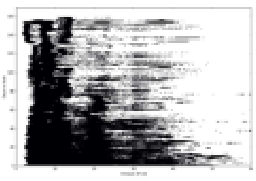

Figure 10 - Exhaust dT_std and its relation to time-to-failure

It can be seen that there appears to be an increase in dT_std when there are less than 50 days to the next fault. The vast majority of points however lie in the region of dT_std below 15, and a time-to-failure model cannot be based on this indicator alone.

If we look at the rolling skewness and rolling kurtosis of dT_std we also see increasing values with lower time-to-failure, as visualised in the following figures.

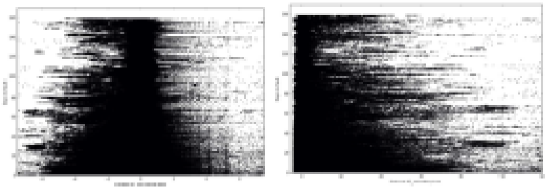

Figure 11 - Rolling skewness (left) and rolling kurtosis (right) of dT_std plotted against days to fault

Next, we proceeded with grouping data according to days-to-fault and tried to define statistics on these groups that would correlate with days-to-fault. The most promising indicator is plotted in the figure below. This heuristic indicator is a 14 days rolling median of the average for each group of the ratio dT_std^3/dT_min^2. This computed feature gives us an indicator that rises when we get closer to the next fault.

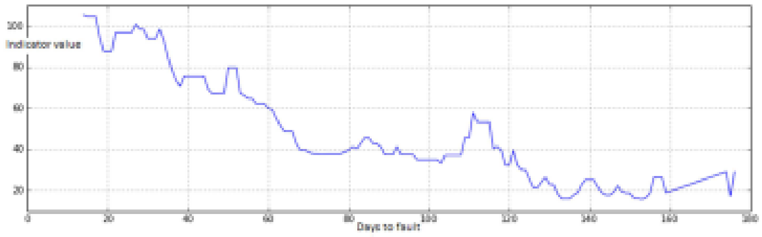

Figure 12 – Heuristic indicator relating to days-to-fault

However, this type of indicator only works at a general level, i.e. when doing statistics on all the available data at a given number of days to the next fault. When applying this indicator to actual time series data the results are much less interesting. While in some fault instances, the indicator rises before the fault, in many others it behaves much more erratically and cannot be used reliably.

The latest analysis performed shifted the focus from considering only features related to the exhaust temperature spread to include also other available measurement related to these fault types. The added measurements are presented in Table 6:

Table 6 – Added measurements

Fuel Gas Supply Pressure	GG Input Pressure
Fuel Gas Supply Temperature	GG Exhaust Pressure
Fuel Gas Supply Flow	GG Exhaust Average Temperature

These measurements and the exhaust temperature spread measures were then used in input to time-to-failure models generated empirically from the available data using different techniques, including ensembles of neural networks (ENN; Roverso, 2008), gradient tree boosting regression (GBR; Friedman and Greedy, 2001), and support vector machines (SVM; Vapnik, Vladimir and Kotz, 2006).

The following figure shows the results of an SVM model, where 5% of the full data set was used for modelling, and the remaining 95% for testing. The test results are plotted sorted by days-to-failure so that a clear visual interpretation can be made, where both the actual time-to-failure (the smooth line) and the model estimation are shown.

It can be seen that the model follows well the general trend even though it underestimates time-to-failure when there are more than 20 days to the next failure, and overestimates time-to-failure when this is below 20 days. The overall mean absolute error of the time-to-failure estimation over all the test data is about 11 days.

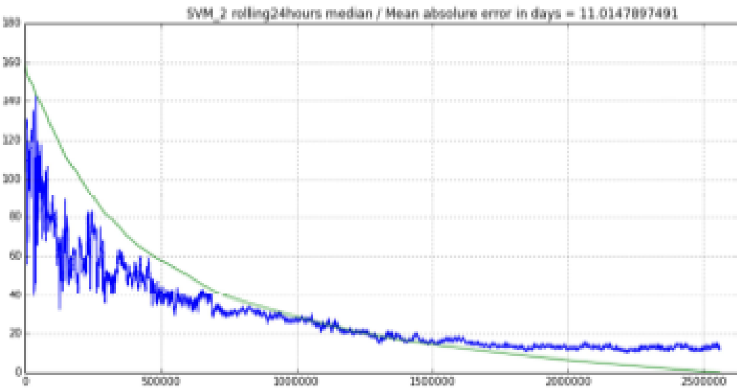

Figure 13 - Days-to-failure prediction (y-axis) of SVM model

Very similar results were obtained with the other modelling techniques mentioned. In order to improve on these results, it was decided to attempt to focus the modelling on that portion of the data that shows most correlation with time-to-failure. If we look at Figure 14 where exhaust dT_std is plotted against time-to-failure, it can be seen that the most significant difference occurs at values of dT_std greater than 15.

If we construct time-to-failure models based only on this subset of the data, where 25% are used for modeling and 75% for testing, then we obtain significantly better results, as shown in the test performance of a GBR model, where the mean absolute error of the time-to-failure prediction is less than 5 days on the test data.

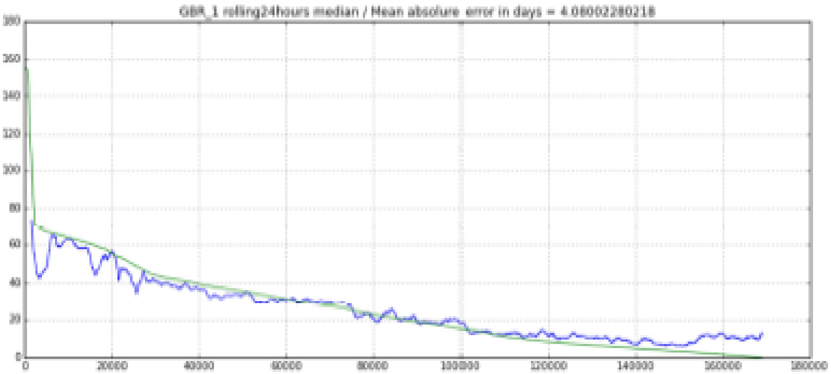

Figure 14 - Days-to-failure prediction (y-axis) of GBR model on subset of data

These preliminary results can be considered indicative of the real possibility of predicting time-to-failure based on the available data with sufficient confidence to be able to track the prediction over time and possibly use this to better inform a condition based maintenance program for turbo generators.

4 - Conclusion

As demonstrated herein there are some promising alternatives in terms of technical approaches that can allow for the operator the means to adopt and improve a predictive maintenance approach for critical equipment/failure modes. However, the maintenance organization must orient its work-processes and decision-process towards diagnostics through systematic data acquisition, processing and analyses in order to allow even better Remaining Useful Life estimations and business results in the near future. An important improvement in data acquisition is to ensure the records entered by maintenance personnel contain the necessary information related to the nature of the observed events. The quality of the maintenance records is an important issue here. Another point is the need to adjust the monitoring sets and databases according to critical faults. The absence of important variables in the historian database (although it is presented on the supervisory systems) must be corrected.

As conclusions at this stage we can state: 1) the operator can count on RUL estimations for decision support since it devotes efforts and endures on the purpose of improving the monitoring policies regarding critical assets as for offshore facilities; 2) the proposed model for time-to-failure estimates shows good and promising results with an overall mean absolute error about 11 days. For the time-to-failure models, significant results were obtained where the mean absolute error of the time-to-failure prediction was less than 5 days when used on the test data.

These preliminary results can be considered indicative of the real possibility of predicting time-to-failure based on the available data with sufficient confidence to be able to track the prediction over time and possibly use this to support decisions in a condition based maintenance program for turbo-generators. In this sense, the present project should be sponsored in order to obtain formal proof of concept at the end of its term and to report the lessons learned so far.

As recommendations for further work we can state: 1) to improve the study by including data from other turbo generators from the same family and for the remaining years (2013 and 2014); 2) to verify if some identified trends coincided with periodic maintenance and/or operations conducted on these machines; 3) to explore other approaches to RUL estimation, e.g. through Gas Path Analysis; 4) to establish reference thresholds in order to provide criteria for decisions and for the modelling using fresh data from the field and; 5) The collaboration between research groups from different areas of expertize should be encouraged.

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Modelling of System Failures in Gas Turbine Engines on Offshore Platforms

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Abstract: The system reliability of gas turbine engines on offshore platforms, maintained (i.e. repaired) upon process failures, is considered in this study. A set of condition monitoring (CM) data (i.e. failure events) of a selected gas turbine engine is considered, where the system maintenance actions with minimum repair conditions (i.e. that should not disturb the failure rate intensity) are assumed. A nonhomogeneous Poisson process is used to model the age dependent reliability conditions of a gas turbine engine and maximum likelihood estimation (MLE) for calculating the same model parameters is implemented. Finally, a summary on the system behavior under failure intensity, mission reliability and mean time between failures (MTBF) is also presented in this study.

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Keywords: System reliability, failure rates, failure intensity, gas turbine engines, maximum likelihood estimation, nonhomogeneous Poisson process.

1. INTRODUCTION

Industrial power plants are life critical systems in offshore platforms and their operational behavior (i.e. failure rates) can be used to encounter their diagnostic and prognostic challenges. Since these power plants play a crucial operational role in the oil and gas industry, this study proposes to understand the system failure behavior under aging conditions and that can also be used to formulate optimal maintenance policies. In general, these power plants consist of various engine-power configurations (i.e. reciprocating engine, gas-turbines, etc.) to satisfy the power requirements of offshore platforms. These engines are operating under harsh ocean environmental conditions; therefore condition monitoring (CM) and conditions based maintenance (CBM) applications should be implemented to overcome the respective degradation conditions.

This study is based on an offshore power plant with four industrial gas turbine engines/generators and that is located in a floating production, storage and offloading (FPSO) unit. The offshore platform is located in Campos Basin in Rio de Janeiro and an additional study on the same platform is done in (Machado *et al.*, 2014). These FPSO units have often been used by the offshore industry to receive, to process and to store the hydrocarbons produced from nearby offshore platforms and sub-sea production systems. This system consists of 4 turbo-generators consisting of aero-derivative gas turbine engine with normal capacity of 25000 (kW) coupled with electric generators with normal capacity of 28750 (kVA). The required grid load of the offshore platform approximately 35-45 (MW) and each generator is rated for approximately 12-15 (MW). Therefore, at least 3 generators in the isochronous mode should be operated to satisfy the requirements of the offshore platform.

In general, gas turbines have been used under open cycle and combined-cycle application in various power plants. In combined cycle approach, the exhaust gas temperature can be used to run steam generators as an energy recovery approach. As the power plant consists of several gas turbine engines, the system reliability measures on a selected gas turbine engine is considered in this study. Therefore, the system failure intensity of a gas turbine has been considered to model the overall power plant behavior. Furthermore, it is important to identify the system failure situations in these power plants ahead of time; therefore the optimal maintenance policy should be implemented to minimize the operational cost. That has been done by analyzing the CM data from the respective gas turbine engine.

2. SYSTEM RELIABILITY

Complex systems can often be repaired after failure events and those system failures can be modeled as stochastic processes. A system operational period (i.e. system age) that starts at $t = 0$ and continues until $t = T$ with a number of failures $N(T)$ is considered in this model. Furthermore, these failure events are recovered by a same number of repairs with negligible time periods. The time periods for those failures from $t = 0$ can be considered as $X_1, X_2, \dots, X_N$. The $i-th$ successive operational period between two failures events can be considered as $X_i - X_{i-1}$ where $i = 1, 2, \dots, N$. These failure events are often been considered as an independent, identically distributed (IID) random variable that can be molded as a Poisson process (HPP) with the respective failure rate (λ). One should note that these repairable systems have often been modelled as Poisson process models and the inter-occurrence times (i.e. functioning time failures) in those events are independent events with exponential behavior, in which can be presented in system failure rates.

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However, the system failure rate with an increasing (i.e. deteriorating), constant (i.e. neither deteriorating nor improving) or decreasing (i.e. improving) trends can be observed by the Laplace trend test (LTT). Hence, the LTT test statistics can be written as (Kim et al., 2004):

$$U_L = \frac{\sum_{i=1}^{n} X_i}{N} - \frac{T}{2} \Bigg/ T\sqrt{\frac{1}{12N}} \tag{1}$$

When the LTT value is greater than zero, the system has an increasing trend (i.e. decreasing reliability) and the Laplace trend test value is less than zero, the system has a decreasing trend (i.e. increasing reliability) can be concluded. This test statistics approximate a standard normal distribution, therefore the significant level of the results can also be observed from the standard normal table. Therefore, this test has been considered as the first step in this CM data analysis.

However, a Poisson process model with a constant failure rate (i.e. homogenous Poisson process) cannot capture the system reliability throughout its life cycle. Therefore, that has often been limited to a section of the system life cycle. Hence, the system operational considerations such as mission reliability, reliability growth or deterioration, and maintenance polices cannot be included in these models (i.e. constant failure rates). Therefore, a nonhomogeneous Poisson process for modelling of the system failure events in a gas turbine engine is also considered. One should note that the time intervals between two respective failures in a nonhomogeneous Poisson process cannot be IID, because the system age has effected on the system failure rate. Hence, the system failure rate intensity of a system can be written as (Crow, 1990):

$$\mu(t) = \lambda\beta t^{\beta-1} \tag{2}$$

where $\lambda > 0$ and $\beta > 0$ are system parameters and t is the age of the system. One should not that when $\beta < 1$, $\mu(t)$ is decreasing (i.e. the phase of infant mortality), when $\beta = 1$, $\mu(t)$ is a constant (i.e. the phase of useful life) and when $\beta > 1$, $\mu(t)$ is increasing (i.e. the phase of wear-out). It is assumed that the system has restored to its previous conditions after each failure with "minimal repair", where the intensity of the system failures has not been disturbed (Crow, 1975). Therefore, this behavior can also be described under the famous "bath-tub curve" for a system life cycle (Klutke *et al.*, 2003). Similarly, the power laws mean value function (i.e. the expected number of failures,) for a nonhomogeneous Poisson process with the failure intensity in (2), the expected number of failures for the same system during the system life time of $(t_{i-1} \quad t_i]$, can be written as:

$$\mathrm{E}[N(t_{i-1} \quad t_i) = n_i] = \int_{t_{i-1}}^{t_i} \mu(t)dt = \lambda t_i^{\beta} - \lambda t_{i-1}^{\beta} \tag{3}$$

where $N(t_{i-1} \quad t_i) = n_i$ is the number of failures that are experienced during the same system life time. One should note that (3) represents the expected number of failures (i.e. mean value) during the same system life time. Hence, the probability of encountering n_i failures during the same system life time can be written as:

$$\mathrm{P}[N(t_{i-1} \quad t_i) = n_i] = \frac{\mathrm{E}[N(t_{i-1} \quad t_i)]^{n_i} e^{-\mathrm{E}[N(t_{i-1} \quad t_i)]}}{n_i!} = \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i} e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)}}{n_i!} \tag{4}$$

Therefore, the mission reliability (i.e. the probability that the system operational conditions that are satisfied without any failures) of the system for the same system life time can be written as:

$$R(t) = e^{-\int_{t_{i-1}}^{t_i} \mu(t)dt} = e^{-\int_{t_{i-1}}^{t_i} \lambda\beta T^{\beta-1}dt} = e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)} \tag{5}$$

However, to calculate the conditions derived in (3), (4) and (5), the parameters for the nonhomogeneous Poisson process model in (2) should be estimated. Hence, maximum likelihood estimation (MLE) is proposed to estimate those parameters and there are several optimal properties of MLE can be identified with respect to other parameter estimation methods (Myung, 2003). Considering the failure events in (4), the likelihood function can be written as (Smith and Oren, 1980):

$$\begin{aligned} L(\lambda,\beta) &= \prod_{i=1}^{N} \mathrm{P}(N(t_{i-1},t_i) = n_i) = \prod_{i=1}^{N} \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i} e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)}}{n_i!} \\ &= \prod_{i=1}^{N} e^{-\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)} \prod_{i=1}^{N} \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i}}{n_i!} = e^{-\lambda T^{\beta}} \prod_{i=1}^{N} \frac{\left(\lambda t_i^{\beta} - \lambda t_{i-1}^{\beta}\right)^{n_i}}{n_i!} \end{aligned} \tag{6}$$

Considering (6), the log likelihood function can be written as:

$$\log L(\lambda,\beta) = -\lambda T^{\beta} + \sum_{i=1}^{N} n_i \left(\log\lambda + \log\left(t_i^{\beta} - t_{i-1}^{\beta}\right)\right) + \log n_i! \tag{7}$$

The partial derivatives of both parameters, λ and β, should be considered in (7) to calculate the maximum likelihood values for the respective parameters and that can be written as:

$$\begin{aligned} &\frac{\partial}{\partial\lambda}\log L(\lambda,\beta) = -T^{\beta} + \frac{1}{\lambda}\sum_{i=1}^{N} n_i = 0 \\ &\frac{\partial}{\partial\beta}\log L(\lambda,\beta) = -\lambda T^{\beta}\log T + \sum_{i=1}^{N} n_i \frac{\left(t_i^{\beta}\log t_i - t_{i-1}^{\beta}\log t_{i-1}\right)}{\left(t_i^{\beta} - t_{i-1}^{\beta}\right)} = 0 \end{aligned} \tag{8}$$

Hence, the maximum likelihood values of λ and β in (8) satisfy the following conditions:

$$\begin{aligned} &\hat{\lambda} = \frac{\sum_{i=1}^{N} n_i}{T^{\beta}} = \frac{N}{T^{\beta}} \\ &-\lambda T^{\beta}\log T + \sum_{i=1}^{N} n_i \frac{\left(t_i^{\beta}\log t_i - t_{i-1}^{\beta}\log t_{i-1}\right)}{\left(t_i^{\beta} - t_{i-1}^{\beta}\right)} = 0 \end{aligned} \tag{9}$$

One should note that (9) should be solved iteratively and that has a unique solution for the parameters of λ and β. However, the solution can calculate under time truncated and failure truncated situations. A situation with the observations that are truncated after a prefixed time for a respective number of failures (i.e. the number of failures is a random variable) is considered as time truncated. A situation with the observations that are truncated after a prefixed number of failures for a respective time interval (i.e. the time interval is a random variable) is considered as failure truncated. However, a time truncated situation with respect to the

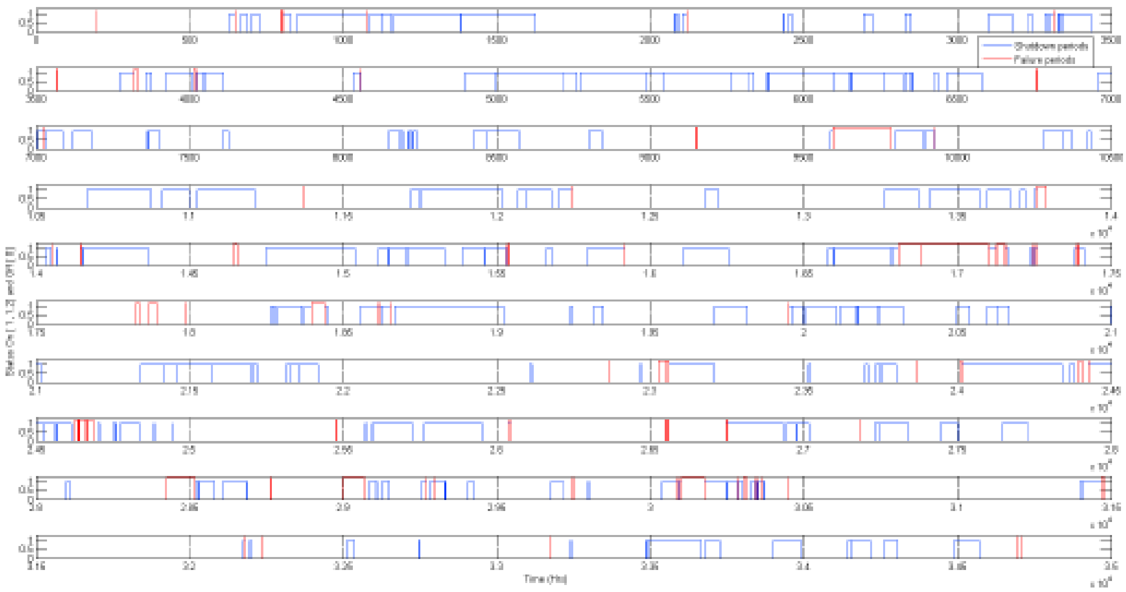

Fig. 1: Shutdown periods and Failure periods for TG-A

system age in a gas turbine engine, is considered in this study. Hence, (9) can be derived as (Crow, 1974):

$$\hat{\lambda} = \frac{N}{T^{\hat{\beta}}},\ \hat{\beta} = \frac{N}{\sum_{i=1}^{N}\log\left(\frac{T}{X_i}\right)} \tag{10}$$

