University of Stavanger

Faculty of Science and Technology

MASTER'S THESIS

Study program/ Specialization: Offshore Technology / Industrial Asset Management	Spring semester, 2012 Open access
Writer: Alejandro Bencomo	……………………………………… (Writer's signature)
Faculty supervisor: Eiliv Janssen External supervisor(s): Jan van den Akker	
Title of thesis: Applications of Condition Monitoring for the Subsea Industry	
Credits (ECTS): 30	
Key words: Subsea Condition Monitoring Health Monitoring CBM SPS	Pages: 80 Stavanger, June 28th 2012

Abstract

With the increased interest in developing offshore fields by subsea completions, also comes the need for minimizing the non-productive time of these systems caused by unexpected failures and lengthy repairs. Maintenance interventions that could be considered simple for surface equipment can become expensive and complicated when executed under water due to the difficult accessibility of the equipment. A simple failure of a subsea component can cause shutdown of a well for several days or even weeks until a repair is carried out, thus affecting hydrocarbon production rates significantly.

Failure of components is unavoidable, but by introducing condition monitoring to subsea production systems (SPS), operators can diagnose and predict failures early, which allows them to plan maintenance activities in advance and reduce downtime. Most of today's subsea control systems collect great amount of data about the process and the operational parameters of the equipment, but this information is not used to determine the condition of the asset and predict future failures. The aim of this thesis is to develop a methodology tailored for conventional SPS, for appropriate utilization of available monitoring techniques and identification of additional surveillance methods needed to guarantee high system availability. Furthermore, this methodology describes how to integrate these monitoring methods into a comprehensive condition monitoring program that is able to detect asset state, diagnose faults, predict future failures and provide decision support for maintenance intervention.

Considerable research and many standards have been written for condition monitoring of complex machinery, mostly for rotating machinery and some static machines for surface or onshore facilities, but little investigation has been done with respect to subsea equipment. The purpose of this research study is to bridge the gap by creating a set of guidelines for implementation of condition monitoring specifically for SPS, and make recommendations for application of these guidelines for the benefit of both field operators and subsea equipment manufacturers.

A methodic process was created to guide the user through the different steps of creating a program for condition monitoring of underwater equipment, with emphasis in the active elements used to measure and control the flow of oil and gas, i.e. control systems (SCM, instruments, sensors, valves, electrical/hydraulic flying leads, etc.) and production equipment (XTs, manifolds and distribution units). Risers, flowlines, umbilicals, structures and subsea processing systems are excluded from this work. The methodology is exemplified with two case studies: First for gate valves with hydraulic actuators and, second for the power supply unit located in the subsea electronic module.

Acknowledgments

I would like to express my gratitude to Cameron for providing me with the opportunity of writing this thesis and contributing with the development of new technologies that will allow the company to be more competitive in these times of rapid growth in the subsea arena.

I would like to thank my company supervisor Jan van den Akker and Tobias Voelkel for their continuous support during the past months. Also, to the engineering department in Cameron Germany who provided me with valuable data for my research.

Last, but by no means least, I thank my academic supervisor Eiliv Janssen for his support and great guidance, not only during my thesis but also during the last year of my career; he nurtured my curiosity for subsea technology and provided me with knowledge in a very interesting way.

Table of Contents

List of tables

List of figures

Acronyms and abbreviations

AC	Alternating Current
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ATA	Adaptive Gaussian Threshold Algorithm
CBM	Condition-Based Monitoring
CM	Condition Monitoring
CPM	Condition and Performance Monitoring
DC	Direct Current
EFL	Electrical Flying Lead
EPU	Electrical Power Unit
ESR	Equivalent Series Resistance
ETTF	Estimated Time To Failure
FBG	Fiber-Bragg Grating
FMECA	Failure Modes, Effects and Criticality Analysis
FMSA	Failure Modes and Symptoms Analysis
FRIEND	FRamo Interactive ENabling Diagnostics
HFL	Hydraulic Flying Lead
HMI	Human-Machine Interface
HPU	Hydraulic Power Unit
I/O	Inputs/Outputs
LCC	Life Cycle Cost
MCS	Master Control Station
MIMOSA	Machinery Information Management Open System Alliance
MODU	Mobile Offshore Drilling Unit
NASA	National Aeronautics and Space Administration
NDT	Non-Destructive Test
NPT	Non-Productive Time
O&G	Oil and Gas
OEM	Original Equipment Manufacturer
PoF	Physics of Failure
PS	Power Supply
RAMS	Reliability, Availability, Maintainability and Supportability
RMS	Root Mean Square

ROV	Remote Operated Vehicle
RUL	Remaining Useful Life
SCM	Subsea Control Module
SDU	Subsea Distribution Unit
SEM	Subsea Electronic Module
SIIS	Subsea Instrumentation Interface Standardization
SPS	Subsea Production System
TCI	Technical Condition Index
XT	Christmas Tree

1 Introduction

1.1 Problem description and background

For the past two decades we have seen a significant increase in subsea field developments, especially as an alternative solution for deep waters, satellite fields or subsea-to-shore schemes. As it can be seen in Figure 1-1, the oil and gas production from subsea wells has surpassed the production from dry wells in 2010.

Subsea development allow companies to exploit fields in a way that would not be economically feasible otherwise, but they also have some drawbacks such as reduced availability and lower ultimate recovery.

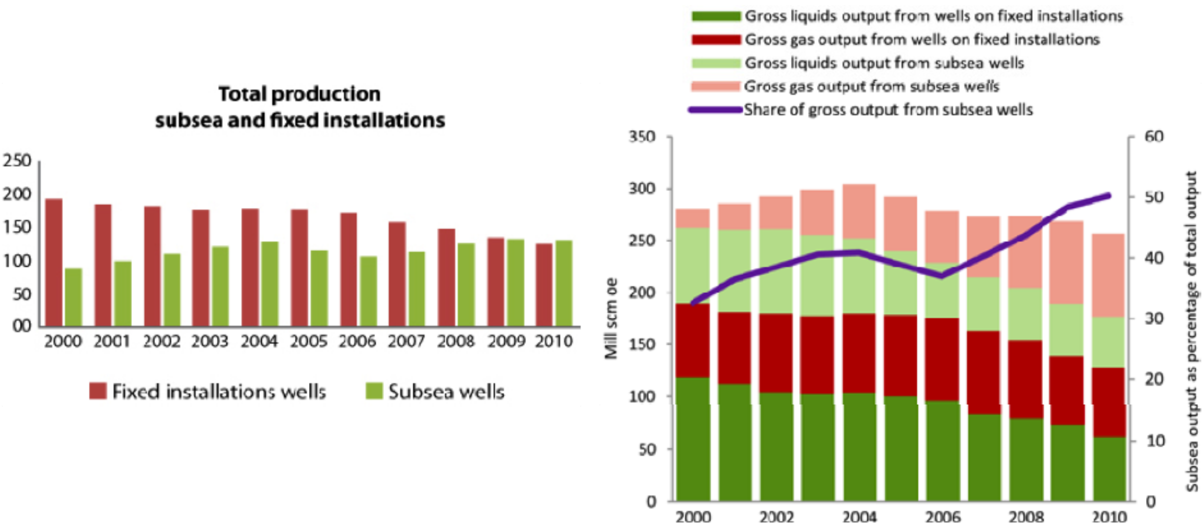


Figure 1-1 - Subsea vs. dry wells [1, 2]

Some studies have shown that availability of subsea assets can be as low as 90 % [3]. Availability can be defined as the fraction of time that a system, subsystem or component is in normal operating condition, and can be calculated as

$$Availability = \frac{MTBF}{MTBF+MTTR} \qquad (1)$$

Where:

MTBF is the Mean Time Between Failures or uptime

MTTR is the Mean Time To Repair or downtime

Availability of subsea equipment is usually lower than topside machinery mainly because repairs on a deck of a platform, where personnel, tools and spare parts are usually readily available, is much easier than intervening a subsea system. A subsea system, on the other hand, requires that a service vessel, Remote Operated Vehicle

(ROV), specialized personnel, subsea tools, etc. be allocated prior performing the repairs, coupled with other factors like weather conditions which have to be favorable for the operation.

The lower recovery factor from subsea wells is a result of limited well intervention of this type of completion in comparison with dry wells. For many platform installations, well intervention is done through the drill rig already installed on topsides, whereas, for subsea wells, a Mobile Offshore Drilling Unit (MODU) or intervention vessel has to be hired, which implies high OPEX and in many cases high Non Productive Time (NPT) related to delays in the intervention operation due to bad weather or unavailability of rig/vessel. In an investigation done by Statoil, Hydro and the Norwegian Petroleum Directorate (NPD) it was determined that subsea completions can have a an ultimate recovery factor up to 20% lower than dry wells with direct access from the platform [4].

As a result of the issues mentioned above a Subsea Production System (SPS), must have high Reliability, Availability, Maintainability and Supportability (RAMS) in order to be cost efficient. This study will focus on improving reliability and availability of SPS's through advanced Condition Monitoring (CM) techniques with the ultimate goal of minimizing NPT.

The subsea industry currently faces several challenges with respect to condition monitoring, such as:

- Lack of specialized CM equipment for subsea applications due to the short history of the subsea industry.
- Intermittent operation of many of the processes (e.g. triggering of a subsea control module solenoid valve) makes failure prediction difficult.
- Current conditions monitored in conventional SPS's provide process data, but little or no information about the integrity of the equipment.
- Remoteness and difficult accessibility of the subsea equipment, makes calibration, upgrades and maintenance of CM equipment difficult and very expensive.