Hence, the unbiased estimator for the variable, β can be written as (Crow, 1975):

$$\bar{\beta} = \frac{N-1}{N}\hat{\beta} \tag{11}$$

As the next step, the confidence bounds for the parameters of λ and β should be derived. Considering the parameter, $\hat{\beta}$, the confidence bounds for hypotheses testing the true value of β are derived by using a Chi-square distribution with $2M$ degrees of freedom (Crow, 1975):

$$\chi^2 = \frac{2M\beta}{\hat{\beta}} \tag{12}$$

(12) can be used to test hypotheses on β. By considering M is moderate, the statistics of ω can be written as (Crow, 1975):

$$\omega = \sqrt{M}\left(\frac{\beta}{\hat{\beta}}-1\right) \tag{13}$$

where (13) is distributed approximately with mean *0* and variance *1*. Hence, the approximate confidence bounds for β, were the $(1-\alpha)\cdot 100$ percent lower and upper confidence bounds can be written as:

$$\beta_{LB} = \hat{\beta}\left(1-\frac{P_\pi}{\sqrt{M}}\right),\ \beta_{UB} = \hat{\beta}\left(1+\frac{P_\pi}{\sqrt{M}}\right) \tag{14}$$

where P_π is the π-th $\approx 1-\alpha/2$ percentile for a normal distribution with mean *0* and variance *1*. Hence, the $(1-\gamma)\cdot 100$ percent lower and upper confidence bounds for λ can be written as:

$$\lambda_{LB}(\beta_{UB}) = \frac{\chi^2\left(\frac{\gamma}{2},2N\right)}{2T^{\beta_{UB}}},\ \lambda_{UB}(\beta_{LB}) = \frac{\chi^2\left(1-\frac{\gamma}{2},2N+2\right)}{2T^{\beta_{LB}}} \tag{15}$$

One should note that (14) and (15) have often been categorized as the conservative simultaneous confidence bounds on the parameters of λ and β with $(1-\alpha)(1-\gamma)\cdot 100$ percent. As the next step of this study, the estimated and actual system failure events should be compared to observe the goodness for the proposed model. Considering a situation, where the actual system failure events are known, Cramer-Von Mises goodness statistics can be used to test the null hypothesis. Hence, the proposed NHPP model with the estimated parameter values and its capabilities to appropriately capture the actual system failure behaviour can be inspected. Hence, the Cramer-Von Mises goodness test can be written as (Crow, 1974):

$$C_M^2 = \frac{1}{12N}+\sum_{i=1}^{N}\left(\left(\frac{X_i}{T}\right)^{\bar{\beta}}-\frac{2i-1}{2N}\right)^2 \tag{16}$$

Considering the hypothesis H_1 for the system failures are following a $\bar{\beta}=1$, where the constant failure rate is associated. Hence, the hypothesis H_2 can be presented as that the failure rate follows a nonhomogeneous passion process with the proposed intensity function and $\bar{\beta}$ is unspecified. If the hypothesis H_2 has proven to be accepted, the parameters estimated for λ and β are acceptable. Hence, if C_M^2 is greater than the selected critical value, the hypothesis H_2 is rejected and if C_M^2 is less than the selected

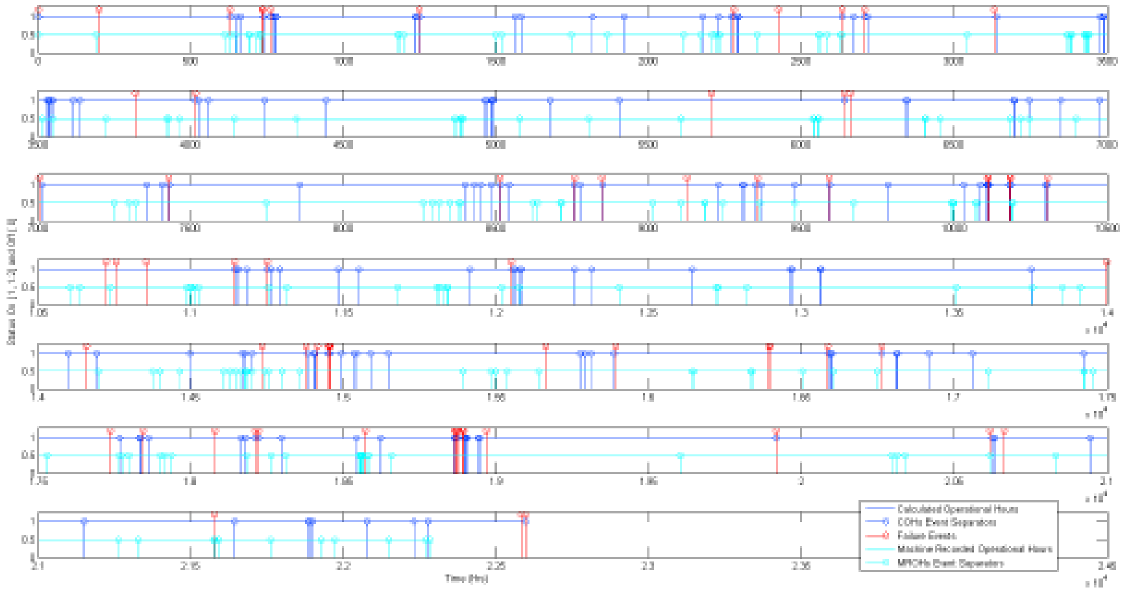

Fig. 2: Operational hours and Failure events for TG-A

critical value, the hypothesis H_2 is accepted at the respective significant levels.

Finally, the mean time between failures (MTBF) is calculated for the proposed model. Hence, the instantaneous MTBF can be written as:

$$\hat{M}(t) = (\hat{\mu}(t))^{-1} = \left(\hat{\lambda}\hat{\beta}t^{\hat{\beta}-1}\right)^{-1} \tag{17}$$

The confidence interval for $\hat{M}(t)$ (i.e. estimated value of $M(t)$) provides a measure of the uncertainty around the calculated value. The two sided $(1-\alpha)100$ percent confidence intervals on $M(t)$ can be written as (Crow, L. H., 1977):

$$\Pi_1 \hat{M}(t) \le \hat{M}(t) \le \Pi_2 \hat{M}(t) \tag{18}$$

where Π_1 and Π_2 can be obtained from the available data tables in (Crow, 1977) for the $(1-\alpha)\cdot 100$ percent lower and upper confidence bounds.

3. PARAMETER ESTIMATION

The system shutdown and failure events for a selected gas turbine engine (TG-A) for the last 4 year period (i.e. the total operational period) is presented in Figure 1. This CM data consist of a total monitoring period of 34708 (Hrs) of the shutdown and failure periods of the selected gas turbine engine. That has been divided into 3500 (Hrs) operational intervals under 10 plots in the same figure, in which has the improved visibility. The shutdown periods are represented under blue color blocks and the system failure periods are represented under red color blocks (see Figure 1).

Considering the CM data of the gas turbine engine, the cumulative non-shutdown period for the same gas turbine engine is derived, where the shutdown periods have been removed and the non-shutdown period are combined to calculate a cumulative total operational period. One should note that the combination point of two non-shutdown periods is considered as an event separator. These event separators are introduced to keep track of the non-shutdown periods. Furthermore, the respective failure periods are adjusted in accordance with the removal of the non-shutdown periods. Therefore, the cumulative non-shutdown period has reduced to 23649 (Hrs) from the total operational period of 34708 (Hrs). Then, the lengths of the failure periods are removed from the cumulative non-shutdown period and the failure events are introduced. Therefore, this approach has reduced the operational period (i.e. system age) for the respective gas turbine engine, where the total operational hours has reduced approximately to 22596 (Hrs) (i.e. $T = 22596\,(\text{Hrs})$) from the cumulative non-shutdown period of 23649 (Hrs).

The system operational period (i.e. calculated operational hours (COHs)), the event separators, and failure events are presented in the Figure 2. Furthermore, the machine recorded operational hours (MROHs) with the separators that were recorded by the gas turbine engine itself are also plotted in the same figure. It is expected that the MROHs should overlay within the COHs and the failure events. However, the MROHs have been shifted left with respect to the COHs and the failure events as presented in the figure. One should note that the MROHs consist of fewer hours than the COHs of the same gas turbine engine.

The number of failures for the same gas turbine engine with respect to the system age is presented in plot (a) of Figure 3. Furthermore, the respective MROHs and COHs values with respect to each failure are presented in plot (b) of Figure 3

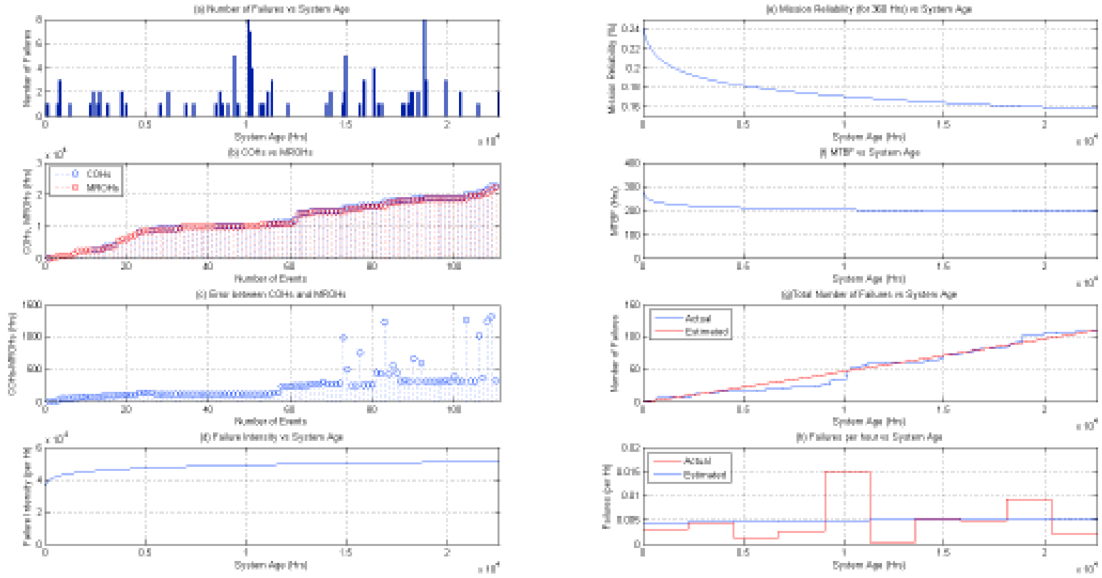

Fig. 3: System event data for TG-A

and the respective errors between the MROHs and COHs values are presented in plot (c) of Figure 3.

Even though, it is expected that the MROHs and COHs may have same values for respective failures, there are some deviations. In some situations, the error value is increased to a larger value initially and that is decreased to a much lower error value. This results show that the MROH values may have some time delay on recording the data with compare to the COH values. Furthermore, it is noted that the system start-up and shutdown hours have not been recoded under the MROHs due to the fact that it may not operate the MROH counting system during the start-up and shutdown periods. Therefore, the MROHs consist of fewer hours than the COHs and the errors between those two values are increasing (see plot (c) of Figure 3). However, the COHs data have been used for the parameter estimations process, the calculation of the failure intensity function with respect to the system age. Furthermore, it is concluded that the same machine has been used throughout the entire period (i.e. machine has not been replaced with another machine) by considering the MROHs. Then, Laplace trend test in (1) has been used to evaluate the behavior of the system failure rate and the calculated value can be written as:

$$U_L = 1.1894 \tag{19}$$

The Laplace trend test value is greater than zero, therefore the gas turbine engine with slight increasing failure rate (i.e. decreasing reliability) can be concluded. The significant level (from the standard normal table) of the results in can be further analyzed, where $|U_L| = 1.1894$ can approximate the statistical significance to 88%. Therefore, the proposed nonhomogeneous Poisson process model in (2) is a suitable candidate (within the respective statistical significance) for modeling the system reliability in a gas turbine engine. As the next step, the estimated values for the failure intensity function are calculated by considering (10) and that can be written as:

$$\hat{\lambda} = 0.0028\,,\ \hat{\beta} = 1.0542 \tag{20}$$

Therefore, the gas turbine engine characterization slightly under the wear-out phase can be concluded. The respective failure intensity function for the selected gas turbine engine with respect to the system age is presented in plot (d) of Figure 3. Hence, unbiased estimator for β in (11) can be calculated as:

$$\overline{\beta} = 1.0447 \tag{21}$$

The approximate confidence bounds for β, where 90% lower and upper confidence bounds in (14) can be calculated as:

$$\beta_L = 0.9254\,,\ \beta_U = 1.1831 \tag{22}$$

The lower and upper confidence bounds for λ can be written as:

$$\lambda_L = 6.5879 \cdot 10^{-4}\,,\ \lambda_U = 0.0121 \tag{23}$$

Hence, 81% conservative simultaneous confidence bounds on the parameters λ and β are presented in (22) and (23) equations, where $\alpha = .1$ and $\gamma = .1$. The mission reliability for 15 day (i.e. 360 (Hrs) intervals is presented in plot (e) of Figure 3. The mission reliability represents the probability that the selected gas turbine engine survives without any failures within the next 15 days (i.e. 360 (Hrs) with respect to its age. As presented in the figure, the mission reliability is decreasing with respect to the system age despite the present maintenance actions.

Furthermore, the expected number of failure with next 15 days (i.e. 360 (Hrs) at the end of operational hours of 22596 (Hrs) has also been calculated by using (3): the calculated value is 1.8476 failure events per 15 days (i.e. MTBF is approximately 194.85 (Hrs). Therefore, it is concluded that every 16 days 2 system failures in average can be observed under the present operational conditions. The instantaneous MTBF for the same gas turbine engine under the same operational period is presented in plot (f) of Figure 3. One should note that the MTBF value has reduced to 194.85 (Hrs) at the end of the operational period and that can be approximated as 8.12 (days). Therefore, it can be concluded that a system failure can occur approximately every 8 day in average for this gas turbine engine. Hence, the estimated lower and upper bound for the MTBF with the two-sided 90% confidence interval can be written as:

$$156.27\,(\text{Hrs}) \le M(T = 22596(Hrs)) \le 246.48\,(\text{Hrs}) \tag{24}$$

where the table values can be extrapolated as (AMSAA, 2000) $\Pi_1 = 0.802$ and $\Pi_2 = 1.265$. Therefore, the system can face a failure in approximately 6.51 (days) to 10.27 (days). The actual failures (Actual) of the gas turbine engine and the predicted failures (Estimated) with respect to the system age are presented in plot (g) of Figure 6. The average failure rate for actual and estimated situations using for 2256 (Hrs) by considering 20 intervals are presented in plot (h) of Figure 3. These results present an increasing failure rate with respect to the system age. Finally, the Cramer-Von Mises goodness-of-fit for the derived parameters λ and β is conducted. The requirement of Cramer-Von Mises goodness-of-fit to be N=110, $\alpha = 0.01$ then $C_T^2 \approx 0.34$ (AMSAA, 2000). So the model to be accepted for the same significant level is $C_M^2 < C_T^2$. A Cramer-Von Mises goodness of test for this model is calculated:

$$C_M^2 = 0.4315 \tag{25}$$

Hence, the hypothesis H_2 for the presented model should be rejected due to $C_M^2 > C_T^2$ for the significant level of $\alpha = 0.01$.

4. CONCLUSIONS

An overview of the mathematical reliability modelling of gas turbines in offshore platforms is presented in this study. The system CM data has been analyzed and the failure intensity, the mission reliability and the MTBF conditions for the present system status have been derived. However, the hypothesis H_2 for the presented model is rejected and there are three challenges can be observed with respect to the available data. Firstly, the β value is approximately equal to 1. Secondly, the system start-up failures and operational failures are combined in this data and that should be separated. Thirdly, the differences between the actual and the predicted failures are not strongly consistence with actual failure situations (see plot (g) Figure 3). One should note that several repeated failures can be observed around 10111 (Hrs) and 18924 (Hrs) of the system age in the same figure. These two situations have influenced on the failure model in the gas turbine engines and that effect should be compensated to improve the model accuracy, in which has been proposed as the future work.

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System Failures of Offshore Gas Turbine Engines in Maintenance Perspective

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Abstract: Several system failure events of a selected gas turbine engine with respective to its maintenance actions are considered in this study. These system failure events are derived from condition monitoring (CM) data of a selected gas turbine engine and modeled into a nonhomogeneous Poisson process (NHPP) under maximum likelihood estimation. Various erroneous data intervals are noted in the CM data of the gas turbine engine and removed from the respective analysis. The CM data set is divided into several intervals due to the erroneous data intervals and the modified data set is used to estimate the parameters of the respective models of system reliability. These models represent the failure intensity levels of the gas turbine engine during various sectors of its life cycle. These failure intensity levels consist of increasing and decreasing reliability trends and those variations are compared with system faults and maintenance periods to observe the respective reasons. Finally, the reasons among these system faults and maintenance periods by considering the inputs from the maintenance crew are also summarized in the conclusion of this study.

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Keywords: Gas Turbine Engines, System Failures, Failure Intensity, Condition Monitoring, Condition based Maintenance, Offshore Power Plants.

1. INTRODUCTION

System failures and maintenance actions of an offshore power plant with several gas turbine engines to satisfy the power requirements of an oil and gas field are considered in this study. The industrial power plant is facilitated with four gas turbine engines/generators in a floating production, storage and offloading (FPSO) unit located in Campos Basin, Rio de Janeiro (Machado *et al.,* 2014). These gas turbine engines are equipped with condition monitoring (CM) facilities to monitor the system health under harsh ocean environmental conditions with appropriate maintenance actions and that process is categorized as condition based maintenance (CBM). Therefore, the system degradation (i.e. health condition) of each gas turbine engine is monitored with various sensors under CM. Catastrophic failure situations in the entire power plant can be avoided by monitoring each engine degradation condition and executing appropriate maintenance actions. One should note that CBM is enabled by CM activities, where appropriate maintenance decisions/actions are taken by the crew to improve the power plant availability. It is also believed that appropriate diagnostic and prognostic tools should be developed to identify the present and future health conditions of gas turbine engines under CMB approaches.

The environmental effects can degrade the system performance of offshore gas turbine engines as discussed previously. Therefore, appropriate maintenance actions under the required system integrity and safety levels with essential component upgrades should be initiated to improve the availability of the power plant. However, the ageing effects of offshore gas turbine engines may require additional maintenance actions to cope with fatigue and corrosion issues of the components. Furthermore, old system components should be replaced with new ones to improve operational availability of offshore gas turbine engines in some situations. That process is associated with not only respective maintenance costs but also health, safety and environment (HSE) and service quality (SQ) considerations. The respective maintenance costs can have a direct relationship to the respective system reliability in such situations. These maintenance actions are a part of the overall maintenance strategy of the respective oil and gas operator. In general, system reliability in the oil and gas industry is categorized under three main divisions: availability, safety and maintainability. Since the present economic downturns, the oil and gas industry focuses to identify the most critical requirements for these oil and gas platforms, where various cost-effective maintenance actions are introduced under the required availability, safety and maintainability considerations.

System maintenance is often done after complete system failures (i.e. run-to-failure maintenance) in various industries, where the respective HSE and SQ considerations are neglected in some situations. However, this approach can be improved by considering planned system maintenance (i.e. preventive maintenance) in some situations. That consists of implementing periodic time maintenance intervals regardless

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of the system health condition and improves the system availability in a majority of industrial systems. However, such preventive maintenance actions can be expensive for some industries with complex machineries (i.e. systems with a large number of subsystems and components) such as gas turbine engines. Therefore, CBM as a cost effective solution is adopted by such industries, where actual health conditions of respective systems are monitored, continuously and appropriate maintenance actions can be chosen and executed appropriately.

In general, industrial maintenance actions can be divided into three categories of corrective, preventive, and predictive. Those actions are also executed under various maintenance strategies of run to failure maintenance (RTFM), on condition maintenance (OCM) and condition based maintenance (CBM) as discussed previously. As a summary, RTFM approaches focus on corrective measures, OCM approaches focus on corrective and preventive measures, and CBM approach focuses on all corrective, preventive and predictive measures. Therefore, CBM is considered as the most suitable approach to overcome respective diagnostic and prognostic challenges in the oil and gas industry. This study focuses on understanding system reliability of a selected gas turbine engine with respect to its maintenance actions. System reliability is quantified with respect to the failure events of the selected gas turbine engine. It is also expected that these failure events also relate to age related system degradations and that should be reflected in the respective failure intensity levels of the gas turbine engine. Hence, the respective failure intensity levels of the gas turbine engine are calculated from the CM data.