This thesis has been written in collaboration with Cameron, provider of flow equipment products including Subsea Production Systems, as part of the development of a business strategy called "Intelligent Field". Cameron provided valuable information with regards to subsea equipment design and operation, and reliability data and studies.

1.2 Scope and objectives

The scope of this thesis is to evaluate the CM technologies available in the market and recommend a CM strategy that can be used in SPS's with the main goal being the reduction of non-productive time for oil and gas offshore operators.

The main objectives of this thesis are:

- Investigate various surveillance techniques currently used in subsea and other industries.
- Recommend CM techniques that can add value to SPS's.

- Provide a methodology and detailed guidelines for implementing a health monitoring system that helps operators visualize the status of subsea equipment and facilitates the decision making process for maintenance activities.
- Demonstrate the applicability of the methodology with use of practical examples.

1.3 Delimitations

This thesis is limited to Subsea Production Systems; specifically to the active equipment used to measure and control the flow of oil and gas, i.e. control systems (SCM, instruments, sensors, valves, electrical/hydraulic flying leads, etc.) and production equipment (XTs, manifolds and distribution units). Risers, flowlines, umbilicals, structures and processing systems (boosting, compression and separation) are excluded from this work.

Special emphasis is given to Cameron equipment; however, the condition monitoring technologies and solutions described herein can be applied to subsea equipment from different manufacturers. SPS's are described in detail in section 2.5.

1.4 Methodology

Initially, a thorough literature review was done about CM applications in fields other than subsea oil and gas production. Then the current equipment surveillance technologies used in subsea and other industries were investigated and compared in order to see how subsea equipment providers and field operators can benefit from other -more mature- industries. Meetings with CM equipment/software suppliers were held in order to get more in-depth knowledge about their products and the different options available. Also, studied was how Cameron competitors are handling condition monitoring as part of their service strategies, with the purpose of knowing where Cameron stands in the subsea arena.

The author met with different CM package providers to better understand the systems available in the market and determine what would be the most suitable solutions for Cameron.

The International Organization for Standardization (ISO) has created several guidelines for condition monitoring [5-9] that are closely related to this research, and as a result these guidelines were examined. However, these standards are quite general and a revised methodology for CM implementation was created in accordance with Cameron needs. The procedure included flowcharts with detailed explanation of every process and the use of two case studies to demonstrate how it should be used.

The thesis was written mostly in Cameron office in Stavanger. During the course of this research the author traveled twice to Cameron office in Celle, Germany where subsea control modules are designed and fabricated. Discussions were held in Celle with subsea software engineers to obtain detailed information about how the control system works and find the best monitoring applications for these technologies (i.e. what to measure?) In addition to meeting with engineers in Germany, the writer took advantage of the large network of professionals working in Cameron around the world to gain knowledge about other subsea products such as xmas trees, manifolds and valves.

1.5 Structure of the report

This report is structured as follow

Chapter 1 **Introduction**	Description of the problem, the scope of work of this report with the goals delimitations and methodology used to develop this research.
Chapter 2 **State of the art**	Definition of intelligent energy and different maintenance strategies, with focus on condition based maintenance. A discussion is given on the trends in condition monitoring techniques in subsea and other industries. At the end of the chapter, subsea production systems are explained and illustrated.
Chapter 3 **Methodology**	Explanation of the methodology created for implementation of condition monitoring program for Cameron subsea production system. The procedure is summarized by a process flowchart.
Chapter 4 **Case studies**	Two case studies are presented that explore the different issues encountered during implementation of condition monitoring techniques in subsea equipment and to describe with examples the methodology proposed in chapter 3.
Chapter 5 **Discussion and recommendations**	Discussion about the methodology proposed and the factors that affect condition monitoring of subsea systems due to their singularity. Recommendations are given for future work in this area and for improvements in the way condition Cameron currently handles monitoring.
Chapter 6 **Conclusions**	This thesis ends with concluding remarks on the investigation performed and the contributions to the industry.

2 State of the art

2.1 Intelligent Energy

The offshore industry has undergone many changes since the first offshore well completion in 1947 in the Gulf of Mexico. More specifically in subsea, we have seen tremendous changes with respect to downhole instrumentation and subsea controls, as depicted in Figure 2-1.

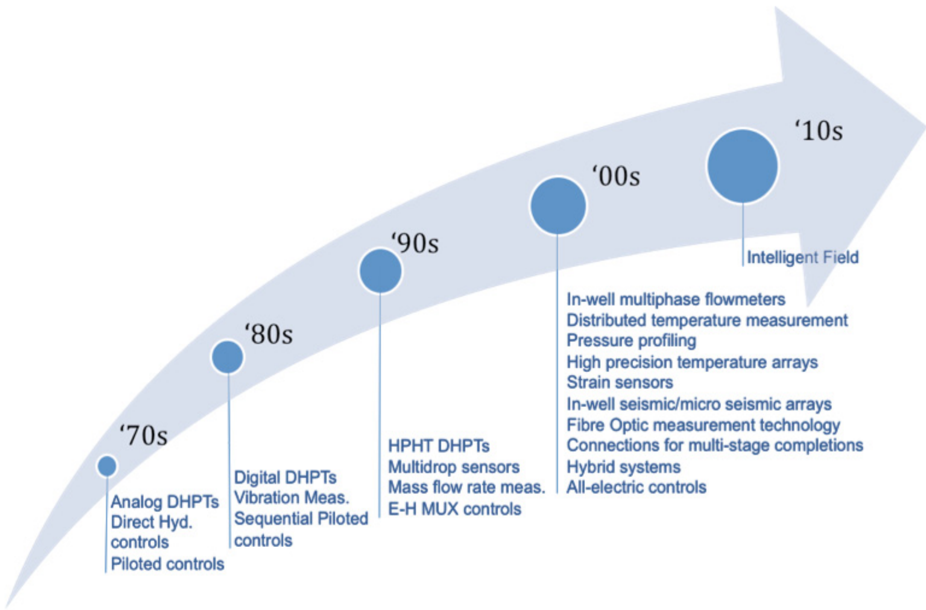


Figure 2-1 - Evolution of downhole instrumentation and subsea controls

While the development of new technologies in previous decades was centered purely on the instrumentation, in the last 5-7 years there has been an increased interest in *Intelligent Energy*. This novel term is defined as the deployment of state-of-the-art technology and procedures that enable operators to monitor, analyze, control and manage their field remotely and in real-time with the ultimate goal of optimizing production, reducing downtime and enhancing safety performance. Intelligent Energy is a new holistic way to manage oil and gas fields.

Major oil companies introduced the Intelligent Energy concept in the middle of the last decade. More recently, service providers and Original Equipment Manufacturers (OEM) have also adopted this concept to offer solutions for their clients that are in alignment with the their goals. The Intelligent Field concept has been given different names depending on the company: *Smart Field* (Shell), *Integrated Operations* (Statoil), *Field of the Future* (BP), *iField* (Chevron), *Digital Oilfield* (Petrobras) and *Digital Energy* (Schlumberger) [10]. The term Integrated Operations (IO) is commonly used in Norway. Cameron approach to Intelligent Energy has been named *Intelligent Field* and its purpose is to develop a more holistic field solution business vs. product offerings, i.e. *Integrated Systems Solutions*.

An Intelligent Field usually is composed of: 1) Advanced instruments to monitor the processes and equipment in every stage, 2) an integration platform where all different software and databases can be accessed in one place and remotely, 3) Collaboration rooms with numerous screens and communication systems where onshore operators can access the field data in real-time and communicate effectively with offshore operators or experts located remotely. The idea is to monitor and control many of the offshore processes from the office, in an environment (virtual or real) that allows collaboration between multiple disciplines without the need to travel offshore.

The benefits of an Intelligent Energy scheme are many: increased production; higher ultimate recovery factors; safer and cleaner operations; lower operating costs; better interdepartmental collaboration; better communication between operators, contractors and suppliers; and extended field life. The economic benefits vary among operators, Shell for example, ensures that by implementing their Smart Field technology they can increase production up to 10% [11], while a research conducted by the Norwegian Oil Industry Association (OLF) in 2006 revealed that the implementation of Integrated Operations in the Norwegian Continental Shelf could yield an increase in Net Present Value of NOK 250 billion [12].

As Edison et al. [10] show in Figure 2-2, the implementation of an Intelligent Field strategy must follow a series of progressive steps in order to maximize the returns in the shortest time possible.

First, the system should have a set of **advanced instruments** that allow the user(s) to monitor the equipment and process conditions reliably and in real-time. A thorough study must be done to identify what parameters need to be measured in the wellbore, subsea equipment and surface facilities, that will provide the information necessary to make decisions with respect to operation and maintenance.

Once the instrumentation is in place, the data have to be gathered, stored and made available to the different parties involved in the intelligent field, from service and equipment providers to field operators. It is very important that the system is designed in a holistic way, allowing for the **integration and collaboration** of different departments and organizations, including suppliers and contractors.

The amount of data monitored in an intelligent field can be enormous. To give an idea, for an all-electrical X-mas tree, 1.3 million data points are measured every day. In order to interpret the data, software engineers have to create algorithms that can turn raw data into real time **intelligent alerts**. Moreover, **event management** should be based on standard process flow and procedures. However, generating alerts that provide critical conditions is not enough; the system should provide **advanced analysis and forecasting** with respect to equipment failures and performance of the wells.

The last step is to use all the data collected and analyzed to make decisions with respect to **asset optimization**, i.e. plan maintenance activities, revise depletion strategy, assess safety of the operations, etc.

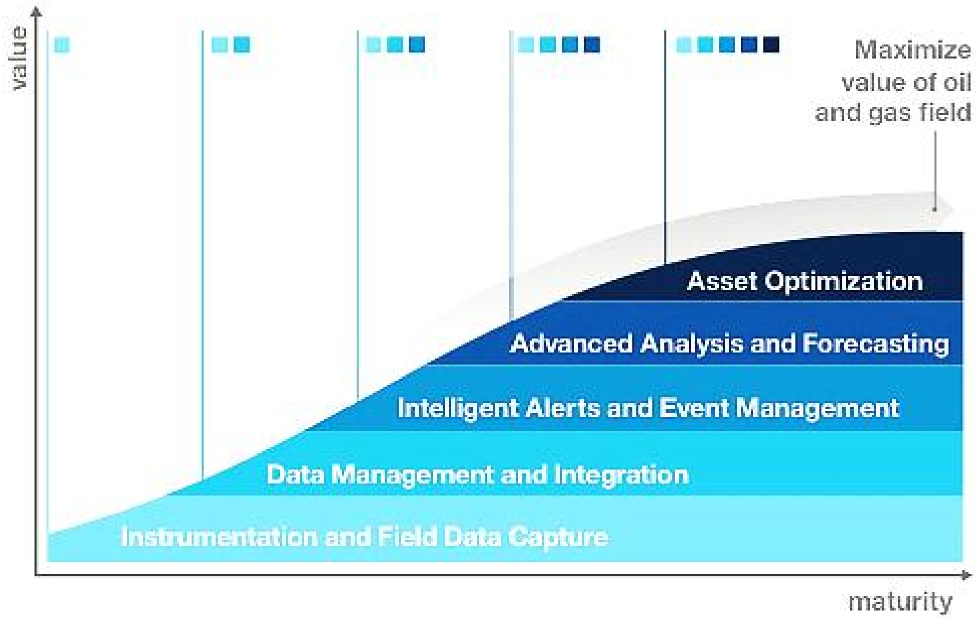


Figure 2-2 – Path to implementation of intelligent energy concept [10]

One of the fundamental pillars of the intelligent field concept is the use of advanced condition monitoring techniques that help asset managers to minimize downtime and increase life of the field by optimizing their maintenance strategies based on the state of the equipment. Sensors in subsea equipment have been used since the beginning of subsea production, mostly to monitor operating conditions, but little has been done with regards to equipment survey. In this thesis the author investigates how the current equipment surveillance technologies can be used by Cameron to develop a holistic asset management solution for their clients that is an integral part of the intelligent field strategy.

2.2 Condition Monitoring

Condition Monitoring can be defined as the surveillance of equipment operational parameters and/or process variables of industrial machinery to determine its health. The main objectives of CM are: 1) Determine the equipment mechanical state and 2) Generate trends of the equipment degradation to predict failure. As a result, companies can plan maintenance activities so they can be performed at the most convenient time to minimize NPT.

CM is part of predictive maintenance concept and it comes from an evolution of different maintenance strategies. At the beginning of the industrial era, maintenance was considered a hinder to production. The first maintenance approaches were based on replacing parts/equipment when they failed or performed at levels not acceptable for the production process. This approach known as corrective maintenance was merely reactive and therefore very inefficient. Since production had to be stopped inadvertently and repair activities were not planned, a lot of time was lost in finding the root cause of the failure, planning the repairs, obtaining the spare parts and allocating resources, which then translated into high operating costs and loss production.

It is worth mentioning that corrective maintenance is unavoidable; yes, it can be reduced to a minimum using the techniques explained hereinafter, but the risk of unexpected failure cannot be completely eliminated. Nevertheless, and regardless of the maintenance strategy followed by a company, they always have to have a corrective maintenance strategy in place so sudden failures can be repaired as quickly as possible. Some measures that facilitate the execution of unanticipated repairs are local storage of critical spare parts, maintenance personnel on-call, availability of equipment assembly drawings and repair manuals on site, and service agreements in place with OEMs for immediate assistance.

Future developments of maintenance strategies gave origin to preventive maintenance, a more efficient method, also known as *time-based maintenance* [13]. Preventive maintenance is based on the fact that machines degrade over time, thus replacement of wearable parts is scheduled on fixed-intervals (e.g. change oil of a 4-stroke engine every 10000 km). One of the main problems with time-based maintenance is that parts wear differently, depending on operating and process conditions, intermittency, external loads, material quality, etc. and as a result replacement of parts can occur too early or even worse, breakdowns can occur between replacement intervals if the part degraded faster than expected.

The issues aforementioned led to conception of new maintenance philosophies such as predictive maintenance, also referred to as Condition-Based Maintenance (CBM). With this approach maintenance engineers try to predict failures and determine the optimum maintenance intervals based on the current condition of the equipment and the trends in degradation of components. Predictive maintenance uses condition monitoring techniques as means to track the degradation (monitoring of effects) of equipment/parts and then uses this information to predict failures. The process of how CBM systems works is shown in Figure 2-3.

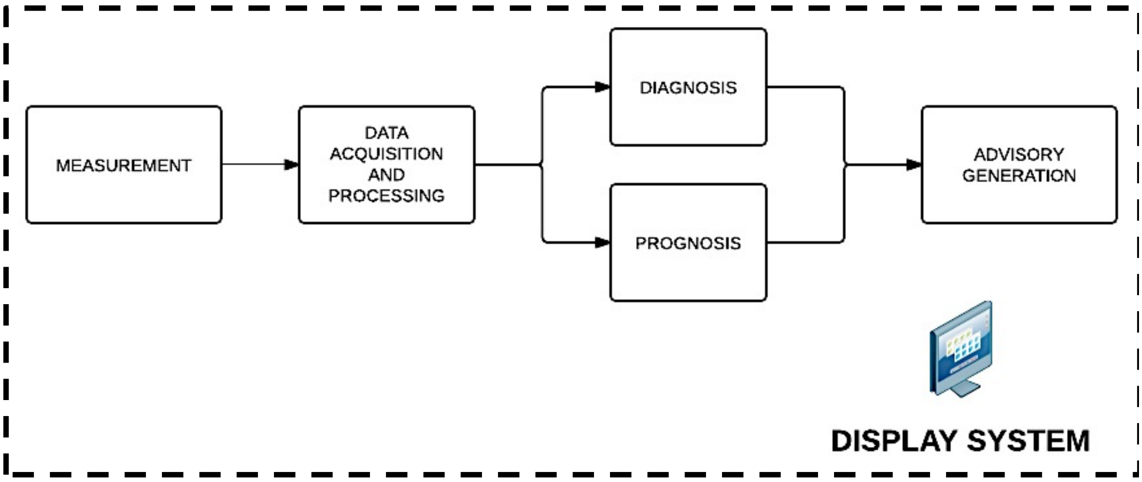


Figure 2-3 - CBM process

First the data is measured using sensors installed on the equipment or by mobile measurement equipment used periodically. Then the data is gathered, stored in a database and processed for further analysis. Processing the data can be sampling, compression, aliasing, transformation, etc., depending on the parameter measured and the output needed. After the data is ready, it is then analyzed. This is a two-fold process, on one side the information is used to determine the current degradation state of the equipment or component (diagnosis) and on the other side the data is used to generate a degradation trend and predict future failure (prognosis). The diagnosis and prognosis are usually performed with the aid of algorithms. Finally, a decision is made to recommend maintenance action. The decision making process can be done manually by experts or automated by use of numerical models. Essential information such the current state of the equipment and degradation trends are displayed throughout the monitoring process in a user-friendly format to provide the operators with a good overview of the equipment condition.

According to the German Institute of Standardization (DIN) the CBM methodology is based on understanding the degradation (wear out) level of the asset in order to determine its overall condition. As depicted in Figure 2-4 [14], the remaining useful life of an asset can be defined as wear out reserve and for most mechanical systems it reduces overtime as equipment degrades with use. When the equipment is in new condition the wear out reserve is 100%; then this reserve decreases over time due to equipment degradation. The figure shows a repair carried out **after** the equipment has failed. The CBM concept is introduced to monitor the asset continuously or periodically to identify the current state of the equipment and generate trends that can predict when the damage most likely will start, so maintenance activities can take place **before** this point, and bring the equipment back to its original condition. The ultimate purpose of CBM is to find the optimum time to perform maintenance, i.e. not so early that the equipment would still have significant life remaining and not so late so that the equipment would suffer irreversible damage or break down.

In recent years, predictive maintenance has gone one step further and evolved into proactive maintenance or Condition and Performance Monitoring (CPM) which allows the system to monitor the root causes of the integrity issues, based not only on equipment condition parameters, but also on **process parameters** [13]. A

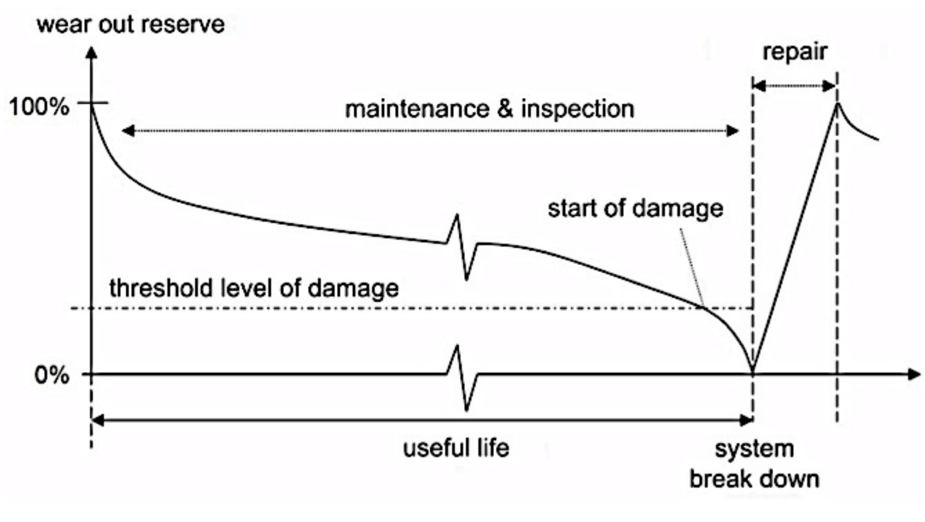


Figure 2-4 - Wear out reserve change over time [14]

common example of CPM is the monitoring of compressors where temperature and pressure measurement are used in conjunction with drive torque and speed are used to determine performance of the compressor over time and then infer degradation state and trend.