The health conditions of gas turbine engines are observed under two different industrial levels. The first level consists of the top-down concept: the engine degradation with respect to its current usage level is identified and compared to the average engine performance throughout its life cycle. The second level consists of the bottom-up concept: the component health conditions and maintenance information are used to determine probable effects of the engine degradation. This study overlaps both concepts, where engine health conditions with respect to the failure intensity levels are estimated for various sectors of the system life and that information is compared with its maintenance actions. Furthermore, the respective maintenance actions and recorded information are discussed with the crew to derive the conclusions at the end of this study.

CM and CBM have often been a part of engine health management approaches. A summary of such engine health management approaches of gas turbines is presented Perera *et al.* (2015a). These approaches are often based on real-time measurements (i.e. physical parameters), event data (i.e. system failures and shutdowns) and maintenance records (i.e. overhauls and repairs). Hence, engine health management approaches can predict various system failures of gas turbine engines and prevent overall offshore power plant failures. Various mathematical models are developed under these health management approaches and divided into two sections: gas path analysis (GPA) and performance seeking control (PSC). These approaches develop mathematical models for gas turbine engines consisting various parameters that relate to the health conditions of the respective components. The parameters of such mathematical models are estimated by various algorithms with sensor measurements (i.e. pressure, temperature and rotational speed values of the respective components).

Several engine health management applications that relate to GPA are presented in the respective studies of (Simon and Simon (2005), Pu *et al.*, (2013)). Similarly, additional engine health management applications that relate to PSC are presented in the respective studies of (Espana (1994), Gilyard and Orme (1993), Orme and Schkolnim (1995), and Simon and Garg, (2009)). However, GPA and PSC based engine health management approaches in gas turbine engines encounter various industrial challenges and that are summarized as: 1) sensor noise (i.e. bias and variance values in the measurements) can degrade the parameter estimation process, 2) system parameters can have various nonlinear relationships and the respective models and sensor measurements are inadequate to identify those relationships and 3) a large number of sensors are required to estimate the total number of health parameters in gas turbine engines. Even though some solutions to such challenges are proposed in the recent literature (Simon and Garg (2009) and Xuewu *et al.*, (2009)), the complex nonlinearities among the system parameters can still degrade GPA and PSC based health management approaches in gas turbine engines. Therefore, a system failure events based health management approach for gas turbine engines is considered in this study, where the respective failures are categorized as stochastic events. The failure intensity of a selected gas turbine engine is modeled as a nonhomogeneous Poisson process (NHPP) (Perera *et al.* 2015a, b) under such situations. These types of models (i.e. stochastic process) are used in many reliability studies for predicting the failures of various systems and components (Rausand and Hoyland, 2004).

A similar concept is adopted in this study to calculate the system failure intensity levels of a selected gas turbine engine. Hence, this is a simplified approach with compared to GPA and PSC based health management approaches of gas turbine engines and that can also be used to evaluate the respective maintenance actions. The failure intensity levels of a selected gas turbine engine are captured with a nonhomogeneous Poisson process (NHPP). One should note that the parameters of the NHPP model represent the respective component health conditions of the gas turbine engine. These component health conditions also relate to various failure intensity levels of the gas turbine engine in different system age intervals. Therefore, the respective future system failures and failure transitions can also be predicted by using these models and such information can also be used to overcome diagnostic and prognostic challenges in gas turbine engines.

2. SYSTEM FAILURES

The respective system failure events of the selected gas turbine engine are presented in Figure 1. One should note that the failure events are presented with respect to the system

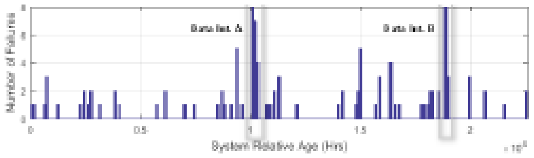

Fig. 1. Actual system failure events of the gas turbine engine.

relative age (i.e. without maintenance intervals) in the same figure. These events are extracted from the respective operational and maintenance data (i.e. CM data) of the gas turbine engines. However, two erroneous data regions are identified during this analysis with repeated system failure events. Those regions are noted as data interval (int.) A and B in the same figure. It is concluded that these repeated failure situations can degenerate the system failure intensity calculations, therefore such intervals are removed from the data analysis. Further details on such erroneous data intervals, detection methodologies and removal steps are presented in Perera *et al.* (2015a, b). The erroneous data intervals divide the system relative age into several segments (i.e. data interval (int.) 1, 2 and 3) and the results are presented in Figure 2. These erroneous data intervals are bounded by cyan lines in the same figure. The system failure events of data interval 1 and 2 are used to calculate the respective failure intensity levels of the gas turbine engine during its relative age period (i.e. without maintenance intervals). One should note that these failure intensity levels are derived from a NHPP model and that is denoted as:

$$\mu(t) = \lambda\beta t^{\beta-1} \qquad (1)$$

where $\lambda > 0$ and $\beta > 0$ are the system parameters and t is the system absolute age (i.e. the total operational life without maintenance intervals) of the gas turbine engine. One should note that offshore gas turbine engines are repaired upon various system failures, therefore those maintenance actions influence the system failure intensity levels under various sections of the system life. It is considered that the respective system failure events are recovered by a similar number of maintained periods during this model development. These maintenance actions are considered as "minimal repair" (i.e. as bad as old) under the NHPP model. One should note that NHPP models can represent system failure intensity levels under both increasing and decreasing reliability trends. Therefore, that can facilitate to develop the most suitable and simple mathematical models for system reliability applications. A decreasing failure trend in such a model represents an improving system reliability situation possibly due to better maintenance actions. An increasing failure trend in such a model represents a decreasing system reliability situation possibly due to lack of proper maintenance actions and/or age related system degradation conditions. In general, it is expected that the respective gas turbine engines should have increasing failure trends due to harsh environmental and age related system degradation conditions.

It is also noted that the system event data of gas turbine engines are available only for a sector of the system life. That sector of the system life is categorized as its relative age (i.e. system operation period without maintenance periods), where the system relative age is less than its absolute age. The system approximate absolute age is estimated in an internal recording system and that values is used to correct the system relative age (Perera *et al.*, 2015a, b). However, the failure events and respective maintenance periods are recorded under the system relative age, therefore the final results are also visualized under the system relative age to simplify the respective presentation.

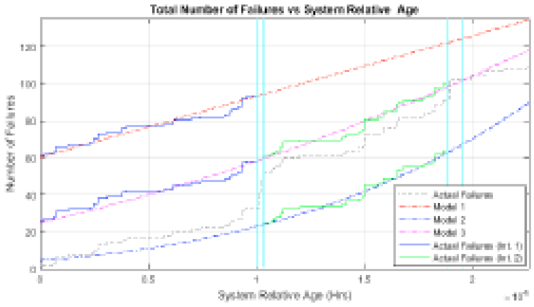

Fig. 2. Actual and predicted system failure events.

Data interval 1 (see Figure 2) is assigned with the time interval $(0 \quad 10000(Hrs)]$ in the system relative age (i.e. without maintenance periods) and the estimated parameters of the NHPP model (i.e. the system failure intensity level) are calculated as:

$$\hat{\lambda} = 0.0040, \ \hat{\beta} = 0.9824 \qquad (1)$$

where $\hat{\beta} < 1$ for this data interval. Hence, some reliability improvements in the gas turbine engine are noted in this data interval (Perera *et. al.*, 2015a,b). The actual and predicted failure events for the same data interval are presented in Figure 2 as Model 1. The actual failure events are projected into this model to compare with the estimated failure events during this period. One should note that this model also predicts the number of system failures for the pre and post sectors of the system relative age. The data interval, $(10000(Hrs) \quad 10307.5(Hrs)]$ in the system relative age (i.e. without maintenance periods), is considered as an erroneous data region and that is removed from the data analysis. Data interval 2 is assigned with the time interval $(10307.5(Hrs) \quad 18950(Hrs)]$ in the system relative age (i.e. without maintenance periods) and the estimated parameters of the NHPP model (i.e. the system failure intensity level) are calculated as:

$$\hat{\lambda} = 1.0336.10^{-15}, \ \hat{\beta} = 3.6771 \qquad (2)$$

where $\hat{\beta} > 1$ for this data interval. Hence, some reliability degradations in the gas turbine engine are noted. The actual and predicted failure events for the respective data interval are presented in Figure 2 as Model 2. One should note that the actual failure events are also projected into this model to

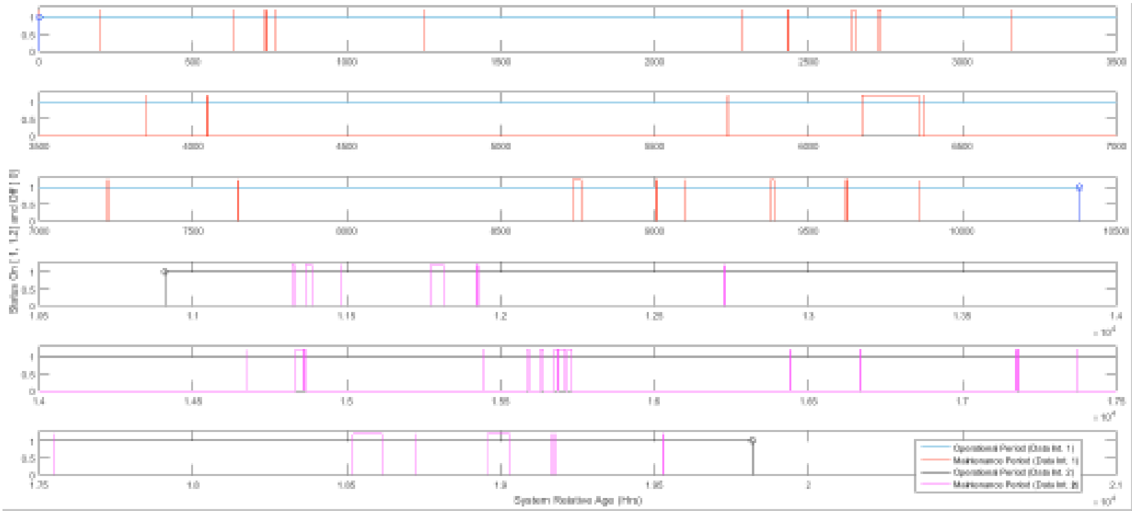

Fig. 3. System maintenance periods for data interval 1 & 2.

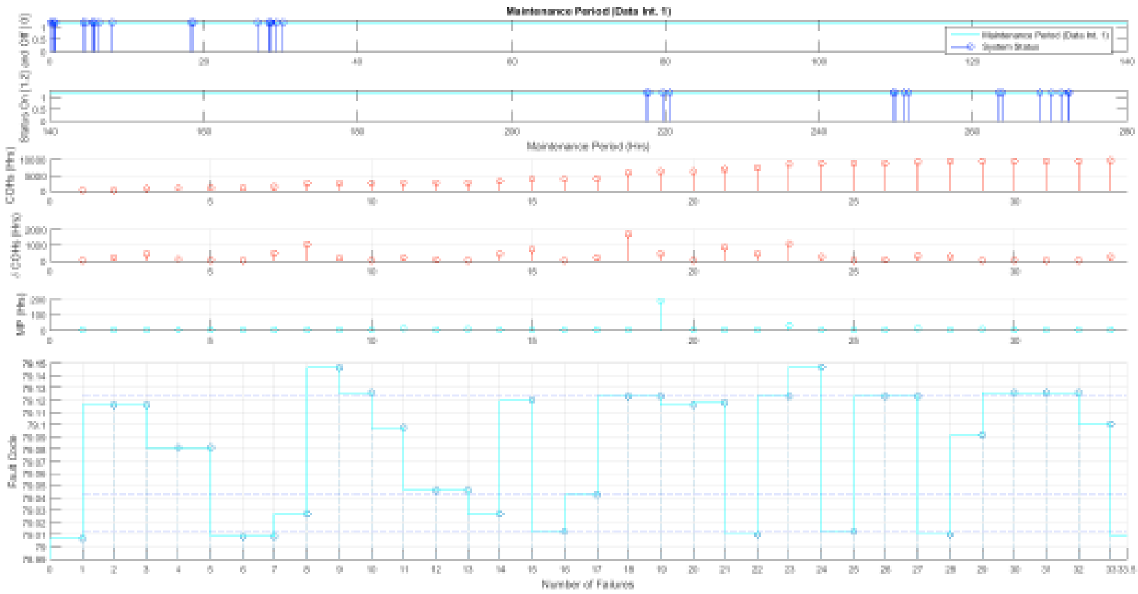

Fig. 4. System maintenance periods and failure events for data interval 1.

compare with the estimated failure events during this period. The data interval, $(18950\,(Hrs)\ 22596(Hrs))$ in the system relative age (i.e. without maintenance periods) is considered as an erroneous data region and that is removed from the data analysis. Data interval 3 is ignored from this model derivation due to its short time period.

The number of system failure events in the first, second and third data intervals are identified as 33, 39 and 8, respectively and the first and second erroneous data intervals are identified as 19 and 11, respectively. In the next step, data interval 1 and 2 are assigned with the same relative age time frame as two discrete data intervals. The estimated parameters of the NHPP model (i.e. the system failure intensity level) for these combined data intervals are calculated as:

$$\hat{\lambda} = 2.0736.10^{-7}, \quad \hat{\beta} = 1.9008 \tag{3}$$

where $\hat{\beta} > 1$ for this data interval and the respective calculations are presented in (Perera *et. al.*, 2015a,b). Hence, some reliability degradation conditions of the gas turbine engine are noted. The actual and predicted failure events for the same data interval are presented in Figure 2 as Model 3. Similarly, the actual failure events are also projected into this model to compare with the estimated failure events during this period. One should note that the first part of the system absolute life (i.e. unknown CM period) of the gas turbine engine consists of an unknown number of system failures. However, these failure events are predicted by the respective models (i.e. model 1, 2, & 3) with respect to their failure intensity levels. Therefore, each model starts with a unique number of initial failure events in various positions of its system life (i.e. the number of initial system failures) (see Figure 2). Similarly, the number of possible failure events in each erroneous data interval are also predicted by the same models.

It is noted that the failure intensity level in data interval 1 (i.e. Model 1) shows some improvements (i.e. $\hat{\beta} \approx 1$) in system reliability of the gas turbine engine. However, the failure intensity level in data interval 2 (i.e. Model 2) shows a considerable reduction in system reliability (i.e. $\hat{\beta} >> 1$). Furthermore, the failure intensity level in the combined model (i.e. model 3) shows less reduction (i.e. due to both data intervals) in system reliability (i.e. $\hat{\beta} > 1$) with compared to the model 2. Hence, it is also concluded that the overall failure intensity level of the gas turbine engine dominates by the failure intensity (i.e. failure events) of the last part of the system life and that may have a reliability decreasing trend in generally (i.e. model 3). It is also believed that these failure intensity levels relate to system maintenance actions of the gas turbine engine. In addition, the availability of the CM data can also influence the failure intensity levels of the gas turbine engine, where a longer CM data period is required to derive an accurate system failure intensity level. As the next step, the respective maintenance actions in the respective data intervals are investigated to reason those failure intensity level variations.

3. SYSTEM MAINTENANCE

The respective system operational and maintenance periods for data interval 1 and 2 of the gas turbine engine are presented in Figure 3. The system operational periods are divided into two data intervals (i.e. data interval 1 & 2) by considering the previous failure intensity levels. One should note that the first and second data intervals consist of 33 and 39 maintenance periods, respectively. The system relative age (i.e. with the maintenance periods) is divided into 6 time segments and that are presented in this figure to improve the visibility of maintenance periods. As the next step these maintenance periods are combined to observe maintenance frequency of data interval 1 and the results are presented in the top two plots of Figure 4. The results show that relatively small time intervals are distributed along these maintenance intervals with one large maintenance interval in the middle. The system operational periods are modeled as single instances (i.e. pulses) in the same figure. This representation is used to observe the respective maintenance actions of the gas turbine engine with respect to the failure intensity levels.

Several failure events (i.e. 33 events) are also reported during data interval 1 and those events in the system relative age are presented in the third plot (i.e. from the top) of the same figure. Then, the time difference between two consecutive failure events with respect to each failure event is presented in the fourth plot (i.e. from the top) of Figure 4. One should note that the time period between 17th and 18th system failure events is relatively large with compared to other maintenance periods. This represents a situation, where the gas turbine engine was running for a relatively long period without any maintenance actions just before the 18th system failure. The maintenance periods (MP) with respect to each failure event are presented in the fifth plot (i.e. from the top) of the same figure. The results show that the 19th maintenance period has a relatively long period and that may be influenced by the 18th system failure of the gas turbine engine. However, this is categorized as an unusual situation because the largest operation period without any maintenance has occurred just before the 18th failure event but the largest maintenance period has occurred just after the 19th failure event. Therefore, the respective system faults are further investigated to understand this unusual failure and maintenance situation.

Various failure events are identified with respect to subsystem and component faults of these gas turbine engines and that denote by a code system (i.e. 79.xxxx). One should note that 34 fault codes with respect to subsystem and component failures of gas turbine engines are identified under CM data. The fault codes with respect to each failure event are presented in the bottom plot of Figure 4. The results show that the both failure intervals (i.e. 18th and 19th) are having the same fault code (i.e. 79.1230) and that failure is categorized as "waste heat recovery unit (WHRU) inlet/bypass damper linkage failure." This system failure was repeated during this period and resulted in a long maintenance period of the gas turbine engine. Furthermore, the gas turbine engine was operated without any maintenance actions for a considerably long period with compared to other failure events as mentioned before.

However, the same long period without any maintenance has influenced on the slight improved system reliability situation in data interval 1. A considerable large maintenance period and repeated system failures are also resulted due to such actions. Hence, it is concluded that these actions are facilitated for a considerable system degradation situation and that eventually leads to a long maintenance period. The fault code (i.e. 79.042) relates to the failure that is categorized as "liquid upstream pressure fault shutdown" is also noted during the 17th failure event. The same fault (i.e. 79.1230) is repeated in between the 26th and 27th failure situations of the gas turbine engine. However, the fault (i.e. 25th failure situation) is different from the above situation (i.e. 79.042) and relates to the fault code (i.e. 79.012) that is categorized as "start system speed: crash re-engagement shutdown." These failure situations are occurred under a relatively low maintenance period. However, it is inconclusive to say these previous faulty situations may influence on the respective system failures and maintenance periods in this gas turbine engine.

A detailed discussion that had with the maintenance crew is summarized in this section. The WHRU uses water to recover additional heat that is created by the gas turbine engine. A set of dampers are used in this process, where the heat from turbine exhaust gases is transferred to this water circulating system under gas turbine engine operational conditions as an heat recovery approach. In some situations, these dampers are aligned slightly differently directions and that drives gas turbine exhaust gases into the atmosphere. Such situations are categorized as the WHRU is in "bypass mode", where the exhaust gases are diverted from the stove. The operational conditions of these dampers are essential and it must be properly controlled and may not obstruct the outlet of the gas turbine (i.e. both simultaneously closed is an unwanted conditions). To avoid inadequate operational conditions, some manufacturers are adopted a mechanical link that also improves the safety of gas turbine engines. The position monitoring of this mechanical link is done by a programmable logic controller (PLC) with a status table. However, various inappropriate positions of the link are resulted in WHRU failure situations in gas turbine engine. Furthermore, the maintenance delays are often associated with this type of instrumentation and that resulted in long operational periods without proper maintenance actions. In addition, few qualified maintenance crew members are available for the required maintenance of the same equipment. One should note that a similar situation is noted in the maintenance data (see Figure 4) in this study and that resulted in a relatively longer maintenance period.

It is also noted that the crew is also familiar the WHRU failures that take relatively large maintenance periods (i.e. due to breakage of the mechanical link of the damper WHRU). This link is a mechanical arm between the actuator and damper itself as discussed previously. Furthermore, this failure can also be associated with a positioning failure of the same damper which is controlled by the PLC as a broken link. However, the maintenance crew also noted that the frequency of these types of failure events are increasing with respect to the system life of gas turbine engines. The lack of knowledge on the configuration details and operational conditions of WHRU is also another reason of the frequent failure events. In a majority of such failure situations, the crew has to wait for the gas turbine engine to cool down until it reaches the safe temperature to perform maintenance work. That is also another reason for the long associated maintenance period in this system fault of the gas turbine engine. It can also be concluded that these reasons have influenced on the failure intensity levels of the gas turbine engines.

4. CONCLUSION

The system failure intensity levels of a selected gas turbine engine are identified in the first part and the respective maintenance activities are compared with the same system failures in the second part of this study. The system failure intensity as the average engine performance level is categorized and calculated by the respective event data (i.e. CM data) from a selected gas turbine engine. One should note that the system failure intensity can be used to evaluate present and past maintenance activities (i.e. maintenance interventions with consistence intervals) as described in this study. Hence, these results can be used for both operational and maintenance requirements of offshore gas turbine engines. The maintenance costs can also play an important role in both operational and maintenance requirements. Such costs calculations should consist of the detailed information relate to engine performance deterioration, part replacement-repair rates, maintenance practices, and part conditions by considering collected, documented and analyzed service usage. These cost calculations can be used to identify the most critical and expensive components and their respective maintenance actions of gas turbine engines. Therefore, the most crucial system failures (i.e. the most critical and expensive failures) can be also identified and avoided. That information (i.e. the most crucial system failures) can be used to develop cost-effective maintenance polices for offshore gas turbine engines.

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Big Data Analytics for Predictive Maintenance Modeling: Challenges and Opportunities

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Abstract

Big data analytics, applied in the industry to leverage data collection, processing and analysis, can allow a better understanding of production system's abnormal behavior. This knowledge is essential for the adoption of a proactive maintenance approach instead of conventional time-based strategies, leading to a paradigm shift towards Condition-Based Maintenance (CBM) since decision is now based on the usage of a huge, diverse, and dynamic amounts of data as a means to optimize operational costs. This paper reports an investigation of the emerging aspects in the design and implementation of big data analytics solutions for offshore installations in order to allow predictive maintenance practices.

Condition-based maintenance focuses on performing interventions based on the actual and future states (health) of a system by monitoring the underlying deterioration processes. One of the building blocks of a CBM design and implementation is the prognostic approach/system, which aims to detect, classify and predict critical failures. Considering the massive amounts of data available from a Stationary Production Unity (SPU), the use of techniques that properly deal with such a big data scenario became essential. The use of parallel processing to ingest, transform, and analyze different kinds of data in near real-time basis allows the construction of a valuable tool for implementing CBM.

This paper presents a comparison of different approaches for RUSBoost and Random Forest (RF) classification, in constructing a prognostic system for a specific class of turbogenerator failures from a chosen Petrobras' Floating Production Storage and Offloading (FPSO). Besides the comparison of different classifiers, a contribution of this work lies on the use of data acquired not only from machine sensors (telemetry data) but also non-structured data regarding the most critical failures acquired from official reports, e.g. operator's machine event annotations. Those reported annotations were correlated to telemetry data to identify real critical failures, and simultaneously avoid false positives.

Keyword: Predictive models · condition-based maintenance · failure modeling · big data analytics · random forest · rusboost

Introduction

Optimization of maintenance costs is certainly amongst operators main concerns in the search for operational efficiency, safety, and asset availability. The ability to predict critical failures emerges as a key factor for the business, especially when reducing logistics costs are mandatory, as is the case with the Pre-Salt area in Brazil. Among the activities in these related processes are criticality assessments; field data collection and analysis; degradation mechanism identification, insulation, and modeling; diagnostics and prognostics. These activities demand the engagement of different groups and skills in a collaborative way to achieve the benefits of a proactive mindset and decision throughout the organization.

Experience has shown that significant benefits can be achieved when major maintenance interventions (overhauls, usually performed periodically) can be postponed based on conclusions from the use of degradation models. Such an approach can be complex, but its implementation results may reduce maintenance and logistics costs while keeping availability within required levels. Other important aspect is that the system's campaign cannot always be extended. Due to increased knowledge of the system's past and actual condition and the ability to detect faults at an early stage, there is always a possibility that an intervention could be required before expected. In such cases, the main advantage is the avoidance of random failure disorders (Machado et al, 2014).

In a survey performed by Heng (Heng et al, 2009), the existing methods for predicting rotating machinery failures can be divided into three main categories, as follows:

- ***Traditional reliabilityapproaches*** – event-based predictions;
- ***Prognostics approaches*** – condition-based predictions;
- ***Integrated approaches*** – predictions based on event and condition data.

Traditional approaches to reliability estimations are based on the distribution of event records of a population of identical units. Many parametric failure modes, such as Poisson, Exponential, Weibull, and Log-Normal distributions have been used to model machine reliability. The most popular among them is the Weibull distribution due to its ability to accommodate various types of behavior, including infant mortality in the "bath tub" curve. In our project we attempt to create an integrated solution using big data and analytics techniques to implement a CBM standard procedure for our target problem.

This paper is a result of an ongoing project, a collaboration between Petrobras, EMC2 and COPPE/UFRJ. The focus was set on the development of solutions using big data analytics to predict critical failures of gas-turbine engines of a FPSO's power generation system.

Related Work

Previous work has been done on machine failures in recent studies supported by Petrobras E&P segment. The relevance of such an investigation lies on the fact that the fleet of FPSOs of similar design is growing fast and the operator must improve its ability to avoid critical failures of its turbomachinery.

The first approach was performed in 2011 employing a logistic regression model to calculate the probability of future failure (for the next 24 hours) considering data from the five previous days of operation. The data source (training sets) consisted of machine event records and data from sensors in the plant operational historian database (2010–2012). In this approach, all of the turbogenerator's failures were grouped as a generic failure type. At the final test, with the threshold set at $\{P(failure) >= 0.5\}$, the performance of the constructed model was considered promising despite its limited prediction horizon. One of the proposed future work was to discriminate and rank the failure types, to include information from the maintenance work orders and to increase the prediction horizon to a minimum of 15 days anticipation.

The second attempt was performed in 2013 as a RUL (Remaining Useful Life) approach. In this work, the operator performed the ISO's high-level analysis in order to identify the most critical failure types to investigate. Data from maintenance work orders were assessed and the subsystems of the gas turbine were ranked by its impacts on production. Beyond that, a rank of failure types was obtained from the HMI (Human Machine Interface) and then six empirical models were constructed using samples of SVM (Support Vector Machine) and ANN (Artificial Neural Network) to estimate the remaining useful life regarding a group of failures similar to those presented in Table 3. Again, the results were considered promising although not conclusive $\{RUL <= 20\ days\}$, due to difficulties in acquiring the proper data to confirm model's performance in production. For more details, see (Machado et al., 2014).

Table 1—Technical characteristics of the system under the study (Based on Table A.19 of the ISO 14224) Source: (Machado et al, 2014)

Name	Description	Unit/code
Type of driven unit	Electric generator driven by PT (gas turbine)	PT driven by gas turbine.
Power – design (ISO)	28.337 (38.000 hp)	kW
Power – operating	13.600	kW
Operating profile	Load sharing between three Turbo Generators (TGs)	
De-rating	No	
Speed	Normal 4.800 / Max. continuum 5.040 / Control zone - 4.560 to 5.040	RPM
Number of shafts	2	
Starting system	Motor driven by two pumps of tree installed	Hydraulic
Backup starting system	None	
Fuel	Dual-fuel – operating mostly with gas	Gas or Diesel
NOxabatement	None	
Air inlet filtration type	High speed system	

Table 2—Subsystems' importance of the turbo generators under scope Source (Machado et al, 2014)

Turbo generators of the FPSO (2008 - 2012) [132.012 operating hours in 170.861 hours calendar time]			
System subdivision based on ISO 14224	Maint. Costs Correct. + prev. [%]	Interv. Frequency Correct. + prev. [%]	Down Time Corrective [%]
Compressor + hp turbine + power turbine	20%	9%	24%
Fuel system	17%	13%	21%
Lubrication system	13%	20%	12%
Exhaust	12%	19%	6%
Electric generator*	11%	12%	1%
Air intake	9%	2%	0%
Miscellaneous	5%	8%	19%
Control and monitoring	5%	6%	11%
Fire and gas protection	5%	9%	0%
Starting system	1%	2%	5%
Accessory drive	1%	1%	1%
Combustion system	1%	0%	0%

Table 3—Prioritized event types (failures) Source (Machado et al, 2014).

Rank	Gas turbine's prioritized event types (failure code)
1	overfuel to ignition failure shutdown (OIF)
2	gas downstream pressure fault shutdown (GDF)
3	gas upstream pressure fault shutdown (GUF)
4	liq upstream pressure fault shutdown
5	ignition failure shutdown
6	gas generator exhaust average temperature high shutdown

The third attempt (2014–2015) was a reliability-based approach made using the machine event records and the automated counter of the machine operating hours. With the comparison of these figures for a chosen turbogenerator, a nonhomogeneous Poisson process (NHPP) was chosen as a model for the failure intensity, resulting in a way to recognize the actual age of the machines under analysis. It is considered a complementary model. For more details, see (Perera et al., 2015).

These studies have provided to the Petrobras' turbo-machinery community several good discussions and a set of learned lessons regarding good operation and maintenance practices. Therefore, we believed that it was important to continue this kind of investigation in collaboration with industry, academic branches, and research centers.

The ISO's V-shaped method

According to (Machado et al, 2014), the ISO standards for condition monitoring and diagnostics of machines offer good guidance to establish a CBM standard procedure, especially for our target problem: turbogenerator failures in a FPSO. The ISO 17359 (2011), for instance, provides general procedures for registration, evaluation and estimation of machine condition, and ISO 13379-1 (2012) presents the main aspects for data interpretation and diagnostics techniques.

Despite the absence of consensus on the terminology related to diagnostics (Vachtsevanos et al., 2006), it can be described as a procedure of reasoning to interpret the health condition of machinery equipment using data acquired during its operation. It has a vital role in decision-making, both in aspects of operation and maintenance tasks. In addition, diagnostic procedures should be adjusted according to the potential failures (based on their likelihood and severity) that could occur in a machine (ISO 13379-1, 2012). The principle is shown in Figure 1. The V-shape represents the high-level concerns (maintenance: machine and risk assessment) and the low-level ones (measurements: monitoring, periodical tests, and data processing).

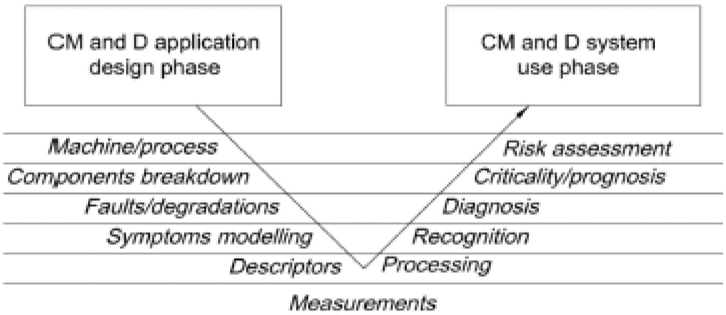

Figure 1—Condition monitoring and diagnostics (CM&D) cycle Source: ISO 13379-1 (2012)

Condition monitoring for offshore installations is certainly a challenge, especially when it comes to data quality and analysis. Having identified the critical functions, it would be possible to identify the critical components, failure modes and degradation mechanisms.

Machine/process

The system under study (Table 1) belongs to the main power generation system of an FPSO unit operating in the Campos Basin - Rio de Janeiro. It has 4 turbo-generators, each consisting of an aero derivative gas turbine with nominal capacity of 25000 kW, driving an electric generator. The main emphasis is given to the gas turbine engines. The required load of the offshore platform is approximately 35–45 (MW) then each generator is rated for approximately 12–15 (MW). Therefore, at least 3 generators should be operated to satisfy the requirements of the offshore platform.

Components breakdown, faults/degradations

From a maintenance perspective, it is of interest for the operator to have a functional tree of the machine. This tree should be composed mostly of the maintainable parts and from the component breakdown one should list all possible failure modes and their respective causes and degradation mechanisms.

Then, the criticality of each of the failure modes should be assessed by the expert´s judgment or from historical data based on significance (safety, availability, maintenance costs, etc.) and the probability of occurrence (refer to Tables 2 and 3). Since even for single components there is a large number of potential failures (a gas turbine can have up to 20,000 components/subsystems and more), it might be reasonable to decide, at this stage, which faults should be covered by the diagnostics. Both the operating conditions best suitable for identifying the chosen faults as well as the reference conditions should be defined.

Symptoms modeling, descriptors and measurements

In the modeling of symptoms, the operator must rely on the expertise within the organization with respect to a particular asset (equipment). Considering the growing importance of these machines in the production chain, we believe there is a place for collaboration between machine manufacturers and condition monitoring systems, experts (internal and external), as well as cooperation with research institutions. It is also important to state that the operator does not necessarily have enough information for failure modeling (e.g. a revised failure tree and/or a revised FMEA).

According to ISO 13379-1, descriptors can be obtained from condition monitoring systems, either directly or after the processing of the measurements. The diagnostics becomes easier when descriptors that are more selective are chosen and hence more selective symptoms. Descriptors have one big advantage over measurements – their selectivity helps to significantly increase the accuracy of the diagnostics.

Data from sensors were stored, processed and analyzed in order to identify: 1) correlations between parameters that best explain the events (e.g. principal component analysis, etc.); 2) patterns of behavior (symptoms) related to the major occurrences; 3) if there were variables that should be included in the monitoring set and; 4) what more can be considered (according to what is available in the historical data-bases) in the correlation of variables with their failure modes or critical components/subsystems.

The process of collecting and storing relevant information (data) from the monitored physical assets for the purpose of condition-based maintenance is considered in the current case as a data acquisition process (or simply the measurements).

In general, all collected data can be subdivided into two groups (Davies and Greenough, 2000):

- ***Events*** – data that includes information on what actually happened, what caused the event and what was done;
- ***Condition monitoring (CM)*** –measurements related to the health state of the machine, i.e. vibration data, temperature, pressure, oil debris analysis data, etc.

Typically, the event data collection requires manual data entry, while CM data, nowadays, is collected with the help of sensors and is done automatically. One thing that we would like to draw the readers' attention to is that both the event data and the condition monitoring data are equally important for successful CBM and that overlooking one type of data can result in limited efficiency of data use and overall problems with CBM (Jardine et al., 2006).

Processing and recognition

Data processing should be started with data filtration/cleaning, since the collected data (especially those entered manually) may contain errors. The most common types of errors include the human factor and sensors fault/malfunctioning. In general, all CM data can be divided into 3 categories:

- ***Value type data*** – single value collected at a specific time (i.e. temperature, pressure, oil debris analysis data, etc.;
- ***Waveform type data*** – time series data collected at a specific time (for example, vibration and acoustic data;
- ***Multidimensional type data*** – multidimensional data collected at a specific time (i.e. different images like X-ray, thermographs, etc.

The following step is data analysis. A number of various models, algorithms and methods are available for data analysis (interpretation) depending on the type of data collected. Signal processing is a name for data processing for waveform and multidimensional data and there are different methods and techniques available for this.

Diagnosis and prognosis

The final step in all CBM approaches is making decisions. The diagnostics of machine failures is basically a procedure of mapping the information obtained in the measurement space and/or features in the feature space to machine failures in the failure mode space (definition according to Jardine et al., 2006). Problems of machinery diagnostics and prognostics using condition-based maintenance approaches are well addressed in the literature for both: data acquisition, data processing and maintenance decision support (Jardine et al., 2006).

Different statistical methods are available for machinery failure diagnostics. Here we will list only some of them. Hypothesis testing has been applied to failure detection (Kim et al., 2001; Sohn et al., 2002) as well as statistical process control (SPC; Fugate et al., 2001). Another method is cluster analysis (Artes et al., 2003). It looks for minimum within-group variance while maximizing between-group variance. Typically, different distance measures/functions are used for pattern recognition.

Another method that can be used for failure diagnosis is the so-called hidden Markov model (HMM). Another fast expanding group of methods is called artificial intelligence (AI) techniques. In the literature, two groups of AI techniques for machine diagnostics are popular among researchers: artificial neural networks and expert systems. In addition, fuzzy logic systems, fuzzy-neural networks and evolutionary algorithms can be highlighted as additional techniques. (Jardine et al., 2006).

Prognostics is a complex task (when compared to diagnostics; (Sikorska et al., 2011). In general, it is divided into two main types: The first includes a prediction of time until machine (component) failure and is called remaining useful life (RUL). The second is used to predict the time that a machine could operate without failure (important for nuclear power plants).

Findings from the HLA

According to the high-level analysis performed by the operator in (Machado et al., 2014), the relative importance of maintenance cost of the power generation system represents 6.5% of the total maintenance costs of the related FPSO for the period considered.

Table 2 presents the relative impacts of the four turbo-generator's subsystems on costs, number of interventions and down time respectively.

At the top of the table, for instance, a set of subsystems can be seen (Compressor + hp turbine + power turbine) that is previously grouped with different criteria than ISO 14224 (2006). Fuel system and lubrication system also come up with important negative impacts on production. Other consideration should be given to miscellaneous as a subsystem that comes in 3rd place in terms of corrective down time. After that, six prioritized machine events were obtained directly from the HMI - Human Machine Interface as follows (Table 3):

In this study, the focus was given to the first ranked failure overfuel to ignition failure, which is denoted from now by OIF.

Research hypothesis: the challenge

One can observe that most failures are related to machine start-ups. This kind of event is occult (hidden failure) and hard to predict. Since we have chosen the OIF according to event recordings, we have found that one critical component is a gas fuel-metering valve GFMV from which a precise behavior is demanded during the start.

Considering that the action (countermeasure) for these events is the replacement of the valve, the question raised for the research team was "if we could detect the abnormal valve's behavior during the run, could we develop a predictive model to assign a probability of failure at the next start?"

Working with this hypothesis, the team extracted sensor data from the P&I industrial repository in order to train offline classifiers. The classification process will be presented in the following section.

Classification processes

In this section, we describe the entire procedure to determine the fault classifier, including the following steps:

- ***Database pre-processing*** – this step includes the removal of all major outliers and adjustment of the sampling frequency to a unique value (1 sample/minute) in all available tags from the 4 turbo-generators;
- ***Event annotation*** – in this stage, the time stamps of all "normal stops" (NS) and "machine failure" (MF) are determined. Removal of repeated NS and MF occurrences (in less than a given time interval) is also performed. For all validated NS or MF situations, a 24h interval is identified where the machine operated without interruption prior to the stop that originated the associated event;
- ***Feature extraction*** – for all NS and MF events, the machine operation within the 24h interval identified in the previous step is characterized by meaningful features that should act as the classifier input;
- ***Classifier training*** – using the features extracted in the previous stage, the classifier of choice is trained, following the event labels defined in step (2).

The result of this four-step procedure is a smart algorithm capable of identifying a faulty operation next time the machine is turned on, based on the features extracted along 24h prior to the machine stop. The detailed implementation of each of these stages is discussed in the following subsections.

Database pre-processing

The available database consisted of several time-series associated to 4 turbogenerators (namely TGA, TGB, TGC, and TGD) of a given oil platform. The number and type of tags associated to each TG varied. For instance, in the original dataset, TGA had 113 tags associated to it, whereas TGB, TGC, and TGD had 112, 104, and 113 tags, respectively. In order to make the subsequent analyses uniform, we removed all tags that were not recorded for the 4 TGs. This left us with only 84 tags for each of the 4 TGs.

The next step was to equalize the beginning and end of all remaining tags. In that manner, all series were trimmed to start at the first minute of February 1st, 2010 and to end at the last minute of December 31st, 2012, corresponding to a total of 1,065 days for each tag.

Some of these tags presented out-of-scale values; above 1E+8, for instance, whereas the remaining values were regularly below 1E+3. On average, these anomalous values occurred less than once in each tag. Such values were readily identified by a simple threshold comparison and replaced by the average value of the neighboring samples.

The compression scheme adopted in the plant information historian removes signals that are too similar from previous ones, leading to series that are non-uniformly sampled in time. This process is easily reversed by a simple linear interpolation to enforce a unified sampling-time interval of 1 sample/minute within all tags. The final result of all above steps is a database of 4 x 84 series of 1,533,600 samples each.

Event annotation

Petrobras records all TG-related events, including "normal stops", "failure occurrences" (as the ones listed in Table 3), "complete shutdown", "maintenance period", and so on, in a single database. From that dataset, one can extract the events of interest for this work and the related timestamp. However, these annotations require some processing before being fed to the classifier. More specifically one must:

- Verify whether there are repeated events in a short interval of time: in some cases, a given failure may occur in consecutive restart attempts. If such is the case, one must consider only the first failure event, and the subsequent one must be disregarded. This situation is illustrated in Figure 2, where 3 OIF occurrences were annotated in an interval of just about 1 hour (red box), but only the first one (green box) is considered for the classifier-training purposes. Following this procedure, only 18 OIF, 11 GDF and 4 GUF events are identified.