2.3 Condition monitoring techniques currently used in other industries

Since the field of CM in SPS's is relatively new, it would be beneficial to investigate the trends in other industries that are more mature in this area.

2.3.1 Maritime Industry

In earlier times of maritime transportation, vessels used to stay docked for long periods of time, and during this time the maintenance personnel performed the required maintenance activities to keep the ships in good condition. Today the maritime industry is much more dynamic; companies try to keep the vessels in transit as much as possible and time at ports are minimized considerably [15]. This change in the way the business is performed has pushed companies to focus on better maintenance strategies such as CBM.

One of the most important developments in the marine industry with regards to maintenance has been the creation of the Technical Condition Index (TCI), which is a measure for integrity, health and performance based on aggregation of technical, financial and statistical parameters. The TCI technique uses a mathematical model to describe the behavior of a system and a hierarchical tree model of the system where one or more TCIs are allocated to each node; then all the TCIs are aggregated from the lowest component level (child) to the top level (parent) to determine their impact on their parent node and finally providing a top level status (TCI) of the system. The index is based on a 0-100 scale, where 0 represents the maximum level of degradation and 100 describes the optimum condition ("like new" state). A system can have several levels and several nodes per level, each node having its own weight depending on the criticality of its condition with respect to the overall condition of the equipment [16, 17]. The top level TCI can be calculated as follows:

$$TCI_{parent} = \frac{\sum_i^n TCI_i * w_i}{\sum_i^n w_i} \quad (2)$$

Where:

TCI_i is the technical condition of child i

w_i is the weight of child *I (fraction)*

n is the number of child nodes

TCI usually uses a traffic light display system (Figure 2-5) to identify the current status of the system and subsystems in a simple layout. When the equipment is in healthy state the display systems shows a green light with no alarms. Once the state of the system degrades to a level that affects performance and/or functionality, the system TCI changes to yellow and an alert is sent to the personnel responsible for the system to take action. The two options are a) start planning the maintenance tasks and/or b) reduce the strain on the affected part(s) by changing the operating conditions in order to extend the life of the equipment until the next maintenance campaign. If the system reaches the red level, this indicates severe degradation and occurrence of a failure or malfunction.

The TCI have numerous advantages over traditional Key Performance Indicators (KPI) since it provides information about the system as a whole and not just only as a list of indicators for individual components. This arrangement can convey general information about the health of the asset to managers, and at the same time it can drill down the data to the component level to facilitate root causes analysis to engineers when degradation is detected. The aggregation approach of the TCI makes it also a very good option for complex systems, with large number of parts. Lastly, this index lets operators do benchmarking of similar equipment (e.g. vessels in a cargo fleet) when comparing them by their individual TCI.

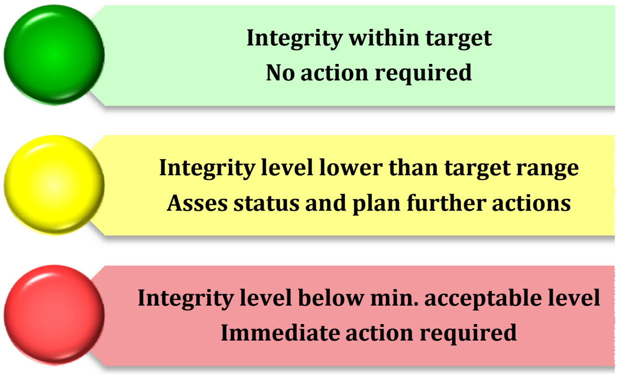


Figure 2-5 - Traffic light diagnosis system

The TCI concept started out as a project for ageing management of complex systems and was developed by the Norwegian Marine Technology Research Institute (MARINTEK) and the Norwegian University of Science and Technology (NTNU) in collaboration with Statoil, Kværner, Elkem and Forsmark Kraftgrupp [15].

This methodology has been used widely in the maritime industry and it is gradually being implemented in other industries such as onshore processing facilities and subsea production systems.

2.3.2 Railway

In the railway industry, just as in the maritime industry the time the locomotives are standing idle is being reduced to increase efficiency. Additionally, trains are travelling faster, more routes are being added everyday and railroads degrade overtime; increasing the risk of collision and/or derailment. Therefore, in order to improve safety, reduce lifecycle costs of rolling stock and railways, and ensure trains arrive on time, the railway industry has developed new ways of condition monitoring for locomotives, wagons and railways.

One of the issues in the railway industry is the deterioration of wheels and bearings. Technologies used for monitoring the integrity of these parts including infrared technology to detect high temperatures in wheels and bearings, acoustic bearing detectors (microphones) used to record sounds from wagons to detect bearing defects by analyzing vibration, and strain gauges and accelerometers are used to measure lateral and vertical forces that identify wagons at risk of derailment and defects on wheels [18].

To detect defects or degradation of the rail tracks, custom machine vision systems have been developed. Machine vision consists of using photo or video cameras, lights, sensors and processors to identify problems such as missing bolts, surface defects on rails, rail corrugation, condition of timber and concrete crossties, and uniformity of the ballast [19].

Some locomotive manufacturers have taken the CM one step further, by adding remote monitoring and diagnosis to the locomotives of their clients. In this way the OEM can receive the data in real-time and detect anomalies in the system that could jeopardize the performance and/or integrity of the machines. This system works automatically, i.e. there is no need for maintenance engineers to monitor the data continuously. Only when the system detects an issue with the health of the locomotive, an alert is sent to CM experts for further investigation and recommendation of action to the locomotive operator. Moreover, the diagnosis system is always evolving to become more accurate by being updated with important information from the customer and repair shop after the inspection or repairs are performed, and as a result, comparing the failure diagnosed with the actual condition of equipment.

2.3.3 Power Generation

The power generation industry is greatly influenced by the price of commodities, and energy demand. Based on these two factors, operations in power plants are not constant; operators must adapt their processes continuously to find a good balance between demand and supply. For example, at periods of high demand, companies can operate their turbines at high capacity in order to meet demand. Another important aspect is that electricity must always be available, i.e. power outages should be avoided at all cost. For this reason, power plants have to have very high reliability levels.

In order to overcome the issues mentioned above, the power generation industry has made significant contributions to the development of new techniques for equipment surveillance. In the last decades, the efforts towards improving CM have concentrated mostly in diagnosis and failure prediction systems using advanced algorithms, neural networks, expert systems, etc.

One novel approach is the use of incremental training algorithms to improve traditional statistical model for failure prediction. Traditional statistical models compare recorded data (e.g. measured outlet pressure on a gas turbine) vs. an estimate. This estimate is a value calculated by an algorithm based on historical data. The novelty of incremental training algorithms is that it not only relies on old historical data for the estimation of the normal expected value for the parameter measured, but it updates (or trains) itself continuously with the data recently recorded. The advantage of this method is its capability to adapt to changes in operational behavior (caused by degradation of components). One of the disadvantages of incremental training algorithms is that they require periodical assessment from technical experts to validate normal and abnormal trends;

however, these interventions tend to reduce in frequency over time as the system "learns" [20].

Another trend seen in the power generation industry is the use of Artificial Neural Networks (ANN) for modeling production of pools of power plants to maximize production. ANN models help operators to decide the optimal compromise between maintenance interventions, power generation levels and plant utilization during a given time period. Conventional physical models can lead to long calculation times and high CPU usage due to the large amount iterations needed. ANN reduces CPU processing time and occupancy considerably [21]. ANN modeling allows combining evaluation of power plant condition with economical impact evaluation caused by future degradation or faults predicted.

2.3.4 Aerospace

For obvious safety reasons, a flying vehicle cannot afford failure of its critical components at any time during flight. This is why aerospace is one of the industries where CM is most advanced.

Adaptive Gaussian Threshold (ATA) Algorithm is one novel concept in aerospace for failure detection when historical information is scarce. This methodology is able to recognize new behavior patterns that were not considered during the modeling of machine failure. The system creates normal operation parameter thresholds for new conditions based on features that represent normal condition and check the results when new data is obtained.

The National Aeronautics and Space Administration (NASA) is well known for its strong research and development program. Together with its subcontractors, NASA has developed many cutting edge technologies used today in the aerospace field and many of these inventions have been exported to other industries as well. NASA uses most of the common CM techniques such as vibration monitoring, Non-Destructive Tests (NDT) and lubricant analysis, but they also work with other less common monitoring methods, such as infrared thermography, ultrasonic noise detection and electrical CM [39].

In addition to the advanced predictive testing and inspection technologies used at NASA, the agency has also made some contribution to equipment diagnosis and failure trending software. Traditionally, physical models were used to monitor the health of the equipment onboard space vehicles. However, as technology advanced these models needed an immense computing capacity in order to perform, which makes the system very complex. In an effort to improve the models, NASA and one of its contractors developed software for CM trending and failure prediction. This new program uses a hybrid physical model that combines simplified analytical model and classical analysis techniques to provide diagnosis, prognosis, and decision support [22]. When compared to traditional physical models, this hybrid model has the following advantages:

- Allows for real-time or near real time diagnosis
- Earlier identification of degradation symptoms
- Low CPU usage
- Considerably lower number of false alarms

The software is currently used in the aerospace industry only, but it has a great potential to be used in other areas such as medical, process plants, power generation, etc.

2.3.5 Discussion

In the last two decades we have seen a rapid growth and development of new CM techniques and applications. However, many of the methods used in the industries aforementioned are still being developed for subsea applications. Due to the stringent requirements for underwater technology, new sensors have to go through severe qualification programs before they can be used. Nevertheless, this has not been a showstopper for many of the CM equipment providers and many new sensors for subsea applications have been launched during the past 5 years. Development of complex underwater systems such as Ormen Lange subsea compression, and installations in remote locations such as the Snohvit field in the Barents Sea have also been a significant driver for the conception of new measurement technologies.

The most important trend in CM is by far the use of Artificial Intelligence (AI) methods, such as Neural Networks and Fuzzy logic. Normally a standard SPS has a modern control system that collects huge amounts of data about the process instruments located subsea. The challenge is to use this data in the most effective way to determine equipment condition and predict failures, and AI techniques can do exactly that.

2.4 Condition monitoring techniques currently used in subsea

Even though subsea systems have existed for more 50 years, it was only a few years ago that Oil and Gas (O&G) companies have considered CM for subsea equipment as an essential part of their asset management strategies. OEMs have taken different approaches, but all of them have the same goals: to increase reliability, reduce NPT, maximize production and minimize Life Cycle Cost (LCC). In this section an overview about what subsea OEMs are doing with respect to CM is presented along with the latest developments done by researchers and instrumentation manufacturers.

2.4.1 Subsea equipment manufacturers' approach to condition monitoring

In 2009 General Electric (GE) launched the Subsea Monitoring and Remote Technology Center (SMARTCenter), which is an operation hub located in the UK where they monitor remotely subsea production systems around the world. In this technology center a team of engineers perform remote fault diagnosis, equipment performance trending and provide recommendations for maintenance intervention and valuable information to flow assurance engineers. The SMARTcenter is also connected to other GE's center of excellence around the globe, allowing further collaboration between GE experts in the UK and maintenance engineers other locations. Some of the benefits of this technology center are quicker response to issues with equipment failures, alarms and trends; reduced number of trips offshore which then translates into lower mobilization costs and increased efficiency in the use of internal resources [23, 24]. Some of the parameters monitored by GE are:

- Hydraulic leakage
- Umbilical resistance degradation

- Choke erosion (estimation)
- Valve signature
- Communication and power

Framo Engineering (a Schlumberger company), supplier of subsea pumps has also opened an online support center for CM. They have called it FRIEND (FRamo Interactive ENabling Diagnostics). This center is located in Bergen, Norway where they can do remote surveillance of subsea pumps continuously and create performance trends to optimize production, troubleshooting and predict failures. The system works by transmitting subsea operational data in real-time from the topside facility to the support center via satellite, where the data is processed and analyzed by Framo engineers, while at the same time the data can be visualized by the end user via internet interface.

In addition, the system has an automated alarm system that notifies Framo engineers on duty of abnormal situations for further action. One of the most interesting features of FRIEND is the possibility for the end user to access a virtual workspace where they can access the information about the subsea system operating conditions in real time, export data, access maintenance data, generate reports, and request spare parts [25].

Another novel approach taken by Framo and Schlumberger is the ability of their SCM (named subC-pod) to connect future sensors without need for reconfiguration of the system, just "plug in and play". This is achieved by adding connectivity for external sensors (e.g. sand detector) through switchable 24VDC power supplies and by adding the new sensors automatically to the subsea communication network. Data transmission to the topside facility is done by fiber optic cable, which allows high-speed communications, up to 100 MB/s, but most importantly it avoids electromagnetic interference normally caused by high voltage transmission in the umbilical needed for subsea pumps [26].

Schlumberger (SLB), a company that provide downhole sensors and subsea control modules among many other products, offers a parallel surveillance system that allows to monitor and control SPS's together with wellbore equipment. The system depicted in Figure 2-6, is comprised of a subsea control module that monitors and operates the XT and an additional control module and communication hub (subC-net) for the downhole sensors and valves [27]. This system allows for integration of sensors used in different applications from different vendors, for further processing by the MCS and transmission to an onshore operation center.

Another CM service offered by Schlumberger is integrity surveillance of risers, flowlines and jumpers; detection of leaks and distributed temperatures measurements for hydrate prediction.

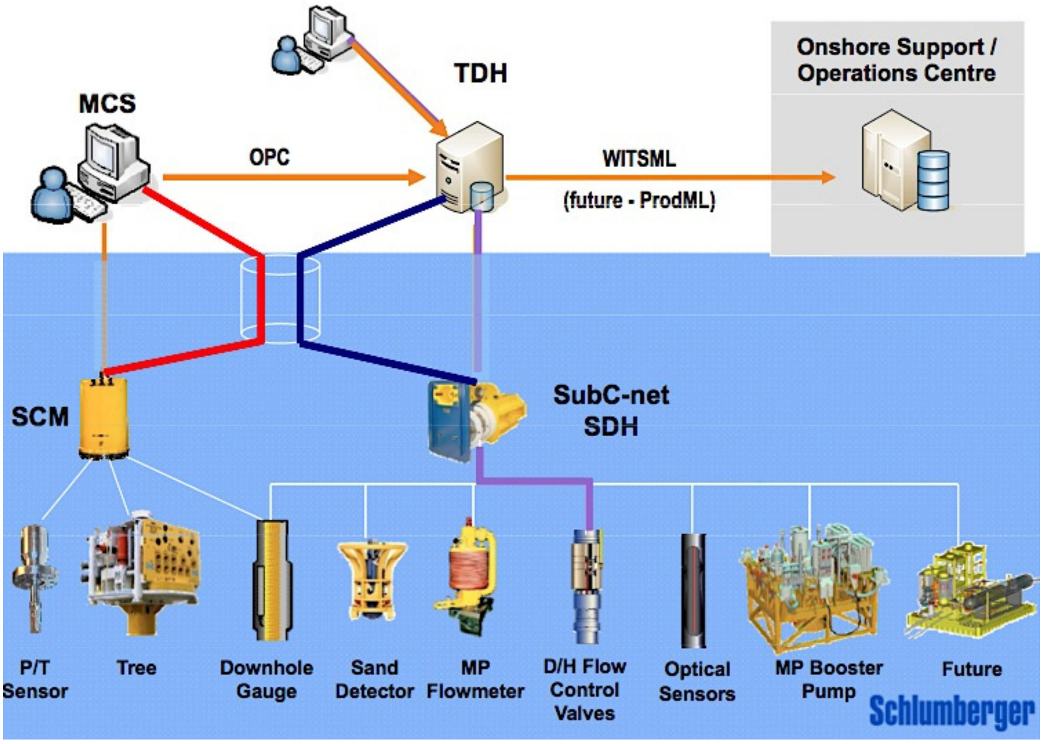


Figure 2-6 - Schlumberger parallel surveillance system [27]

Aker Solutions has also made some developments in CM of subsea equipment. It has its own e-field program, which is based on surveillance of instrumentation, analysis of data, operational optimization and advanced control through intervention in real time, and remote operations [28]. The information about this system available publicly is very limited and therefore cannot be discussed in detail in this report.

FMC has CM program for subsea equipment as well: *Condition and Performance Monitoring* (CPM). This system monitors electrical and mechanical components continuously and provides real-time processing to determine current operating conditions and early detection of degradation and-or reduced efficiency [16]. The CPM program, which uses the Technical Condition Index (TCI) explained in section 2.3.1 as the main tool for asset diagnosis, is divided in 4 main process areas:

Monitor and report: the equipment is monitored; abnormal trends are identified (TCI) and reported in-real time to FMC onshore operation center and customer.

Diagnosis, advice and alert: a full diagnostic is developed by FMC with possible assistance from the end user and/or experts located remotely, then appropriate maintenance action is suggested.

Recover and maintain: the maintenance activities are carried out and related information is entered in a database for future reference

Knowledge Management: condition and defects on the equipment are compared to the initial failure analysis to corroborate the prediction and then the TCI model is updated based on the findings.

FMC also uses some advanced technologies for equipment surveillance such as, optoelectronic leak detection based on fluorescence spectroscopy. This system is based on the principle that different substances absorb more or less light depending on their composition. An arrange of LED lamps emit light, record the light reflected and determine if the there are any substances other than seawater around the instrument. Since hydrocarbons and hydraulic fluids have specific fluorescence signatures, the detection system can be calibrated for the liquids present in the particular equipment monitored, which allows the sensors to detect very small leaks. The radius of detection reaches up to 5m, making it ideal for monitoring of subsea trees, templates and manifolds. Other benefits are: low power consumption, long lifespan of the lamps, low probability of false alarms, qualified for water depths up to 3000m and small footprint. As an option, the system can be fitted with a digital camera that allows confirming the presence of a leak detected by the sensors, without the need to use ROVs for this purpose [29, 30].

A summary of the sensor technologies and prognosis/diagnosis systems used by the main subsea equipment providers is presented in Table 2-1.