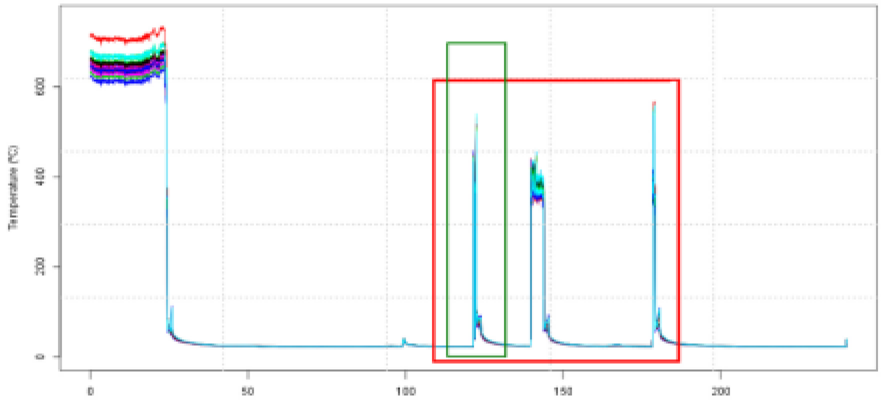

Figure 2—Eliminating redundant events (identified by the temperature spikes in red box) and keeping only the first one (green box)

- Verify whether the machine was active for 24h before any event: for each event of interest ("normal stop" or "failure") as identified in the previous step, we search for a 24h interval where the machine operated continuously before it halted due to a normal stop or an undesirable failure. If properly identified, this interval will be the one employed to extract the features that characterize the machine behavior before stopping. This procedure is illustrated in Figure 3 where an OIF event is regularly identified and the upper arrow is indicating the end of a continuous 24h interval (1,440 samples) where the machine operated before halting.

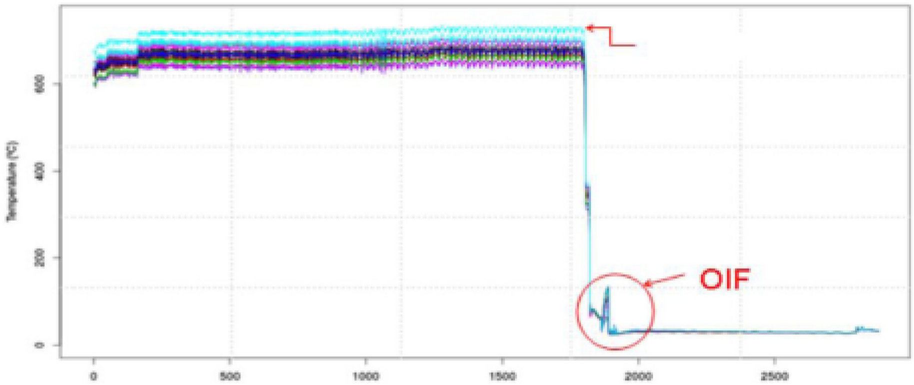

Figure 3—Given an identified event of interest (in this case an OIF), we search for a 24h interval (1440 temperature samples above a given threshold) where the machine operated continuously. Such interval will be the one employed in the feature extraction to characterize the machine behavior before its stop.

Feature extraction

Given the 24h interval selected as given in the previous section, we use the available time series of the event-related TG to characterize the machine's performance before the event.

For the main failures listed in Table 3, the temperature variance across the 17 sensors radially displaced along the TG exhaust section seems to be a good indicator of the fuel burning process: larger temperature variances can indicate to a bad fuel burning, which is often associated to a fuel-valve malfunction that causes the OIF, GDF and GUF faults. Other features associated to the exhaust temperature pattern include the minimum, maximum, mean values along the 17 sensors.

Other tags associated to these failures include "fuel flow gas", "GG temperature exhaustion", "GG pressure exhaustion", and "GG differential input pressure".

Classifier training

All the pieces of information listed in previous sections are collected into a single input vector, which is fed to the classifier along with the pertinent corresponding operation class ("normal" or "failure").

The 193 "normal stop" (NS) events and the 33 "failure operation" (FO) events (including the 18 OIF, 11 GDF and 4 GUF occurrences, as indicated in before) were partitioned in 6 data blocks with 30 or 31 NS and 5 or 6 FO events each. From these 6 blocks, 3 were employed in the classifier training process where the other 3 were used to evaluate the classifier performance on unknown data (data not considered in the training process). This block-selection procedure allows 20 different block combinations (hereby referred to as folds) for the training or testing stages, what enables one to assess the classifier effectiveness and robustness to the different data employed in its training.

Experimental results

Among the several classifier families found in the related literature, the RUSBoost classifier was shown to be quite suitable to the problem at hand. In particular, this classifier handles quite well the unbalanced total number of NS and FO events and the low correlation among the several input features with the failure event, aspect which is readily compensated by all Boosting-based classifiers (C. Seiffert et al., 2010).

In this section, we assess the results for the Random Forest and RUSBoost classifiers in three different experiments:

- ***Experiment 1*** – In this initial experiment, 134 NS were considered along 18 OIF instances, and both algorithm families (Random Forest and RUSBoost) were employed;

- ***Experiment 2*** – In this case, all 193 NS events are considered along with the 33 failure annotations (FO), as discussed previously. Due to its better suitability to analyze unbalanced classes, as yielded in Experiment 1, only the RUSBoost classifier was considered in this experiment;
- ***Experiment 3*** – In this case, the 193 NS events are evaluated according to the number of times it was misclassified during the training stage of Experiment 1. All NS events that were misclassified at least once are disregarded. Only the remaining NS events are divided into 6 groups and employed in the training and testing stages as before. Once again, due to its better suitability to analyze unbalanced classes, only the RUSBoost classifier was considered in this final experiment.

Experiment 1

In this initial experiment, the 18 OIF and 134 NS instances were divided into two congruent sets, for training and testing. Results for the Random Forest and RUSBoost algorithms are respectively summarized in Figure 4 and Figure 5 below.

TRAINING			TEST		
Estimated Class	Original Class		Estimated Class	Original Class	
	OIF	Not-OIF		OIF	Not-OIF
OIF	9	0	OIF	1	5
Not-OIF	0	67	Not-OIF	8	62

Figure 4—Classification results for the Random Forest classifier: 100% accuracy in the training stage but only 1 out 9 OIF failures was identified during the test procedure. Not-OIF can be seen later on as Normal Stop (NS).

TRAINING			TEST		
Estimated Class	Original Class		Estimated Class	Original Class	
	OIF	Not-OIF		OIF	Not-OIF
OIF	9	3	OIF	5	19
Not-OIF	0	64	Not-OIF	4	48

Figure 5—Classification results for the RUSBoost classifier: 96% accuracy in the training stage and 5 out 9 OIF failures identified in the test procedure.

From Figure 4, one readily notices how the Random Forest algorithm provided an excellent performance in the training stage, but showed little capacity for generalization, achieving quite poor OIF identification results in the test stage. Meanwhile, as shown in Figure 5 the RUSBoost algorithm presented a 96% accuracy during training, and a better ability to identify the OIF events in test, at a price, however, of a reduction in its ability to recognize properly the NS events.

Experiment 2

In this experiment, 19 out of the 20 training folds provided 100% accuracy in detecting the NS and FO events. Due to its better generalization capability, as given in Experiment 1, only the RUSBoost classifier was considered here. The testing results for this algorithm are shown in Figure 6 for the 20 folds, where TP (true positive) indicates a correct detection of a failure and TN (true negative) a proper detection of a normal restart.

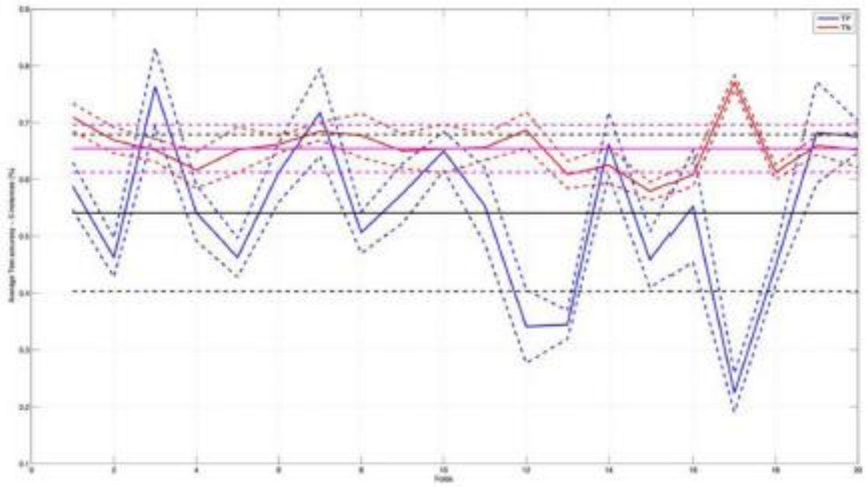

Figure 6—Classification results for the RUSBoost classifier: 96% accuracy in the training stage and 5 out 9 OIF failures identified in the test procedure.

Considering all 20-fold testing results, one gets an average TP of 54% and an average TN of 65%. Above all, as seen in Figure 6, one readily observes a quite erratic behavior of the classifier in each fold, what indicates low capacity of generalization of the classifier with respect to the new data employed in its testing stage.

Experiment 3

In this experiment, the 193 NS events were evaluated according to their misclassifications during the training stage of Experiment 2. The result from this analysis is shown in Figure 7, where one observes how 96 NS instances were never misclassified. Using only these 96 NS events, dividing then into 6 groups of 16 events, the same procedure employed in Experiment 2 was reproduced in the current experiment. The testing results for this Experiment 3 are shown in Figure 8. In this case, considering all 20-fold testing results, one gets an average TP of 59% and an average TN of 71%, corresponding to a significant improvement with respect to the results achieved in Experiment 2.

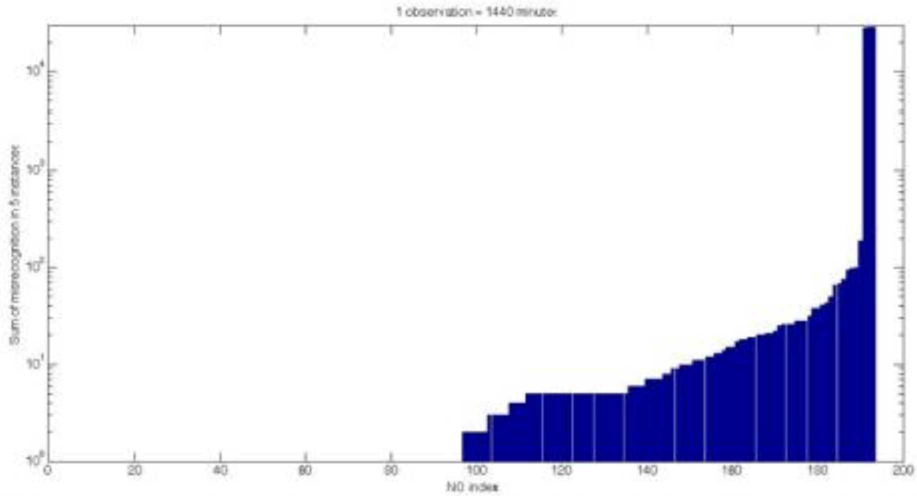

Figure 7—Histogram of NS misclassification in training stages of Experiment 1. From this analysis 96 NS events were selected to Experiment 2.

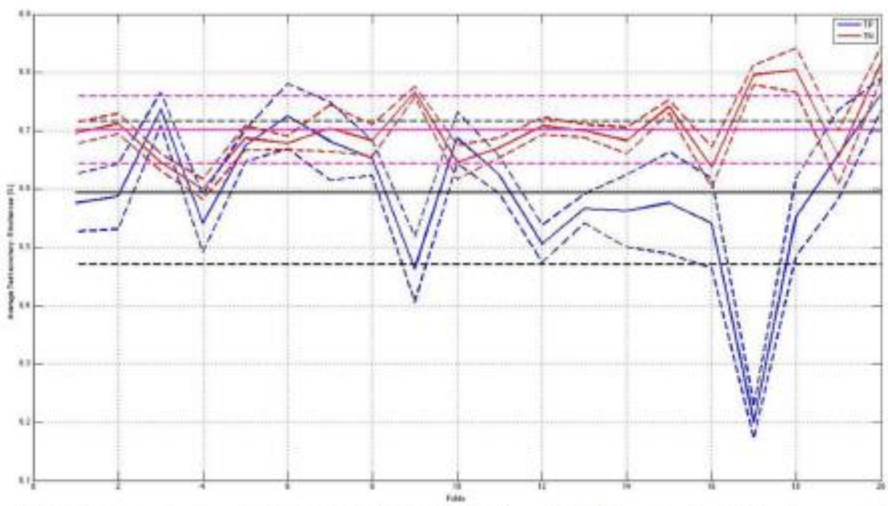

Figure 8—Classifier testing results along 20 different data folds in Experiment 2: TP (true positive) indicates a correct detection of a failure and TN (true negative) a proper detection of a normal restart.

Final considerations and future work

Starting from a challenging research hypotheses such as to model and predict hidden failures, the present study discusses the modeling of machine's failures by the use of big data analytics approach with different classifiers.

In the search of a smart algorithm capable of identifying a faulty operation next time the machine is turned on, based on the features extracted prior to the previous machine stop, some classifiers have been tested in a series of experiments and these results were presented.

Among the problems encountered in this research are: data collection difficulties in terms of data-base standardization. The sets of tags (sensors) associated to each turbo-generator have varied considerably and beyond that, some tags presented anomalous values which are, in some cases, different than outliers.

From the use of predictive models, once we can have useful models in the near future, another problem that raises is regarding the decision-making in which the process must include the model's predictions. In that sense, a future work is to consider more than one model result in a voting system which would be able to provide reasoning for decision.

As demonstrated in this paper, at the end of each modeling phase, we usually come with several models with their different capabilities. In order to rank the models, it is necessary to assign a price for false positives and false negatives according to production processes and also to market aspects.

Finally, following the steps proposed by the ISO's standards for condition monitoring and diagnostic of machines the criticality/prognosis and risk assessments are to be considered towards the design of a framework for the decision-making process.

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Appendix B – Interview questionnaire

Table B1 – Interview questionnaire

Questions for maintenance experts   **(*Questionário para especialistas em manutenção*)**
1 - In what function/role is the professional in charge of data collection classified in your maintenance organization? (*Em qual função/posição está o professional encarregado da coleta de dados em sua organização de manutenção*?)
2 - In what function/role is the professional in charge of data analysis classified in your maintenance organization? (*Em qual função/posição está o professional encarregado da análise de dados em sua organização de manutenção*?)
3 - What can you say about the CM&D process?   **(*O que você pode dizer sobre o processo de monitoramento e diagnóstico de máquinas* ?)**
4 - How are the maintenance decisions (derived from diagnostic results) registered and made available for future analysis? (Como as decisões de manutenção (derivadas de resultados de diagnóstico) são registradas e disponibilizadas para análise futura?)
5 - What can you say on the lessons that can be learned, from the maintenance decision-making process? (*O que você pode dizer sobre as lições que podem ser aprendidas, a partir do processo de tomada de decisão de manutenção*?)
6 - In what function/role is the professional in charge of the technical interface with suppliers classified in your maintenance organization?   **(*Em qual função/posição está o profissional encarregado da interface técnica com os fornecedores em sua organização de manutenção*?)**
7 - Can you mention (3 or 4) of the most frequently monitored maintenance key-performance indicators in your organization?   **(*Você poderia mencionar (3 ou 4) dos indicadores de desempenho-chave de manutenção mais frequentemente monitorados em sua organização de manutenção*?)**
8 - What were some barriers, if any that you encountered in the implementation of the CM&D related processes? (e.g., staff turnover? Lack of key support or Lack of technical assistance?)   **(*Quais foram algumas barreiras, se houve alguma que você encontrou na implementação dos processos relacionados ao monitoramento da condição e diagnóstico de máquinas? (e.g., aspectos como rotatividade de pessoal, falta de suporte ou assistência técnica*?)**
9 - How did you overcome the barrier(s)?   **(*Como foram superadas as barreiras*?)**
10 - Some offshore operators are implementing machine-monitoring centers, as a way to develop and retain analytical and predictive capabilities. Does your company have those Centers?   **(*Alguns operadores estão implementando centros de monitoramento de máquinas, como forme de desenvolver e reter capacidade analíticas e preditivas. A sua empresa tem esses centros?*)**
11 - What recommendations do you have for future efforts such as these?   **(*Que recomendações você tem para futuros esforços como esses?*)**
12 - Is there anything else you would like to add?   **(*Tem alguma coisa que você gostaria de adicionar*?)**

B2 - Interview protocol

Introduction - Thank you for attending this meeting today. My name is Mario Marcondes Machado, and today I would like to talk to you about your experience with Condition Monitoring and CBM related processes for my PhD study.

My background - I am Mechanical Engineer from Brazil (2000). I had my master's degree in Transportation Engineering from the Federal University of Rio de Janeiro – UFRJ (2005). My experience in industry starts in 1992 in the air transportation sector (12 years) in flight operations and, in the academia, lecturing in Aeronautical Sciences (2004-2005). From 2006, I started in the Oil&Gas industry working on maintenance. Since then I have been working on CBM implementations and maintenance management assessments, mainly regarding rotating equipment in the offshore operational environment.

Purpose - The purpose of this study is to investigate the key-elements of PM programs (e.g.., CBM, RCM, TPM etc.) in order to capture lessons that can be used in future implementations.

Duration - The interview should take about 20 - 40 minutes.

Confidentiality and consent - All responses will be kept confidential. I will ensure that nothing in the PhD thesis / report will identify you as the respondent. You don't have to talk about anything you don't want to, and you may end the interview at any time.

Are there any questions about what I have just explained?

Are you willing to participate in this study?

I, the undersigned, understand that I am about to be interviewed by Mario Marcondes.

______________________________	________________,	____/____/___.
Interviewee	Place	Date

Closing the interview - I will analyze the information you gave me and once I have the interview transcript, I will send to you a copy in order to conduct a check for eventual misunderstanding or misinterpretation.

Thank you very much.

B3 - Survey questionnaire

1. Which are the normative sources/references followed in the development of your maintenance related processes and standards? (e.g., ISO, IEC etc.)
____.

2. In what function/role is the professional in charge of data collection classified in your maintenance organization? (i.e. regarding the performance of critical equipment/systems - indicate the degree of involvement)

	Responsible	Informed	Approval	Cooperates	Supports
Reliability Engineer	( )	( )	( )	( )	( )
Maintenance Engineer	( )	( )	( )	( )	( )
Maintenance Technician	( )	( )	( )	( )	( )
Maintenance Planner	( )	( )	( )	( )	( )
Plant Manger	( )	( )	( )	( )	( )
Headquarter Manager	( )	( )	( )	( )	( )

3. In what function/role is the professional in charge of data analysis classified in your maintenance organization? (i.e. regarding critical equipment/systems - indicate the degree of involvement)

	Responsible	Informed	Approval	Cooperates	Supports
Reliability Engineer	( )	( )	( )	( )	( )
Maintenance Engineer	( )	( )	( )	( )	( )
Maintenance Technician	( )	( )	( )	( )	( )
Maintenance Planner	( )	( )	( )	( )	( )
Plant Manger	( )	( )	( )	( )	( )
Headquarter Manager	( )	( )	( )	( )	( )

4. How are the diagnostic results communicated to the decision-maker?
( ) In routine meetings
( ) By e-mail / text message
( ) Other(s) please specify. ____.

5. Does your preventive/predictive maintenance process follow up the results of every diagnosis? (i.e. Was the diagnostic correct or not?)
( ) Yes. Frequently
( ) Yes but rarely
( ) No

6. How are the maintenance decisions (derived from diagnostic results) registered and made available for future analysis?
( ) In meeting minutes
( ) In a specific database
( ) Other(s) please specify. ____.

7. How are the lessons learned, in the maintenance decision-making process, used?
____.

8. What kind of maintenance related events/issues are recorded for future consultation/analysis? (Indicate the priority level)

	High Priority	Moderate Priority	Low Priority
Catastrophic Failures	( )	( )	( )
Frequent Failures	( )	( )	( )
On Demand Failures	( )	( )	( )
Expensive Repairs	( )	( )	( )
Long Lasting Repairs	( )	( )	( )
Spare Parts related issues	( )	( )	( )
New Solutions to Frequent Problems	( )	( )	( )

9. In what function/role is the professional in charge of the technical interface with suppliers/vendors classified in your maintenance organization? (i.e. regarding maintenance plans, spare parts and consumables supply)

	Responsible	Informed	Approval	Cooperates	Supports
Reliability Engineer	( )	( )	( )	( )	( )
Maintenance Engineer	( )	( )	( )	( )	( )
Maintenance Technician	( )	( )	( )	( )	( )
Maintenance Planner	( )	( )	( )	( )	( )
Plant Manger	( )	( )	( )	( )	( )
Headquarter Manager	( )	( )	( )	( )	( )

10. From the following list, can you indicate **-** What are the most frequently monitored maintenance key performance indicators in your organization?

( ) Total Maintenance Cost per Quantity of Output
( ) Availability related to Maintenance per Total Maintenance Cost
( ) Corrective and Preventive costs levels per Total Maintenance Cost [%]
( ) Operational Availability (Uptime during required time) [%]
( ) Preventive Maintenance related Downtime [%]
( ) Corrective Maintenance related Downtime [%]
( ) MTBF [Hours]
( ) Man-hours used for Planning [%]
( ) MTTR [Hours]
( ) Maintenance Backlog [Hours]
( ) Maint. Man-hours used in Corrective Work [%]
( ) Maint. Man-hours used in Preventive Work [%]
( ) OEE (Overall Equipment Effectiveness)
( ) Other(s) please specify. ____.