Table 2-1 - CM technologies used by major subsea equipment suppliers

Technology	GE	Framo	FMC	Aker	SLB
Monitoring Technology					
Acoustic leak detector	✓	✗	✗	*N/A**	✗
Fiber-Bragg Grating	✗	✗	✗	*N/A**	✓
Optoelectronic leak detection system	✗	✗	✓	✗	✗
Fault Diagnosis and Prognosis System					
Remote monitoring center	✓	✓	✓	✗	✓
Internet portal for customer/3rd party access	*N/A**	✓	*N/A**	✗	✓
Flow assurance support	✓	✗	✓	✓	✓
Technical Condition Index	✗	✗	✓	✗	✗
Choke erosion estimation	✓	✗	✓	✗	✗
Valve signature analysis	✓	✗	✓	✗	✗

2.4.2 Latest technologies in subsea sensing technology

Since condition surveillance of subsea equipment applies not only to new equipment, it is important to have non-intrusive products that can be installed in existing equipment without disturbing production. Norwegian company ClampOn has developed a series of CM sensors that can be easily installed by ROV and required

* N/A: no public information was available by the time this report was written

little to no calibration. The products offered are sand monitors, PIG detectors, leak detectors, vibration monitors, and corrosion-erosion monitors.

The most common way to avoid corrosion of structures is by using cathodic protection together with corrosion resistant materials and protective coatings. Cathodic protection is designed for the lifetime of the field and is normally very reliable, but needs to be monitored to make sure it works as expected. Cathodic protection is monitored by using permanent mounted sensors (see Figure 2-7a) that provide readout of the anodes performance, or by measuring cathodic protection potentials of the anode using a contact probe handled by ROV (see Figure 2-7b).

a) ROV-operated probe

b) Permanent monitoring panel

Figure 2-7 - Cathodic protection monitoring systems [31]

Another Norwegian company, NAXYS, offers an innovative solution for leak and vibration monitoring of subsea pipelines, structures and equipment. The product shown in Figure 2-8 is called the Acoustic Leak and Vibration Detector (ALVD) and is installed on subsea structures (templates and manifolds). The equipment uses hydrophones arranged in three dimensions to record acoustic signals, compare them with baseline signatures for leak and vibration and then it generates an alarm in case of a deviation between the baseline and value measured. This system is planned to be installed in the subsea compressor in Ormen Lange [32]. One of the limitations of using hydrophones to detect leaks is that they can only detect medium to large size leaks. When the nature of the system requires more accurate leak detection (small leaks), Moodie et al. [29] recommend using a fluorescence detection system.

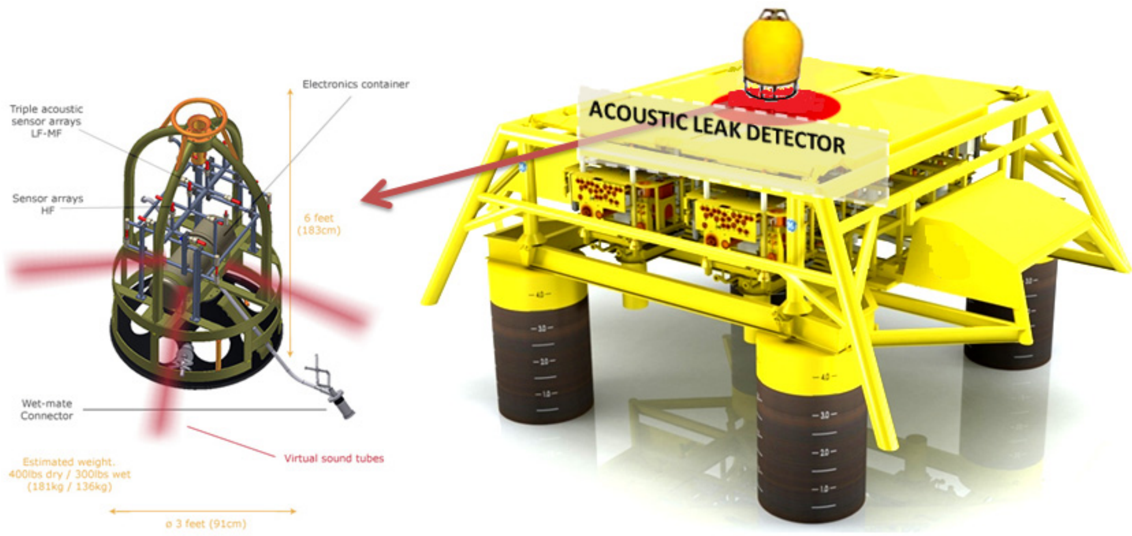


Figure 2-8 - NAXIS acoustic leak and vibration detector [33]

A novel non-intrusive method for CM in underwater applications is the use of Fiber-Bragg Grating (FBG) sensor. This technology uses fiber optic to measure temperature, pressure and strain on the equipment. Based on these measurements, one can determine vibration, fatigue, temperature and pressure of production fluids and pipe bending. FBG works by the principle of Freshnel reflection, where light travelling through optical fiber reflect some wavelengths and transmit all the others. Changes in temperature or strain experienced by the fiber, affect its striations and consequently the amount of light reflected, which can be used to calculate temperature, pressure and strain experienced by the equipment where the sensors are mounted. This technology has many advantages over conventional sensors: it is non-intrusive, does not require periodic calibration, it can be integrated to SCADA systems, it is corrosion resistant, sensors are small, it is simple to use and it has very low signal loss over very long distances. Recently, FBG sensors were being used as support for flow assurance, since they can provide temperature and pressure profiles along pipelines and risers with great accuracy allowing flow assurance engineers to predict and detect hydrate formation [34]. There are many uses and potential benefits of the FBG technology [35], as shown in Table 2-2.

Table 2-2 - Applications and benefits of FBG sensors

Type of Measurement	Application	Potential Benefits
Temperature and pressure profile	Accurate monitoring state of the system	Good visibility of process conditions Detect insulation degradation Reduce use of inhibitor during shut-in/restart operations
Trends and changes in the temperature profile	Infer solid deposition	Detect cold spots More efficient use of hydrate inhibitor Thinner insulation required (if FBG sensors are considered in original design of new installations) Optimization of pigging frequency
Strain	Riser fatigue monitoring	Prediction of riser failure
Vibration	Slug detection	Better flow assurance control

2.5 Subsea Production Systems

The international standardization organization [36] describes a SPS as the system and subsystems "necessary to produce hydrocarbons from one or more subsea wells and transfer them to a given processing facility located offshore (fixed, floating or subsea) or onshore, or to inject water/gas through subsea wells". A typical SPS is illustrated in Figure 2-9.

A SPS is comprised of the following elements:

- Subsea Christmas tree(s)
- Production control system. Typical system breakdown for Electro Hydraulic Multiplex type:
  - Subsea Control Module (SCM)
  - Hydraulic Power Unit (HPU)*
  - Electrical Power Unit (EPU)*
  - Master Control Station (MCS)*
  - Umbilical(s) for electrical power, electrical signal, hydraulic power, service fluids and chemicals*
  - Umbilical terminations assemblies (topside and subsea)
  - Subsea Distribution Unit (SDU)
- Wellhead system(s) including associated casing strings

* Located topside

- Template or structure for supporting subsea equipment
- Manifold(s)
- Instrumentation
- Subsea processing equipment*
  - Separator
  - Compressor
  - Pump
- Flowlines and tie-in spools*
- Risers*
- Pig launcher/receiver*
- HIPPS
- Electrical Flying Leads (EFL)
- Hydraulic Flying Leads (HFL)

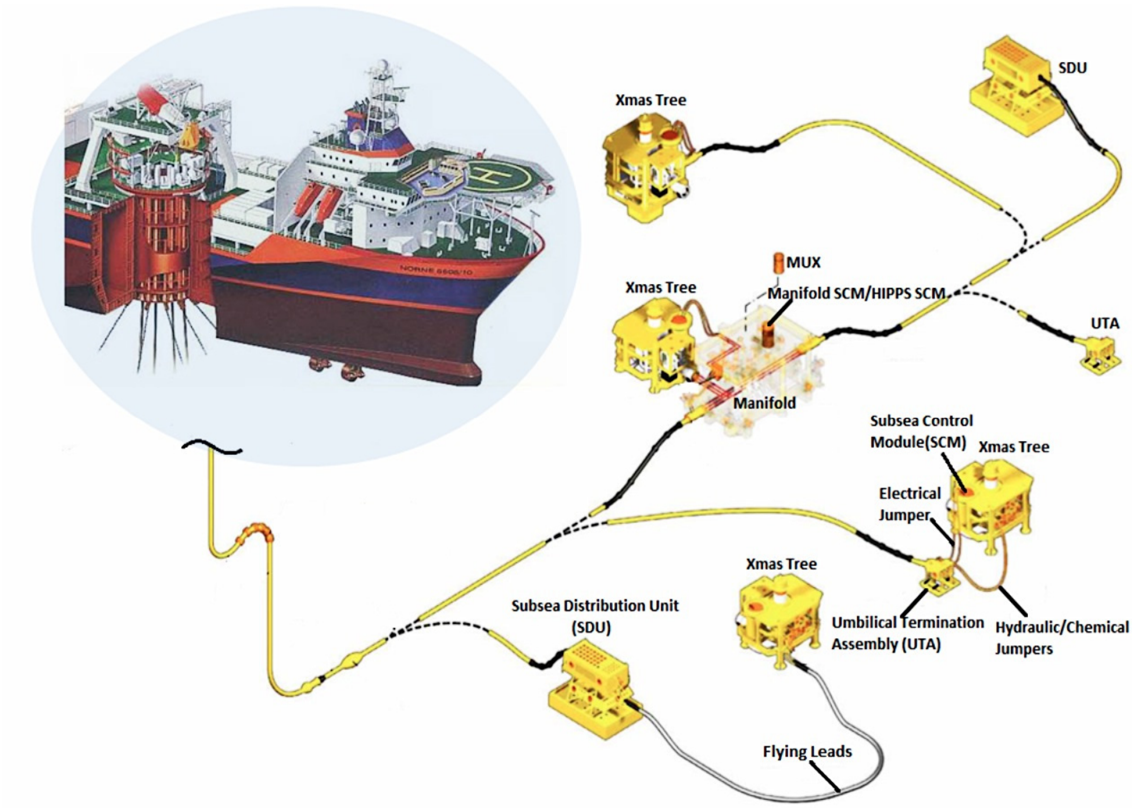


Figure 2-9 - Typical subsea production system

* Out of the scope of this thesis

SPS's can have many configurations, from stand-alone wellhead and XT to satellite fields to full subsea developments including manifolds, subsea pumps, compressors and/or separation system. In many cases various pieces of equipment are provided by different suppliers, and therefore sensors and instruments must be compatible so they can be integrated into a single CM program. One way to achieve this integration is by using sensors, instruments and control systems that follow Subsea Instrumentation Interface Standardization (SIIS) guidelines. SIIS is a joint industry project created with the goal of developing a standard interface between subsea control module and subsea sensors. Monitoring systems based on SIIS use CANopen communication protocol as the standard for supervision, remote control, shut down and data transfer.

3 Methodology for implementation of condition monitoring program for subsea production systems

The main purpose of this section is to provide guidelines to set up an appropriate CM program for subsea production systems with particular focus on subsea XTs, subsea control modules, manifolds, electrical/hydraulic flying leads and templates.

There are several ISO standards [5, 6, 8] related to condition monitoring that have been studied to create this methodology. The result is the procedure shown in Figure 3-1, where the key points of these standards have been condensed into a single flowchart to facilitate the process of implementing a CM program for subsea production systems.

This step-by-step procedure has to be carried out individually for all the subsystems in the SPS until all the equipment to be monitored have been analyzed. Once the evaluation is complete, a display system must be designed for the system as a whole to present the data analyzed by the CM system.

This methodology is based on industry standards [5-8, 37, 38]; however, the techniques described in these documents are intended for onshore or surface rotating machinery. Consequently, the guidelines presented herein have been tailored for subsea equipment.

The methodology is divided in five major blocks: *system classification, measurement, data acquisition and processing, diagnosis and prognosis,* and *advisory generation*. The steps involved in each block are explained in the following pages.

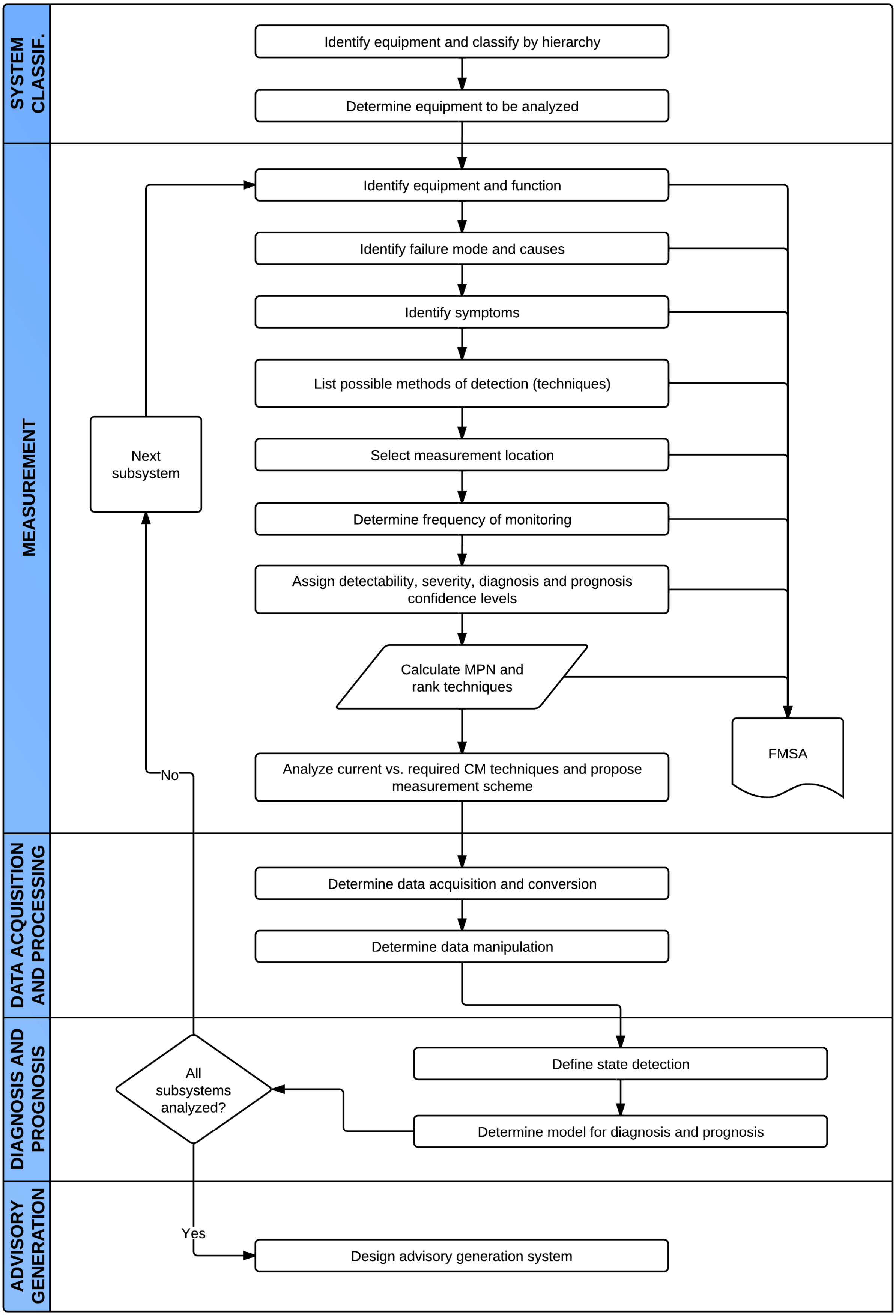


Figure 3-1 - Flowchart for implementing a condition monitoring program

3.1 System classification

3.1.1 Equipment hierarchy levels

The first step necessary to implement a CM program is to divide the system to be monitored into subsystems and organize them by levels of hierarchy. This classification, also known as system architecture, will allow for better identification of the equipment to be analyzed in the next stage. Appendix A shows a detailed breakdown of a typical SPS into subsystems at equipment hierarchy levels.

3.1.2 Determine equipment/subsystem to be analyzed

Once all the pieces of the equipment have been classified and organized by hierarchy level, choose the first subsystem to be evaluated. The level of detail at which the subsystem will be assessed will vary in accordance with the maintainable characteristics of the equipment. For instance, for manifolds it is recommendable to study the equipment down to level 2 (refer to appendix A) because that will provide enough information of the failure cause, whereas for electrical components it is better to analyze the equipment to the lowest level.

3.2 Measurement

Perform a comprehensive equipment assessment that will allow the user to find the most appropriate techniques for condition monitoring of the system. The assessment is achieved by doing a Failure Mode and Symptoms Analysis (FMSA), which is a variation to the Failure Modes, Effects and Criticality Analysis (FMECA) technique widely used in reliability engineering. The output of the FMSA is a table where the information presented in the following pages is populated in a table.

3.2.1 Identification of equipment and function

This is the first step of the FMSA, to identify the subsystem and components to be analyzed in order to understand the failure modes and failure mechanisms better. Describe the main function of the system and subsystems. General arrangement drawings and exploded views of the equipment can be useful for visualization of the system.

3.2.2 Failure modes and causes

Use of reliability data available is recommended to find the possible failure modes and causes in SPS's. Several sources are used for this purpose: OREDA database, Cameron internal reliability database DRACAS and Cameron internal field performance report system. The OREDA database is a project that originated in Norway to compile and exchange offshore reliability data from different oil and gas operators around the world. Access to the database is restricted only to the operating companies participating in the program, but since Cameron is one of the main contributors to the subsea equipment database, OREDA has granted access to Cameron equipment data to be used in this report.

The three database systems mentioned above provide a good overview of the majority of failure modes expected in a SPS; however, the information collected from the databases should not be used blindly. Expert judgment should be considered to get the most out of the data available and to spot possible errors.

Failure modes can be related to fatigue, wear, ageing, overload, corrosion, environment, equipment misuse or a combination of these factors.

3.2.3 Failure symptoms

Identifies the symptoms that allows for detection of the failure modes and that can be used to diagnose the health of the system. Symptoms can be related to the equipment, for example high voltage on a circuit board in the SCM; or to the process, for instance low process fluid pressure.

Sometimes it is not so obvious to identify the symptoms that reflect failure modes. Designers of the CM system have to think “outside the box” to determine those measurements that will provide the information needed about the health of the system.

3.2.4 Methods of detection

List the possible methods of detection for each symptom. A symptom can be detected by one or several methods, but could also be undetectable. The methods of detection should be specific and include the type of instrument/sensor used (e.g. acoustic leak detector).

Detection of failure symptoms can be done by direct or indirect measurement. An example of indirect measurement is the monitoring of choke erosion. To access inside of a subsea choke to measure its degradation is not possible (or at least practical) without stopping production and bringing the choke to the surface. The solution to this problem is to estimate the erosion level by measuring differential pressure across the valve, flow rate and choke position, and see if there are any changes over time that could be attributed to degradation of the internal parts.