11. What was/is the most challenging difficulty observed in the implementation of the preventive/predictive maintenance related processes?

12. About your experience, please inform:

Company / Affiliation: ________________
Position (Function / Role): ______________
Experience in current position (years): _____
Total experience in industry (years): _______.

Appendix C – Summary of interviews transcripts

Interview #1 **- Background & Experience:** *MSc in Applied Physics. General Field of expertise in Automation and Control. More than 35 years in the Oil&Gas industry, including 10 years in Condition Monitoring related jobs: (i) Pumping systems; (ii) Gas compressors; (iii) S_ – Gas compressors).* **Current position** – *1st Chief Engineer.*

I1Q1 - In what function/role is the professional/department in charge of data collection classified in the maintenance organization? *Data collection and storage should be handled by the IT department, aiming to check if the system is running OK. That is, if the sensors and data collection and storage devices are operating properly.*

I1Q2 - In what function/role is (or should be) the professional/department in charge of data analysis classified in the maintenance organization? *Data analysis should be handled by the Operation and Maintenance (O&M) departments working together to analyze data and find out algorithms to predict breakdowns. Vendors with specialized knowledge can only participate in this work.*
For example: If for a normal pumping system the time to repair is hours-days, it may be easy to estimate impacts and to decide. For a subsea pumping system it would be totally different, deserving a discussion between O&M personnel trying to find the balance between risks and gains of when and how to do the maintenance intervention. "Repair time" for subsea is normally one month, involving replacement of a 100 ton module. The actual module change-out takes aprox. 24 hours, but it takes 1 month to prepare for it.
In summary: Different levels of interventions should be treated accordingly. The O&M personnel should discuss the alternatives and its respective impacts on production.

I1Q3 - What can you say about the CM&D process? *Condition Monitoring is to measure the parameters trying to understand the behavior of the system in the past. Diagnostics is more about conceiving "What would be the future of the system?"*
In summary: Condition monitoring data are the inputs of our predictive models and it provides information to verify and calculate/estimate (if the formulas are well defined and if the sensors A and B are not drifting) the outputs that will provide criteria for decision-making (e.g. Remaining Useful Life).
An ideal system would indicate, for each possible breakdown mechanism that would force a module change out, the status e.g. as shown below (from car). The "yellow light" should turn on when there is e.g. 30 days left until you must stop.

I1Q4 - How are the maintenance decisions (derived from diagnostic results) registered and made available for future analysis? *All of the Oil&Gas companies have today some kind of system that can provide decision traceability (e.g. CMMS, ERP). Maintenance costs money, and needs to be justified somehow.*

I1Q5 - What can you say on the lessons that can be learned, from the maintenance decision-making process? *Depending on the maintenance criteria (e.g. time-based, cycle-based or condition-based) there are, basically, two types of decisions:*
Short-Term and Long-Term decisions. Some short-term decisions may be related to continuous monitoring systems (e.g. electrical devices), whilst some long-term decisions may be related to periodical monitoring (e.g. subsea equipment). The control room is manned 24/7 and handles short term problems, while the land-based support organisation (manned 8/5) handles more long-term projects.
In summary: The process of dealing with these decisions, and its respective combinations, will provide the lessons.

I1Q6 - In what function/role is the professional in charge of the technical interface with suppliers/vendors classified in the maintenance organization? *Here it is important to establish a division of labor between on- and off-shore personnel. Big interventions/repairs (e.g. two weeks' shutdowns every summer) should be planned and assisted by the on-shore personnel (people on the beach), whilst small importance interventions/repairs should be handled by the off-shore personnel. The platform manager, for example, is involved in the short term and emergency related decisions.*
Example: A fuse blows : Platform personnel replace it immediately.
A larger compressor is needed: Shore-based organisation organize this.

I1Q7 - Can you mention (3 or 4) of the most frequently monitored maintenance key-performance indicators and/or parameters?

(i) For Compressors and Pumps we frequently monitor performance parameters;
(ii) For Hydraulic systems – Leakage and fluid consumption and;
(iii) For Power systems – Insulation resistance.

I1Q8 - What were some barriers, if any that you encountered in the implementation of the CM&D related processes? *Data collection is the easy part. The analysis to provide the Remaining Useful Life (RUL) estimates, for example, that is the difficult one. The obstacle is to prove that CM/CBM can save money for the oil companies. Once we can prove that we can actually do some good in this area, there will be no obstacles (cost benefit analysis).*
I think we must research more on that in order to improve our analytic and predictive capabilities. That is, looking into the future and finding "How to detect breakdowns in advance?"
In addition, Fault Tree Analysis (FTA) and Cost Benefit Analysis (CBA) should be included in that process. We should focus on the most common causes for breakdown, such that we focus on the aspects where there is most to be gained (=most money to save for oil companies).
Any aspect like staff turnover, Lack of key support or Lack of technical assistance? *No. If you are able to demonstrate clearly, the costs and benefits of the alternatives, it is normally easy to get key support.*

I1Q9/10 - On how to overcome those barriers, can we see the implementation of condition monitoring centers (CMC), by most of the operators, as a way to develop and retain analytics and predictive capabilities? *Yes. Some big companies, for example, has 25 people in their center in Amsterdam, monitoring about 2.000 compressors, and __ has at least 10 people in their center, monitoring about 200 compressors.*
Some monitoring services can also be obtained from vendors regarding, for example, electrical devices including intelligent electrical devices (IEDs), since that requires different competences. Compressor and pump vendors may also contribute, as they deliver complex equipment. Electric actuators are becoming more common, and subsea processing involves many new types of equipment.
Considering the company size, a small operator, for example, may prefer to outsource the monitoring services. Here, again, we should apply the cost benefit analysis.

I1Q11 - What recommendations do you have for future efforts such as these?
In discussion with O&M personnel, try to find:
(i) What kind of equipment breakdown occur more often and its respective impacts on production;
(ii) Which algorithms can be used to monitor degradation of these equipment and;
(iii) How to predict and avoid those breakdowns.

I1Q12 - Is there anything else you would like to add? *No.*

Interview #2 **- Background & Experience:** *I am now working in Company A in the maintenance and modification area for 3 years. Before that I worked at M_-NTNU. I've been working since I had my master thesis in 2000, so I have 15 years of experience mostly related to the Oil&Gas business but also to land-based industries and railway transportation, mostly within the areas of maintenance analysis, establishing maintenance programs, structuring that type of information and also within the condition monitoring (CM) domain in that areas.* ***Current position*** *– Specialist Maintenance Engineer.*

I2Q1 - In what function or role is the professional in charge of data collection in your maintenance organization? *Well, depends on what types of data we are talking about. From the Maintenance Programs development side, it is a lot of information which is structured and gathered through the operational phase or the maintenance phase in that area. Then we also have the condition monitoring (CM) part, where then have expert systems or dedicated systems collecting data, for instance, on generators, on pumps and so on. It could be vibration measurements, corrosion probes. You have a lot of different kinds of data and then a lot of different systems gathering that information.[...]*
Maybe there must be a sort of filters between these layers in order to provide something meaningful. *I would say "filters/data processing", which is basically. ... My basic idea of applying CM is that you gather data in order to get the information which you can use in the decision process.*
(Trying to develop question 2)
I2Q2 – It is not based on what kind of function or position/role but in what kind of data. That is, the nature of the data been gathered will define by whom and how this will be processed and transformed in reasoning information for decision. *Yes, because at the end of the day, it is all about making a decision on "what to do next?". [...]*

I2Q3 - *So, going from the planned maintenance scheduled regime and over to the CM scheme where you basically get information and some time you have to make decisions on what to do and when to do it and so on. It tends to be two different mentalities in how you should think on it. I think one of the reasons why we are not really_implementing or having CM implemented broadly across/into the organizations is that the organization is not matured enough to be able to actually utilize the information and have people which are responsible enough and would like to take those decisions. Because… that is an important thing.*

Is it a kind of commitment towards the decision-making process? *And, actually being confident that they can take those decisions without having personal consequences if they do anything wrong. […]*
(Trying to develop Q3 and Q4)
And you also talked about of a kind of maturity level of the organization in terms of being able to cope with uncertainty which is intrinsic and inherent of the condition based maintenance (CBM). *It is a paradox. …One we have a schedule PM program... It is a pump supplier for instance, which basically provides this pump for many applications, many different operational conditions. So you have a lot of different factors which influence on degradation mechanisms and so on. But then you have fixed monthly, yearly and so on. And it is taken for granted that it is correct.*
As soon as you go to the CM domain, you have to make decisions. Some people have to take those decisions in order to have this (assets) working and producing. So you are always speaking about the uncertainty that Ok, you might make a mistake, you might rum this unit until it fails and …that you didn't basically figure it all out before it fail. Then you will have, in many cases, a debate or … some will get some bad comments back within the company. But as long as you follow the schedule program. Then the maintenance department can say Oh! … that was sorry … but we managed to fix the problem when it arose. Then you are more…you are actually appreciating more the fire department, (the fire fighters-those who can fix the problems when they arises) …then if it is the fire fighters which are the heroes within the company…
The Hero' culture. *Basically we are back on the ones who are making decisions and... For ones who have the inputs or have the information structured in such way that they are able to decide, and they should also be confident that if they make a bad decision sometimes and that will happen. If you have to take many decisions each day, at some point you will miss out on something.*

I2Q5 - How are the lessons learned in the maintenance decision-making process? *As I have been into it and from my experience. I have been within several companies discussing with personnel around and what we have seen in many cases is that when we get to the heavy rotating equipment (e.g. compressors, generators etc.) they have dedicated teams, working on that machinery and to some degree, those teams are on the side of the ordinary maintenance organization (maintenance planner and so on). Basically the company has an organization for handling the maintenance as such, and then they have those small teams siting in their own boxes. …, their owl silo. With their B_ system or similar applications, and have this very limited domain which they are following upon and where they can be very dedicated and very skillful as well.*
But then you handle that equipment in a separate silo and you don't get that information between the domains, so basically you end up with having… let say, the Maintenance and the CM domain within the same company. This are, to a limited extent, sharing their knowledge and their approach. That is, or maybe, the most interesting part for the company to see that OK, How are we actually working within those different domains? How can we utilize the skills and the knowledge of the CM silo? That is, the persons siting there having to (i) read info, (ii) interpret information and (iii) make decision from it. And then, How do you take that same thinking over to the maintenance domain? Where you have more and more information. You have a lot or information today that you had 20 years ago. Today you can have information on a lot of levels and on a lot of equipment. It is more to be able to say... What is useful within the organization?

I2Q6 - In what function or role is the professional in charge of the technical interface with suppliers and vendors classified in your maintenance organization? *Well it is not an area that I have been working a lot within. From a project's perspective, …when you start a project,… as I've been involved lately in the N_ extension project then you …basically … when you built this plant you have the maintenance department of the maintenance responsible within the project to decide on the spares and what to put spares. Most of time you take the vendor' recommended list and then go through that. Decide what to keep as spares and then you make those purchases. But … you have different types of spares, consumables, critical spares, long lead times.[…]*
Then we can turn the situation totally around and say, OK we will try to monitor and we know that we are not able to be correct at all times. Seeing from that side, you could say OK for some components we need a safety margin in order to have the operation running. You have to be able to say OK, We know that we are monitoring but we are very unsure of how good we are in detecting degradation mechanisms and in

how far in advance do we get the signs of a failure. Actually knowing your own limitations is even harder. You need to have more skilled in order to know your limitations. When you do research, you find out that you need to do some more research. It is the same in this area as well. When you have reach the level, where you know the limitations of your CM system then you are actually in a good way of …. But I haven't figured out a good method of deciding which type of spares to keep in stock, in order to balance up on a CM system.

There are some models but models… *Well it's a simplification of life and it could be over simplified and then it is useless. Or, it could need a lot of data, which we don't have. Which makes it useless as well. So … do we have a model which balance those different aspects? So, It is not a good answer to your question. I am sorry.*

I2Q7 - What were the most frequently maintenance KPIs monitored in your experience? Can you mention 3 or 4 KPIs to evaluate a Maintenance System and maybe 3 or 4 parameters or group of parameters (performance parameters or so) that you have handled more often? *When it comes to maintenance KPIs. The most commonly used KPIs are those related to the number of work ordered issues and the number of work orders (WO) completed within due date and so on. I don't think they are used mainly because they are providing a good tool for the organization as such. It gives you an idea of the figures, and… Do we have a backlog? And so on. In that respect, you know if you are coping with the maintenance plans.*

But, the main reason why I think it is the most commonly used indicators is that it is that data which you have easy access. Basically, if you run a query from your maintenance management system (CMMS), then it is very easy to count. Every kid knows how to count and to count the number of WO, which are issued, number of WO which are completed and so on.

It is a very simple way of doing it. But when it come to a CM area you basically don't have any KPIs or indicators which are commonly used, as I am aware of it. The indicators which I would have, if I were in a position to, on a daily basis, having to make decision on what to do the next week or the next month. I would like to have an indicator where I could say, OK for the machines or the equipment where I have set up some prognostics model or where the system provides me with, at least, some estimates. How long will it take until we reach some kind of state for this equipment?

And if I could have a list of who is switching that limits for the next month or the next half year … I would actually be able to sort out, OK where should we keep our focus? Which equipment should we plan some interventions? When can we do it? With respect to when do we have other plants shutdown? […]

So, if you had some indicators, where you have, from machine learning and all those data models which are developed continuously today, if instead of providing me a vibration pattern, I could have a sort of a time scale where I could see OK, for the next 6 months this machine will be green and happy. From month 6 and so on, we know that we are in a yellow band.

It might be that you are not able to process the data in such a way that you are able to provide that information right away but…. It could be that you need human inputs on its way.

Are talking about the RUL estimation? *Yeah. It is. That's the only think which is interesting about it. It aggregates information. The reason why I would like to have it on that type of format is that, then it can be used by several people not only the CM experts and then you can have a maintenance department or an asset integrity department.*

Maybe that is why the RUL approaches are becoming more and more important nowadays. It can, let say, reunite all these information in one picture. *Yes, standardized information. When you look at the stock market, for instance, in the Oslo stock exchange, you have around 600 points at this moment. You have all these figures shared around. That gives you inputs on how things are going in the economy. The same type of approach can be applied on the technical level as well.*

I2Q8 - In your experience, what were some barriers, if any that you encountered in the implementation of these CM&D related processes? (Staff turnover, Lack of key support or technical assistance). **Difficulties whatever.** *Since I have been most hands on in the maintenance management domain. I haven't been implementing CM systems myself. But, I think that most of these barriers are on the mental mindsets.*

Comparing a fixed schedule where you, basically can just put out this schedule over to next 20 years. When that is implemented into the maintenance management system, it is fairly simple to govern from a management perspective. You off course you have corrective work and you have a lot of schedules which shall be put in place and so on, but from a management perspective it's a fairly easy concept. To take that fairly easy concept of having a fixed schedule and then turning over to a regime where you basically say OK, we do some routine work related to… digging into the data which we gathered from that we might have to issue WO where we have uncertainty and we can't give any guarantees. And to have a management *which is committed to do that change. I haven't seen that so far. In any of the companies, which I have been involved in. I have been trying to provoke some people on that as well.*

We have to have good leaders. Good decision makers. Isn't it? *They need to know of the processes. Since the CM' guys are sitting in their silos only working within a very limited domain, those people seldomly become the managers of the entire maintenance domain. So, their knowledge won't be at the top and then spread out in the organization. Most of the maintenance roles are covered by personnel which are trained within a traditional PM (Project Management) program set-ups and they are familiar with that and, when you are familiar with something it is a sort of comfort zone. Having a management, which is actually eager on doing that change. I haven't seen... frankly. I've been provoking some of the managers sometimes. […]*
So, when you go offshore everything, in many cases, still today, things are paper-based. Basically, you have the information in the CMMS, you print out the WO, you take that out to the fields, to the machine or the equipment. And then you have to make notes and then when you get back to the office, you have to get back the information into the system. It takes lots of time and one of most commonly used excuses for having the process like that, is that you are within explosion hazardous area and the EX secure equipment is costly or so on. I don't by that explanation. If you think of all the hours lost. Each hour lost on punching data points, will at least cost you a few thousands NOKs for an offshore personnel.
On a 14 days shift. If you then use half an hour extra, I think you will use more than that, you have 7 hours 14 thousands NOKs at least, which is loss of productive time. I don't by that excuse. I think it's mainly related to the management not eager on doing the changes as which are all buying.

I2Q10 - What recommendations do you have for future efforts such as these? *If you are able to process the information to such a level that you make the information available for more personnel than the domain expert in order to take the decisions. When we take the CM systems and the data flows, if you are able to process the information to that step, that it actually gives meaning to more people. That is one basis and that is on the system side. And, then if you have a sort of matured the information which you get from these systems, to a level where you then can have these "seen across". Like on the G_ platform which you have like 15 experts systems, providing information on different formats and so on, … if all of these 15 systems delivered the information in such a way that a group of personnel could interpret that information across. Then we are into the RUL part.*
So basically if all the systems were providing information in that setting, then we could also share that information across the organization and have it available for those in the positions of deciding on what to do and when. To have both that information to that level and also then having that implemented across, that would be very exciting to be allowed to follow such approach / project. That could be very exciting.

I2Q9 - We have seen that some of the big companies (offshore operators) are establishing their monitoring centers. Do you think it worthwhile to have centers, and to concentrate some expertize in those centers? Have you seen this kind of implementations? *Yeah. I've been involved with some of them as well. Back in 2007 – 2008. I was involved in one of them for __.*
So, these centers are silos which are working within their domain they are very specific on their equipment and domain experts.
That's reasonable but, at the same time, you should have these units interlinked with the overall maintenance organization and then we are back to the decision-making process. The decisions ought to be made in those centers usually that is made by the maintenance managers in combination with the operations guys and so on.
So, there is a need to have clarification on what are the roles? What type of information shall the centers (or these expert groups) provide into the overall organization, the overall maintenance process. Then we are back to the … How do they provide inputs for the organization to do the correct decisions.
From what I've seen, These units tend to be quite strong groups in respect to… you have highly skill personnel having very clear opinions on what shall be done and so no. And also having the upper hand on the maintenance department with regards to the knowledge on the equipment. But, that doesn't necessarily mean that they should overrule the priorities of the maintenance departments or the organization. How to balance that without having some common form of providing the information? What to communicate? I agree with you about the need of a better communication between those centers/domains. […]
Now people are talking about the fourth revolution and cyber physical devices, a lot of new terms, e.g. zero-failure, factory of the future etc. A lot of discussion about the future. If you don't have failure, how to learn?
Well, as long as you can... If you know the mechanisms and can monitor it and can take it before it fails then you still learn something. You don't learn how far you could have taken it. You can have some idea

but eventually, you will do a mistake once and while and hopefully you will have the learning effect from that.

I2Q11 - Is there anything that you want to add? *I hope that, what I have shared with you is of value to your work.*

Interview #4 - Background & Experience: *I am educated within Marine Technology with main thesis within maintenance. I take my degree 2003 and started working as a consultant for about 8 years before I started in This Company. So I've been working since 2011 with maintenance management of one of our installation here in This company north. At the moment, I am working with Platform H installation.*

I4Q1 - In what function/role is the professional in charge of data collection classified in your maintenance organization? *We don't have a specific role for data collection. In This company everyone puts data into the system. The operators, mechanics, electricians. From the analytical perspective, we are sitting here onshore. We just receive the data from the offshore organization.*

So all the O&M personnel are, in a certain way, responsible for gathering data and information into the system. *Yes, everyone put data into the system If I want to use the data, I may have to take responsibility myself to do a data wash.*
So, the onshore organization is more involved in cleaning up and processing this information. *Yes.*
Which system is it? *SAP.*

I4Q2 - In what function/role is the professional in charge of data analysis classified in your maintenance organization? *We have a group in This company called Maintenance Management Analyzers. But, that group consists of a variety of competencies. We don't use the exact term as Reliability Engineer or… but let say… Maintenance Engineers.*

Is it an interdisciplinary group devoted to maintenance? *Yes. Not everyone in the group do have the maintenance background either. Some of them are just good at SAP or it could be in automation, for example. But most of the people doing the analysis have a maintenance background.*

I4Q3 - What can you say about the CM&D related process? *I wouldn't say that This company has gone very far within condition-based monitoring. We have for rotating machinery. I think that group is one that has come farthest. And there we have, in City B, we have a group of specialists receiving data from our rotating machinery mostly gas compressors and gas turbines and they receive data into, they have this operational room. I think they are manned 24/7 doing considerations on the data.*
Can we call it a monitoring center? *Yes. Monitoring Centers but that is only for heavy rotating machines. For other purposes, we are more into what I call it the investigating phase. As we have talked earlier, we are engaged in some other projects trying to investigate how we could utilize CM data to tune our maintenance intervals and so on.*

I4Q4 - How are the maintenance decisions (derived from diagnostics results) registered and made available for future analysis? *I would guess that… as mentioned before, the Condition Based Center for heavy rotating machinery are doing that sort of considerations. For general maintenance I am afraid I have to admit that we are pretty much stucked within a calendar-based maintenance. Unfortunately, we do not use, at the moment, Condition Based Data at a very large extent.*

I4Q5 - What can you say on the lessons that can be learned, from the maintenance decision-making process? *Yes. I think we… as a company we are describing …to get there, but we are not there yet. We have started to investigate how could we use Condition Based Data to tune our maintenance or to make decisions but, at the moment, we are not doing it. So, we haven't lessons learned. It is not very present yet. I think that is the Phase 2. We are still on Phase 1.*

I4Q6 - In what function/role is the professional in charge of the technical interface with suppliers/vendors classified in your maintenance organization? *Every installation has an operational group onshore. I am working in our maintenance department here in City S. This is the HQ for installations in north. Mid Norway and north. We have 5 installations in this area.*
Our maintenance department you could call, let say… a 3rd line or back-office. Then we have the operational group onshore called the 2nd line and we have the organization offshore as the 1st line. The

operational group onshore (the 2nd line), they will do the contact with the contractors. They will be in charge of ordering spare parts and so on.

I4Q7 - Can you mention (3 or 4) of the most frequently monitored maintenance key-performance indicators? *Preventive maintenance backlog is one of them. Overall CM corrective maintenance portfolio is one of them and… we have of course, Failure fraction for safety barriers, for example. But, regarding maintenance it is most on backlog hours in our portfolio.*
Anything on the balance between corrective and preventive efforts? *Yeah, but we don't have that as a KPI. We have it as an indicator, not a KPI. We have two systems in This company. One called maintenance or process indicators and the official measuring system whit is with the KPIs. On the processes, … those are more a kind of monitoring the daily operations of the installations and then we have the KPIs linked up to… leaders' bonuses and so on.*
On Condition monitoring parameters… Let say for compressors, generators etc. Can you mention any of them? *Of course, we are monitoring vibration and running parameters as temperature, pressure, flow, speed etc. And regarding oil, we have oil analysis, but those are mostly offline, one mechanical going out taking samples and sending them to the laboratory.*

I4Q8 - What were some barriers, if any, that you encountered in the implementation of the CM&D related processes? *One barrier is of course the personnel "Falkforening". The Unions are not too happy with Condition Monitoring because it …to the last instance, could mean less personnel offshore, for example. That is a relevant question.*
And we are a company with many years' experience with calendar-based maintenance and that's why people are used to it. That is a cultural aspect.
And thirdly, we are a pretty large company. We have around 34 installations, with a large extent of equipment and the amount in itself is a challenge, because when you try to go to a new regime, from calendar-based to condition monitoring, it requires a lot of efforts and that's also a barrier. You have to get many people to go in the same direction… to succeed. There are obvious some resistance regarding CBM.

I4Q9 - How did you overcome these barriers? *We haven't overcome those barriers. We are working on them. Because, as I said earlier. This company is, at the moment, to a large extent, investigating how we could start using more Condition Based Monitoring and we have several projects, at the moment, trying to find… How are we going to do this?*

I4Q10 - We have seeing the implementation of condition monitoring centers (CMC), by most of the operators, as a way to develop and retain analytics and predictive capabilities? Does your company has these Centers? *Yes, as I mentioned, we have one for heavy rotating machinery in City B. I think we have started to look at some valves as well, but in a very early start.*

I4Q11 - What recommendations do you have for future efforts such as these? *One important aspect that we have seen in the projects that has started is that …we usually think that when you say condition-based monitoring everyone understand what you mean, but they don't. And, as a company to internally agree, what to be as a company, … mean by condition-based monitoring and what do we want to put into this aspect. It is relevant. And off course we could lean on some of the standards but again,… we have to agree as a company. This is what we mean …this is where we want to go.*
My personal opinion is that. Things are going pretty fast. Because, when I went to school, we talked about Condition Based Monitoring. OK, today we have predictive maintenance, we have the Internet of Things (IoT) and all those things, in some king of …, they are linked together, but we haven't sorted our minds on… How to use them together? I think that is a bit of a challenge.
A lot of people think that we have come a lot further than we have. The truth is that we are still very stucked within calendar-based, traditional maintenance. And then, to jump from there to the newest … it is a huge step.

About the standards. Can you mention which are the standardization sources more relevant for your company? *We try as much as possible to stick to the ISO standards. In our management systems, when procedures are written we try to incorporate the international standards.*

I4Q12 - Is there anything else you would like to add? *No*

Interview #5 - Background & Experience: *I started with Rotating Machinery in the UK. So, I worked for two companies there M and C. And that was after my bachelor degree in mechanical engineering and between the two jobs I did one year of masters in applied mechanics in Cranfield Universities. And then, when I was about 26 years (after my Master's degree was finished) I applied for S_ international. And I was very pleased to get a job with them. So, I was with S_ for 25 years, I worked in Holland, Borneo, Holland again and then Norway where I worked on the D_ project. A very successful offshore oil production platform, and then I went to Oman (in the gulf). There we had a lot of entirely on-shore projects, on-shore oil production developments. And that was a fascinating place to work because it was possible to experiment and do research on real fields because the cost was so low and it was easy to do things, we did a lot of experimentation, for example open hole completions, sand ingress and there was some very pioneering deep-hard carbonate reservoirs etc. It was a fantastic experience in Oman. To give an idea. The D_ project in Norway which we brought on production in 1993, had one very successful deviated horizontal well, and this was a very new thing in Norway at that time. So, it was amazing when I came to Norway (I left Norway in 1996) and came to Oman and in the year 2000 P_ D_ O_ drilled its 1000 horizontal well…So, that gives us an idea of just how adventurous they were. They drilled their 1,000 first horizontal well in the year 2000. And after that, I came back to Norway, I worked for ___ on the O_ gas projects for a year or two and after that I joined M_ in 2006 and I took a year free from M_, I left M_ last year, in 2014, in October.*

One of the most demanding job was being a Commissioning Manager for the D_ platform. So, for the six months offshore, from May to November, December, we started up commissioning the D_ platform and I think it turned people who have worked on an offshore commissioning phase understand just really how fantastically challenging that is, cause every platform is different, and __ was an operator that haven't operated anything before. They studied things, but it was their first platform. So, we were starting from scratch. Writing commissioning procedures and taking on operation staff. So, that was a very, very demanding job.

D_ was a very advanced project. Extremely successful. A lot of very modern ideas (e.g. the first platform single leg mono-column a single concrete leg. We have combined sea water/fire water pumps, we had a lot of use of aluminium, we had a high integrity power supply systems, so we did not need to have big diesel generator back-ups and so just the gas turbines. A lot of very forward thinking ideas.

I5Q1 - In what function/role is the professional in charge of data collection classified in your maintenance organization? *First of all, on data collection, you need to have a philosophy right up the beginning of the concept design as to: "What kind of maintenance strategy you are going to have" And it's that choice of strategy which you will decide: "What kind of data you will need to gather"; "How often you will need to gather it" and "How long you will need to keep it". And a lot of companies haven't understood that. We got a call from a company, I won't say which company, cos a company operating on the NCS. They haven't operated there before. […]*

So, to answer your question, Who should be responsible, requires a maintenance philosophy to be established in the concept phase, concept selection. And of course, it has to be operations people Who are involved in specifying that philosophy and the engineering team will give assistance on what is possible and what kind of things will be needed.

So, I would say that you need operators (including maintenance operations people) right early on the concept selection phase to work out exactly what kind of data is needed, and how often it is going to be sampled, and how long to keep it for, and what to keep it for.

Trying to put it more on the kind of professional. Because you know these reliability engineers, maintenance engineers, the technicians at the assets. These guys should work in concert according to the policies regarding data. Don't you think?

Also it is necessary to be careful with those terms because … one of the biggest companies in the world …to give maintenance a better profile, because the image of maintenance has not been good unfortunately in the past. Top management doesn't really understand maintenance. They just see that it uses a lot of money. So this company changed the titles of all the Maintenance Engineers and call them Reliability Engineers.

And then suddenly it is a positive thing instead of a negative thing, because management associates maintenance with spending money just to keep something going. But they do understand some of them… at least reliability.

Ah that's rather important. Uptime and Reliability.

So, if you call someone a Reliability Engineer and it has a bit more credibility and a bit less baggage than if you call them Maintenance Engineer.

I5Q2 - In what function/role is the professional in charge of data analysis classified in the maintenance organization? *I can see that probably need to be three disciplines involved. So one would be Reliability specialists. Then, you would need some analysts who are able to handle the data. And it is very important to have the practical maintenance people involved so that they can see what should actually be done with the data. How realistic it could be and so on. So, I would say: the Reliability people, Data Analysis people and Maintenance people.*

I5Q3 - What can you say about the condition monitoring and diagnostics of machines? *I think that there is tremendous potential and room for improvement in this role decision-making process. So, at the moment, in the worst cases, and a lot companies are in the worst case, people who have the data and they work out what they want and…the better people use a Life Cycle Evaluation. So that you can list, in your presentation... you can present of 2 or 3 options, you have to show to the management that you have one preference and that you have considered 2 other things and, in general, managers will always go for the lowest cost solution.*
And if you want to propose the one that is the second lowest cost, they will fight that. They will make you justify it. So, you have to present your case based on Life Cycle Costs that even though it might be the more expensive solution at the beginning, the total of the costs of the next years … that maybe the cheapest solution in the first place.
But it's in this whole area, where I think a lot of opportunities are lost. Because there seems to be no standard model for presenting this. And so, some engineers… so what boils down to in the end … it will come down to 2, 3 or 4 slides on a power point presentation. And that is the only thing that the management will have time to look at.
To get from a lot of data and analysis and selection and life time evaluations and come to 4 slides, 4 sheets of paper, 4 power point slides just trying to convince management. There are some few engineers who are very, very good at that. But the majority of engineers are not good at that. They are simply not good at that. So it will end up, that there'll be lots of meetings. There will be minutes of meetings. There will be arguments and on that power point presentation put together at the end.
And if you compare the amount of time and efforts used on that power point presentation, which exactly will be very little it will end up being very short notice, very little preparation, compared with all the efforts that is gone beforehand with the data and the analysis. But, very often the company will not pick the best solution because the decision-making process has not been treated seriously enough.

I5Q4 - How are the maintenance decisions (derived from diagnostic results) registered and made available for future analysis? *Yes, some people call that a "Regret Analysis". So you go back in time and look at the decisions that were made and see if they were good or bad. There can be a lot of good learning from doing that.*

I5Q6 - In what function/role should be the professional in charge of the technical interface with suppliers? *So the people off-shore. They are not going to deal with the suppliers. They are going to deal with the onshore office. And it's the onshore office who will take contact with vendors if that is needed. But obviously you can't have every onshore office doing its own thing. That is very expensive, so. All companies at their HQ or Head Office or from their operations base from the company, at that level HQ – they are going to specify what standards are required and what specifications are required. And they will also, if they are smart, negotiate Frame Agreements with vendors. The HQ works on that level. Setting up Frame Agreements in accordance with the specifications and standards that are required.*
And then, it depends again, when you talk about the operations onshore, you have examples in your mind but if you think about Norway, for example, so because I can't comment on Brazil because I don't know enough about how your onshore operations offices work. But in __ has its Head Office in S_, and that operations base in K_that you have been to. There, there are lots of people and probably 2 or 3, 4 hundred, although they are going to cut down 2 hundred and sixty people, in __ are going to lose their jobs now.
And at that base that you've been to is a very professional and large operations base with a lot of competence. So they will obviously probably handle technical problems with equipment themselves. They will go straight to the vendor at that on-shore operations level. But that is because it is a very big, very structured and very thorough base.
But if you take a very small country. A country in the middle east or the far east where the operations base is very, very small, and then it might not be that place to negotiate with the vendor. So it all depends on "Where it is, How big they are, What are the competence of their people. They have a mandate. If they are mandated. If they are big and they are mandated to go directly before the suppliers. Then they would do.
And that's probably the most normal situation, so that the standards and frame agreements and specifications are set up by the HQ, the onshore operations handles any problems or takes up negotiations

if the quality isn't up the standards or it's not being delivered in time, and the off-shore people at all simply to execute. And if they can't execute or there is a problem, they report back to their on-shore operations office.

I5Q7 - Can you mention (3 or 4) of the most frequently monitored maintenance key-performance indicators (in your experience)? *Well, first of course will be a… Uptime and Down time. And planned Down time and unplanned Down time. Those are the things that you need to see. To see whether the operation is working in accordance with the plan or if it is just bouncing along from one crisis to another.*

In this same area, more on monitoring parameters. Can you mention 3 or 4 CM parameters or group of parameters – Performance, mechanical, electrical and so on (CM data).
I5Q7.1 - And concerning the CM parameters? Can you mention (3 or 4) of the most frequently monitored ones? *You could probably divide that answer into two different categories of information. So, in any process, there are measurements of pressure and perhaps flow and temperature, in order to control process. So, that is if you like process data, and it is going to be there any way. Even if the design on concept selection was absolutely hopeless … and the process has to work so they will be specified - pressure measurements and temperature measurements and maybe flow measurements any way. That is a very valuable information. You have that from the process information side.*
And then on a CM traditionally rotating machines have always specified things like temperature of the bearings and of the lube oil and vibration levels. Temperature and vibration. And on electrical motors you also have the temperature sensors in the motor windings to tell you whether something is normal or if the temperature is increasing.

I5Q8 - What were some barriers, if any that you encountered in the implementation of the CM&D related processes? *So I think that my three barriers would be:*
1 – You have to put enough efforts into the concept stage;
2 – You need to have very smart people empowered to use that data and get some smart models developed with clever people (e.g. consultants) so that you can do the prediction bit;
3 – Management being unable to appreciate the significance of the decisions they are being asked to make and that the short term lowest cost is almost never the right solution.

I5Q9 - How did you overcome the barrier(s)? *In nearly all oil companies, High people with potential to be top managers. They are very often put first in the HSE and safety, and that is a kind of high profile well regarded and it is an OK experience. I would suggest that the company's policy should be the high flying people spend 6 or 9 months in commissioning and 6 to 9 months in maintenance as part of their carrier progression because commissioning and maintenance will probably give a better understanding of the complexities and the challenges than anything else.*

I5Q10 - Can we see the implementation of machine-monitoring centers by some offshore operators, as a way to develop and retain analytical and predictive capabilities? Do you think this is a good way to proceed? *Yes. Absolutely. And for example __ in city _. I think they are doing a very good job there on setting up all these centers they have. So they have the drilling center, the operations center and there is a condition monitoring center. I think they have identified that is an area they need to focus on. So the answer is, I fully support that and I think it is an excellent move in the right direction.*

I5Q11 - What recommendations do you have for future efforts such as these? You have made some of these recommendations already. *Not really. No, I think I covered most of it. A very clear philosophy in the beginning of each development. Just on how it is going to do it.*

I5Q12 - Is there anything else you would like to add? *There are clever people in the CMC. I think that is a great deal more that can be done. And my personal belief is that a lot of the problems could be avoided, and this is maybe a big ambitious point and personal opinion, that I think often when a field is discovered and the operator sees how much money can bear under that from that start date.*
I think there is often a tremendous pressure to just implement, the old fashioned way of doing things. So, and yes what do we need? Let us put the platform there with the topsides and we have a drilling platform and we will have a production platform, will have a gas separation platform if the water is shallow.
And I think, that if… and it requires smart people with a better vision (with a lot of vision) and the terrific ability to sell their case…

And if those solutions have been rejected and a more ambitions field development concept have been chosen, to keep the development subsea and to go for multiphase, then you can have interchangeable, you can have subsea units that you can pull up and replace as time requires.
And you do away with all this nightmare of steel and cables and electricity in a salt water spray environment which is going to cost an absolute fortune to maintain. So, there are so many examples of it. Even now big companies in Norway. I don't have access to data but I think there were smarter solutions available. Some of the very, very bold decisions that were made, for example.

The Troll gas field is a very good example of this. So, it was very, very close to being a huge Off-shore gas production installation. And one or two people with terrific vision, made themselves very unpopular and said ---No It would be ridiculous to have a full gas processing facility offshore for Troll. All you need is an offshore well-head platform in effect and sending the gas to shore and have all those facilities onshore. And that's what happened. So the Troll gas platform offshore is a relative simple platform and you have K_.

And that used to be called a project which is a ___ project, and there was the T_ offshore group that did the offshore platform and there was the Troll onshore group that did the onshore facility. And if you look at the scale of that K_ gas plant onshore on the west coast of Norway… just imagine if that have been offshore on a separate platform or several platforms, just how much more it would have cost to keep that running than it costs presently when it is onshore. That was a very good decision.

And another good decision was O_. Because the O_ gas project could also have been an offshore platform or an offshore complex. But no, the gas is sent from subsea. There is no platform offshore in O_. It is sent directly from the well head through flow lines to shore and treated onshore on A_at N_ gas plant the O_'s gas plant.

And those are examples of things that would increase the payback of the project dramatically. Even if the numbers don't show it. By avoiding these nightmare of trying to keep old platforms that are rusting and unreliable and then with structure integrity problems. A complete disaster.

So that would be the last point I would than … think much more about subsea and multiphase solutions in the concept phase instead of lumbering ourselves with these old platforms from the steam age. That is what we did in the 50's or 60's. At the end of the steam train era. That is where I put these platforms. And we are still doing it. I am amazed really.
End of the interview

Interview #6 **- Background & Experience:** *Master of Science from the mechanical engineering from NTNU so that was back in 1989. And two years then on S_ with fluid flows and then I started in D_ working with risk management for 5 or 6 years and after that I started in oil companies so I have been working in A_ and B_ and for the last 15 years in S_ with different types of jobs. Offshore Installations on S_. After that, I worked for four years, and after that I __ operations support department in Norway where we supported the operations for D_ and O_ Offshore platform and N_producing gas. Approximately 50 million m^3 gas/day. And in operations support team, I have been in maintenance delivery team, so there I've delivered the preventive and corrective maintenance for offshore installations and I had the land insulation. I had all the turnarounds in my team. Which is called maintenance call for shutdowns and I had day-to-day operation with the collaborative maintenance groups and followed up reliability and availability of the platform work in the maintenance part, where it means an important thing. So I also took the study with P.S. and I educated myself to certify as manager, maintenance expert. So that's why I am with P.S.… so 6 years in operation support and the rest of it with maintenance. I saw maintenance as an enabler for safety and also for production.*

I6Q1 - In what function/role is the professional in charge of data collection classified in your maintenance organization? *We have reliability engineers then setting up the risks, or let's say… the preventive or predictive maintenance part and the frequencies for that. We have established the delivery team that is setting up the work tasks for the different maintenance areas.*

I6Q2 - In what function/role is the professional in charge of data analysis classified in your maintenance organization? *So it's the reliability engineer that is analyzing and setting up the frequencies on what kind of maintenance tasks we should then perform. And then after the schedule is done it is sent to the delivery team that consists of one man on mechanical, one man on electrical and one on instrumentation that will have the knowledge on how to put together the job descriptions and the job packs together. So,* *then, we put the maintenance activities on the integrated activity plan. And we have all these things put together .... not only maintenance tasks but also the construction tasks etc. To ensure that we do everything within the agreed time. And then we put it on the ---- for weekly plan, whether the maintenance tasks, if it's corrective or preventive. And force it down and put it to a weekly schedule and measure that. And we divide it between the safety critical, maintenance (preventive and corrective) and overhaul preventive maintenance scope.*

I6Q3 - What can you say about the CM&D process? *In the meantime, especially for U_..., S_ and N_ issues only ten years there are a lot of different measuring devices put into the hardware that signals into a systems that is monitoring it at putting --- vibration, temperature etc. So we monitor if it is out of the curve to ensure that they are within the right levels.*
And through that it is decided then if things then pass the different thresholds, and it is put in to… Ok, this is ready for maintenance task. So, we have lots of data and the important thing is to find out data signals on the different equipment. For instance on turbines and it's just to find the right levels of different KPIs to measure. So the measure is an important tasks that is really the competence of the Reliability Engineer and also the data programs we use that concern that.
For the old equipment, we don't have that much data points, that much signals, because it is a 30 years old technology, then we have less KPIs then to try to find the important ones to measure.

I6Q4 - How are the maintenance decisions registered and made available for future analysis? *One important feature for us is to have everything into the SAP. So on, the technician goes on the platforms and find something that is wrong. Or the reliability engineer look on this sort of program and something is wrong and a notification will be made that triggers off depending on the criticality of this equipment that is then going ... starting to miss the main .. and depending on the criticality it will be set into a maintenance interval. So. Then we divide that into a latest or ... finish date. Then we say that. Within that time this equipment should be changed out.*
Through those steps ... depending onto this, through those steps and criticality judgement that is done on the site because people on the site have the utmost knowledge about the criticality and can actually put that up. And then it's then transferred further to analysis and then into a maintenance plan.

I6Q5 - What can you say on the lessons that can be learned, from the maintenance decision-making process? *Yes we've learned. And sometimes we… store all the data and let's say ... lessons learned and the different items or maintenance or different maintenance tasks. So, some effort is done for writing down lessons learned etc. And ... also when we have repetitive failures "bad actors" then we use a special code which is called safety A in some, and that goes into root-cause analysis. And that rather try to find the root-cause, because this ..... and to find the root-causes and put that into the program to avoid the equipment from failing again for the same reasons and that is some of the detailed lessons that is put in the history in the SAP. So it is useful for the…, for repetitive failures in that route cause analysis.*

I6Q6 - In what function/role is the professional in charge of the technical interface with suppliers classified in your maintenance organization? *When it comes to spare parts, we have the operational departments in the assets. It is located under the contract and procurement department. It is at the on shore support organization. So they are co-located with logistics and it is also in close contact with the assets.*

I6Q7 - Can you mention (3 or 4) of the most frequently monitored maintenance key-performance indicators in your organization? *What we use then ... on more technical integrity displays and …presenting shapes of the safety critical elements and PM compliance and the plan .... this should be according to plan more than 95% of it should be that… then as a part of our goal is to come up as high as possible. And the same is for the safety critical elements and corrective maintenance compliance (CM compliance) that is also on a parameter. ...and we also are looking on the safety critical elements parameters preventive and corrective that is overdue, that is not done in time. Say that it should be less. Ideally 0%. And we have… should be a very small proportion/portion of that that should be overdue.*
And then we also measure on ... yeah… what we define that the latest and xxx finish date ...and also say that ... this should be done within this time and then we look on… How many overrun that latest allowed date or finish date both for CM and PM. And we also look on the concept of safety critical PM's orders. And our concept is that, it should be less than 5%.

I6Q8 - What were some barriers, if any that you encountered in the implementation of the CM&D related processes? *When it comes to barriers in the organization… Yeah. I think what we have as successful thing is that we are an educated organization so that ....they know about why we do the* *maintenance and the criticality in the maintenance processes. … we have focused on is to ensure that the need … either people have an understanding of the importance of all condition maintenance not maintenance …or of the key elements so in the implementation because people understand and see the criticality … of that decisions … and past decisions.*

I6Q9 - How did you overcome those barrier(s)? *I think we are educated people in the …. Educated people in …. being process oriented. To learn that… to find our process and to follow it. And here in … we call it Operation Excellence that is divided into different areas of importance, for excellent producers and there are areas such that we are looking into maintenance activities and important maintenance activities and we've started an educated organization, and up to that with a deep understanding of it. And we are also focused on the processes and measuring KPIs …and we can see that we´ve got much better execution and planning of the maintenance activities.*

I6Q10 - Some offshore operators are implementing machine-monitoring centers, as a way to develop and retain analytical and predictive capabilities. Does your company have those Centers? *Yeah. System offshore that is measuring. Our philosophy is that everything that can be done onshore should be done onshore. So, data is then sent onshore for analyses and if things come up we have this form … group of … for further discussions. For instance if a turbine start with an increasing vibration… and that could be gathered from the data collection system on the filter/trend program and if it could is also be detected by the offshore technicians working in his round. …And what we have focused on is …to increase the communication between offshore to see each other as value for assets to …with knowledge that can be …tapped into order from onshore to offshore or from offshore to onshore.*
We are focused on neutral respect so they respect each other and both asks and … to each other or we can have a good communication. And this is what we call all over the working environments with video-camera and real time data to enhance that communication to find place.
Yes we have monitoring centers onshore that we also have this discussion with the people offshore when things comes up. And you've got to go face-to-face because sometimes the best monitor is the human senses.

I6Q11 - What recommendations do you have for future efforts such as these? *So, my foundations for future development of maintenance or predictive maintenance. And… I think it is important to have one robust data system that you can receive data and be able to analyze that. You need the people with the operational experience and know-how and with theoretical know how.*
You need an organization that is really good in communicating with each other, when it comes to an open organization that really are also good in root-cause analysis. Yeah. And it is also important when you put at measuring points in different devices that. It is a little bit critical on what signals you really want to get out and what you want to measure because it is almost unlimited ways of fitting on measuring points, and the data collection will be enormous and it is hard to find… to differ between critical things and non-critical things because it is at the final it is too much.
So, having the knowledge upfront on what are the critical KPIs and what you want to measure is important. And to agree on a set of KPIs that is understood not only by the management and the working organization so everyone is looking on the same KPIs and having the same understanding of why they are important.

I6Q12 - Is there anything else you would like to add? No.

Interview#7– Background & Experience

Tenho 35 anos de experiência na indústria. Atuei na função manutenção e inspeção de 2004 a 2010. Uma coisa que a gente estava trabalhando na época, foi definir qual é o papel da função manutenção e então fizemos um Padrão de Gestão. Definiu-se que a razão de ser era "garantir a disponibilidade, confiabilidade, eficiência operacional e energética dos sistemas e instalações, contribuindo para o atendimento das metas de produção, segurança, meio ambiente e saúde, buscando melhores resultados para cada Ativo, nas visões curto, médio e longo prazo. Isso incluía as 3 fases, desde o projeto até obsolescência, que agora estamos vivenciando isso com os descomissionamento das unidades. Frases típicas do padrão: "manutenção é uma função estratégica." Isso é importante porque a camada gerencial tem que validar e respaldar. A manutenção não é só custo, é investimento para conseguir trabalhar em conjunto com a operação, maximizando os resultados.

Q1 - Em que função está o profissional encarregado da coleta de dados nessa organização de manutenção que você viu? *Para poder fazer a gestão da coleta e dados, você tem que estruturar primeiro. Então, um dos trabalhos que a gente fez primeiro foi montar a base de dados no SAP, usando a ISO 14224,*

essa foi a nossa decisão em 2007. É o padrão da indústria e a gente que encampou lá. Na raiz dessa norma tem a semente do MCC, ou RAM (manutenção baseada em confiabilidade).
Nós temos o gestor de dados para a área de manutenção, mas não deixamos de lado a inspeção, onde chegamos até a colocar semente de RBI (ou IBR em inglês), que é a mesma filosofia de MCC só que aplicado a longos ciclos.

Quem você via fazer a análise?
Nós fizemos vários Conselhos, reuniões de engenheiros e técnicos (mecânica, elétrica e instrumentação) a partir das classes de equipamentos que estavam no SAP, para discutir, pois você tinha várias falhas e tinha que definir a taxa de falhas. Se a gente está usando o modelo estatístico de análise, em que o modo de falha é aleatório, ou seja, estou usando um lambda, então ele deveria bater. Isso foi em 2009. A gente tinha diversas classes e gente montou todos os mapas usando a visão funcional. O SAP é uma ferramenta de gestão. Não é pra fazer manutenção. É para gestão da manutenção. Tem que ser um nível gerencial para usar.

Processo de tomada de decisão para preditiva:
Entra mais um fator que é a coleta da informação da condição. Nós terceirizamos essa atividade. A partir da coleta, relatórios seguiam para o comitê gerencial, que era um grupo de análise dos relatórios que vinham da terceirizada, que continham os dados e recomendações. A gente discutia e tomava decisões – vou intervir ou não? Registrava no relatório e encaminhava para o cliente. A princípio a ação da correção cabia às OP's. Aí entravam os indicadores: a princípio, se falhasse o equipamento, e já tinha sido sinalizado realizar a intervenção e a OP não interviu, tínhamos um problema.
Registro das decisões: *O conselho registrava as decisões e recomendações em relatório de preditiva, meio magnético (as Comunicações Técnicas – CT's). Como funcionava o ciclo gerencial: foi negociado no Comitê Funcional que a preditiva ia ser o carro-chefe. Os gerentes de OP concordaram em cumprir. Havia a necessidade de negociar as vagas de bordo o que poderia ser um dificultador. Tinha que ser priorizado. Tinha uma certa restrição, dificuldade de conseguir vaga a bordo, mas a gente mostrava claramente o valor da atividade e negociava. O gerente de OP liberava. Tínhamos 2 grandes indicadores: o ICPM – Índice do Cumprimento do Plano de Manutenção e o ICPD – Índice de Cumprimento do Plano de Preditiva e tinha também o EPM, que mostrava a Eficácia do Plano de Manutenção, que calculava o total de corretiva sobre o HH investido. O ICPM era proativo. O EPM era reativo.*

Lições Aprendidas:
Tudo que se aprende tem que registrar e, se possível padronizar. As lições aprendidas eram incorporadas aos padrões após aprovação nos Comitês Funcionais. Uso do PDCA.
Manutenção é função estratégica. O foco é em disponibilidade através da redução de perdas e aumento de produtividade. Foco em confiabilidade através do estudo de histórico dos equipamentos. A história mostra que o planejamento faz a diferença. Os maiores impactos do negócio giram em torno da falta de planejamento.

Interface técnica com fornecedores
Levanta-se uma demanda. É validada nos comitês funcionais a necessidade de se terceirizar determinado serviço. O fiscal de bordo atestava que o serviço foi feito. A contratada elaborava relatórios dos serviços executados e coletava assinatura do fiscal de bordo. Depois o fiscal centralizador de terra recebia o relatório e transferia para os gerentes de cada contrato. As dúvidas sobre a realização dos serviços eram tiradas com os fiscais de bordo.

Indicadores
ICPM – Índice de Cumprimento do Plano de Manutenção;
ICPD – Índice de Cumprimento do Plano de Preditiva;
EPM – Índice da Eficácia do Plano de Manutenção;
ICPI – Índice do Cumprimento do Plano de Inspeção;
IARI – Índice de Atendimento aos Requisitos de Inspeção;
ICC – Índice de Cumprimento de Campanha **-** *visão proativa;*
Havia controle de backlog.

Barreiras
Dificuldade de vagas offshore. Sentimento por parte dos gerentes de que os planos de manutenção não estavam alinhados, pois algumas tarefas de manutenção eram relacionadas à limpeza, que é o 5s. Muitas tarefas eram relacionadas a limpar, lubrificar, reapertar, secar... A visão mais moderna fala que "da

minha máquina cuido eu". ...As questões eram levadas para os comitês funcionais. Caso tivesse embates, levadas para os comitês de gestão. Os resultados dos indicadores eram mostrados para justificar as questões.

Centros de monitoramento
Sempre tivemos centros de monitoramento.

Recomendações para futuros esforços de implementação
A visão que eu tinha era que você conseguisse demonstrar que você está cumprindo a disponibilidade e confiabilidade dos equipamentos. Que indicadores que podem medir a disponibilidade dos equipamentos? Quantas vezes foi demandado? Fiz uma análise que demonstrou que nas fases iniciais do projeto temos uma taxa de falhas grande e reduz ao longo do tempo porque vai se incorporando o aprendizado.

Interview #8 – Background & Experience
Entrei na empresa em 1986, estou com 32 anos de empresa, mas antes eu tinha vindo da construção naval, na área industrial, trabalhei em algumas empresas na área de fabricação e produção, e aí vim para a área de manutenção em grandes máquinas. Eu também já tinha uma experiência na aviação, onde fizemos trabalhos com turbinas aeronáuticas.
I8Q1 - Em qual função/posição está o professional encarregado da coleta de dados em sua organização de manutenção? *Falando em termos de monitorando da condição e diagnóstico de máquinas, na verdade não existe tal definição. [...] em alguns projetos a gente consegue colocar um profissional, seja na área de operação ou na área de manutenção, mas isso, nesta empresa, a coleta é feita através do PI e é muito pouco embasada para utilização na Manutenção Baseada na Condição.*

I8Q2 - Em qual função/posição está o professional encarregado da análise de dados em sua organização de manutenção? *Em algumas unidades da empresa, principalmente em refinarias, é encontrado pessoal dedicado à manutenção preditiva. Esse pessoal seria o pessoal mais especializado .... na verdade, esse pessoal de manutenção preditiva são técnicos na área de manutenção, pessoal de engenharia, então é um pessoal específico para esse tipo de trabalho, mas não é uma coisa muito difundida dentro desta empresa, em algumas unidades funciona, mais no Refino.*

I8Q3 - O que você pode dizer sobre o processo de monitoramento e diagnóstico de máquinas? *No E&P o que eu conheço ...a gente vê algumas iniciativas muito mais pessoais do que estruturais, não é uma coisa que vem da direção da empresa, então são iniciativas pessoais, isoladas, que dependem muito daquele profissional e se ele sai da área, fica abandonado.*

I8Q4 - Como as decisões de manutenção (derivadas de resultados de diagnóstico) são registradas e disponibilizadas para análise futura? *Voltamos no mesmo ponto. O profissional dedicado, aquele profissional que se dedicou a esse assunto, ele registra em alguns aplicativos, então a gente tem alguns aplicativos, como por exemplo, o S_ da B_e o pessoal utiliza também para fazer registro, e iniciativas isoladas como a gente tem, ou pelo menos tinha no E&P aqui na B_, o T_. Algumas outras estruturas foram instaladas, como ferramentas na verdade que foram adquiridas, que iniciaram o trabalho, mas muitas delas foram descontinuadas, então, o E&P nesse quesito, não tem uma política definida, então, realmente, a iniciativa acaba sendo, assim, isolada e muitas vezes descontinuada.*

I8Q5 - O que você pode dizer sobre as lições que podem ser aprendidas, a partir do processo de tomada de decisão de manutenção? *A gente continua mais ou menos no mesmo processo. Onde o pessoal realmente iniciou esse trabalho, as manutenções deixaram de ser preventivas por horímetro e passaram a ser manutenções on condition onde você analisava e fazia a intervenção em cima de uma análise preliminar. Alguns equipamentos, então, a gente conseguiu perceber que alguns equipamentos começaram a rodar por um período muito mais longo, campanhas muito mais extensas do que se praticava antigamente, baseado apenas em manutenção preventiva – calendário, horímetro, ou por tempo. Onde foi implantado houve ganhos bastante expressivos.*
Você vê a possibilidade de acontecer o contrário, por exemplo, estou monitorando então não vou fazer a manutenção por calendário e aí passo a agir de uma forma corretiva. *Isso, não é toda máquina. Nós temos visto o exemplo dessa U_ de P_. Irmãs dela não tem mostrado o mesmo desempenho, até de uma certa forma meio que denegrindo a imagem do fabricante em alguns casos. Mas a gente fica sem saber se o problema foi operacional ou foi um problema associado à qualidade do equipamento.*
Nessas outras irmãs o SKID era da M_? *Também da M_. A gente viu falhas que eu considero que foram falhas prematuras. Na minha visão, na verdade uma visão particular, sem um fundamento ainda*

consistente, os problemas estão associados à operação e à condição de instalação não adequada, ou seja, o equipamento está sendo operado fora das condições de operação. Não foram bem dimensionadas as condições de operação do equipamento.

I8Q6 - Em qual função/posição está o profissional encarregado da interface técnica com os fornecedores em sua organização de manutenção? *Nessa área de materiais, tenho visto pouca especialização, então, fica muito assim, o pessoal delega, tenho visto muito delegar para o próprio fabricante definir os materiais, a definir a quantidade de sobressalentes e acaba que muitas vezes a gente acaba descartando esse material num determinado período, por causa de validade ou por falta de uso, porque depois de ter especificado os materiais que tem baixa utilização ou baixa oportunidade de utilização e a partir de um tempo desse material em estoque, o custo dele é muito maior que o valor da peça, acaba sendo descartado. O próprio custo de estoque supera o custo da peça, então é melhor que, quando você precisar da peça mande comprar. A gestão desse estoque de material acaba descartando esse material.*

I8Q7 - Você poderia mencionar (3 ou 4) dos indicadores de desempenho-chave de manutenção mais frequentemente monitorados em sua organização de manutenção? *Os mais corriqueiros utilizados na literatura: TMF (Tempo Médio entre Falhas) e Performance. Quando um equipamento apresenta uma performance aceitável, ele é mantido em operação e, a partir do momento que cai abaixo de um nível aceitável você intervém. Mas a gente tem usado outros parâmetros que a gente aprendeu ao longo do tempo. Um deles é o Número de Horas por Partida. A gente utiliza isso muito, na verdade eu particularmente utilizo esse indicador para qualquer tipo de equipamento. Se eu chegar numa instalação onde eu não conheço os equipamentos, a primeira coisa que eu vou fazer é esse levantamento. Ele vai dizer para mim a robustez desse equipamento – se é um equipamento que falha sempre, se ele é muito interrompido, seja por problemas operacionais ou por problemas de manutenção e depois a gente vai segregar.*
Se for uma planta desconhecida para mim, esse é o parâmetro mais utilizado. É o primeiro que vou verificar. Pena que nem todos os equipamentos você tem horímetro e contador de partidas. Aí você fica no mato sem cachorro. A partida é um momento crítico. Um equipamento que parte muito tem uma tendência de falha mais frequente.

I8Q8 - Quais foram algumas barreiras, se houve alguma que você encontrou na implementação dos processos relacionados ao monitoramento da condição e diagnóstico de máquinas? *A maior barreira são os nossos gerentes, porque a gente não tem, principalmente no E&P, se você vai para a área industrial desta empresa, as refinarias, você encontra um pessoal mais técnico da gerência e existe, na verdade, uma visão de prevenção, preditiva e de manutenção mais consistente. No caso do E&P, a gente tem encontrado pessoas que não são da área. Não sabem de manutenção. Você tem um gerente que é um Geólogo. Ele tem uma visão de equipamento muito tosca. Aí você vai ver... que o tipo de manutenção praticada é só corretiva. As pessoas vivem apagando incêndio. Então isso é muito claro. Você olha para o gerente, vê o tipo de formação dele, de onde veio, você vai no histórico de manutenção e vê que o histórico de manutenção é sofrível. O E&P, apesar de sempre falar em operação e manutenção, é muito pouco voltado para manutenção. Tem o discurso, mas não tem a prática. Tem um custo muito alto de manutenção porque os equipamentos estão em áreas de difícil acesso. Tudo que se quiser fazer para descer o equipamento, tem um custo gigantesco, só que isso não aparece de uma forma bem elaborada. Os custos não são bem contabilizados. Também não sei se há outros interesses...*

I8Q9 - Como foram superadas as barreiras? *Não foram. Na verdade, é uma questão de sorte. Quando as coisas estão alinhadas, um bom gerente, uma equipe boa de manutenção e de operação, você alinha isso e a coisa vai bem. Quando isso não está alinhado, fica muito difícil.*

I8Q10 - Alguns operadores estão implementando centros de monitoramento de máquinas, como forme de desenvolver e reter capacidade analíticas e preditivas. A sua empresa tem esses centros? *Na verdade é o seguinte, de novo, a gente tá meio no desvio. Esses centros de manutenção que o pessoal colocou, de acompanhamento das máquinas, realmente eles existem, mas são mais uma decisão gerencial de dizer: "nós temos agora isso aqui e agora nós vamos poder acompanhar nossos equipamentos de terra". Mas você vai lá e vê quem está acompanhando, não são as pessoas que conhecem o equipamento, são meros coletores de dados, mas eles não têm conhecimento dos equipamentos, não tem suporte de engenharia por trás bem participativo.*
É interessante dizer que nós temos um Centro na B_ que é dentro da área de Suporte Técnico da Unidade, mas a participação do pessoal de engenharia no Centro é muito pequena. Porque está todo mundo

envolvido nos seus problemas, no apagar de incêndios, que a participação na preditiva é muito pequena, muito baixa, e por isso eu entendo o seguinte: existe realmente um ganho; quando você vai buscar informações e acha um histórico, mas esse histórico não é trabalhado para uma visão futura, não é trabalhado preditivamente.

I8Q11 - Que recomendações você tem para futuros esforços como esses? *Neste cenário como um expectador privilegiado, nesses 32 anos de trabalho offshore, eu não tenho uma visão muito otimista em relação aos cenários futuros. Porque não existe no E&P, ainda, uma estrutura voltada para definição dos processos de manutenção. Por isso eu também não vejo como a gente possa investir e conseguir apoio para esse tipo de atividade. Apesar da gente ter ouvido falar dos processos de Manutenção Baseada na Condição. Existe um discurso, ... mas ainda não existe na prática a coisa funcionando, pelo menos não chegou até as plataformas de forma visível.*
Existem iniciativas, mas eu não tenho visto que estas tenham chegado até o ambiente operacional offshore.

I8Q12 - Tem alguma coisa que você gostaria de adicionar? *Não.*