3.2.5 Measurement location

Define where the best place to take the measurement is within the system so as to produce the most reliable data. Subsea systems are composed of a large number of components installed over a small area and sometimes the space for additional instruments is limited; therefore, this has to be taken into consideration when determining the location of the measurement/transducer.

Sometimes it is not possible or economically feasible to place the sensor exactly at the source. In this case, the sensor can be installed as closely as possible to the desired measurement location, and the parameter at the desired position can be calculated by modeling the parameter drift over distance. An example of the latter is the measurement of fluid temperature in a flowline: By installing a non-intrusive temperature sensor on the outer wall of a pipe, and then calculating the internal temperature taking into account thermal losses through the pipe wall.

3.2.6 Frequency of monitoring

Determine how frequently the system should take the measurements. For most subsea applications the monitoring is continuous, since periodic monitoring (e.g. ROV visual inspection) can very expensive and support vessels are not always readily available.

3.2.7 Rating

In order to compare the different monitoring methods previously registered they have to be rated based on their efficiency for detection, diagnosis and prognosis, as well as the severity of the failure.

3.2.7.1 Detection

This indicator gives an idea of how good the technique is in detecting the failure, regardless of how well the failure can be diagnosed or prognosticated. Detection is ranked from one to five as follows:

1: There is a **remote probability** that this failure mode will be detected

2: There is a **low probability** that this failure mode will be detected

3: There is a **moderate probability** that this failure mode will be detected

4: There is a **high probability** that this failure mode will be detected

5: It is **certain** that this failure mode will be detected

3.2.7.2 Severity of failure

This is an indication on how severe the consequences would be for the system, environment and personnel if a failure were to occur. The four severity categories are:

1: Any event that could cause degradation of system performance function(s) resulting in negligible damage to either the system or its environment; and no damage to life.

2: Any event that degrades system performance function(s) without appreciable damage to system, environment or life; and with minimum operational impact.

3: Any event that could potentially cause the loss of primary system function(s) resulting in considerable damage to the system or the environment, significant operating impact and/or negligible hazard to life.

4: Any event that could potentially cause the loss of primary system function(s) resulting in serious damage to the system or the environment (potential external leakage), and/or constituting a threat to life.

3.2.7.3 Diagnosis confidence

This ranking reflects the degree of accuracy of the monitoring technique to diagnose the fault. It is ranked from one to five as follows:

1: There is a **remote probability** that this failure mode diagnosis is accurate.

2: There is a **low probability** that this failure mode diagnosis is accurate.

3: There is a **moderate probability** that this failure mode diagnosis is accurate.

4: There is a **high probability** that this failure mode diagnosis is accurate.

5: It is **certain** that this failure mode diagnosis will be accurate.

3.2.7.4 Prognosis confidence

This ranking represents how accurate the monitoring technique is to prognosticate future faults. It is categorized from one to five as follows:

1: There is a **remote probability** that this failure mode prognosis is accurate.

2: There is a **low probability** that this failure mode prognosis is accurate.

3: There is a **moderate probability** that this failure mode prognosis is accurate.

4: There is a **high probability** that this failure mode prognosis is accurate.

5: It is **certain** that this failure mode prognosis will be accurate.

3.2.8 Monitoring Priority Number

In some occasions a failure mode can be detected by different methods. The Monitoring Priority Number (MPN) is a ranking system used to determine which monitoring technique is the most efficient based on the four criteria described previously. The MPN calculation requires multiplying all the four rankings, and then the technique with the highest number is considered as the optimal for the specific failure mode.

$$MPN = Detectability \times Severity \times Diagnosability \times Prognosis\ Confidence \quad (3)$$

3.2.9 Analysis

Once the parameters that need to be measured are defined, one has to determine if the sensors currently available in the SPS system are sufficient. One way to determine what is currently measured is by analyzing the function Inputs/Outputs (I/O) schedule of the SCM.

If the sensors available are not adequate for failure recognition, additional techniques should be added as per FMSA; however, this has to be considered carefully. Current SPS's have a great amount of sensors already embedded in the system, especially in the SCM. One should take advantage of these existing -and proven- sensors when designing CM systems to get the most out of these devices, and adding additional measurements only when it is absolutely necessary.

The measurement equipment must be robust and very reliable; otherwise the use of these new sensors could add more faults to the system. Other factors like cost, size, installation method and sensitivity to external factors (e.g. magnetic field) should be considered as well.

3.3 Data acquisition and processing

3.3.1 Data acquisition

Before the measurements can be used for analysis, the data have to be presented in the proper form. First the information given by the sensors/transducers has to be collected and the analog data have to be digitized, including time stamp and information about data quality. It is highly recommended to use only instruments that are compliant with SIIS (see section 2.5) to simplify the interface with the SCM.

3.3.2 Data manipulation

After the information has been collected and digitized, the raw measurements have to be converted so they can be presented as meaningful descriptors of the equipment condition. This manipulation of data can be signal analysis, sampling, algorithm calculations, feature extraction, filtering and combination of operational parameters (virtual sensors), to name a few processes.

3.4 Health assessment, diagnosis and prognosis

3.4.1 State detection

The way faults are detected is by comparing the measured values against a predefined baseline. If the values fall outside the baseline limits, the system reports this condition as an anomaly by the means of an alert or alarm; otherwise there is no action taken other than keep recording the data. The different warning levels for fault detection are defined in Figure 3-2.

The creation of the baseline is paramount for the CM system and should not be taken lightly. To determine the "anomaly zone" one should use historical data, experts' judgment and research figures; and then set alerts, alarms and trips levels for each parameter measured. Whenever possible the system should evaluate the degree of the fault and convey this information along with the alert.

When the failure mechanisms are simple (linear behavior), the detection of the fault can be done simply by comparison of single parameters measured against a reference value (baseline), but when the system gets more complex, model-based methods are used. Models allow interpretation of multiple variables and/or complex signals by using algorithms. Different types of models are explained in section 3.4.4.

It is also important to mention that baselines should be revisited and refined once operation commences [5], to calibrate the system for possible errors of initial assumptions or to correct for operational changes.

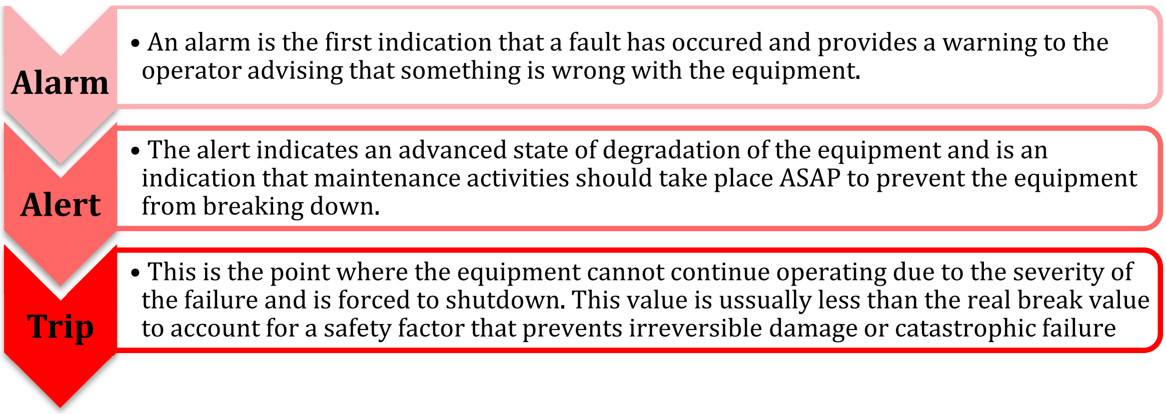


Figure 3-2 - Alarm, trip and alert definitions

3.4.2 Diagnosis

When an anomaly is detected, the system should diagnose the fault and the failure, as well as determining the current degradation state (health) of the equipment. The output of the diagnosis is a characterization of the fault that includes, as a minimum, an estimation of the location of the fault, size of the fault and the time of detection [39]. This information is very important to find the root cause of the problem, so proper actions can be taken to bring the equipment back to its original state by repair, modification or changing operational parameters; while providing valuable data to prevent similar failures in the future.

In order to understand how diagnosis systems work, the concepts of fault, failure and symptoms should be clarified. A failure is a condition that causes a system to perform without achieving the expected results. A fault is said to be the cause of a failure. And a symptom is the observable effect of a failure.

There are several ways to diagnose a failure, but they could be reduced to two main forms: diagnosis models based on symptoms and models based on equipment behavior. In the first case, the diagnosis system tries to find all the possible reasons (causes) of the detected failure based on information available on how the system performs under different circumstances. Behavioral models are more complex; they predict the normal behavior of a system based on knowledge of the process and compare these estimated conditions with the current parameters measured to see if there are any deviations. Both approaches have different variations. Some of the most used models are described in section 3.4.4.

Triggering of the diagnosis system is normally done automatically after the anomaly detection, but the system should also allow for occasional diagnosis *on-demand*. The latter is necessary in some specific scenarios where the operator suspects there can be a fault that has not been detected by the system or when it is required to know the current state of the equipment for reporting purposes or planning of future maintenance activities.

3.4.3 Prognosis

The main purpose of prognostics is to determine the Remaining Useful Life (RUL) or Estimated Time To Failure (ETTF) of the components and to use this information for maintenance planning. Prognostics use models based on the historical measurements to generate trends that provide an estimation of future degradation of the equipment. Estimation of RUL can be done with great extent of accuracy for components subject to progressive deterioration, whereas for parts with random failure mechanisms prognosis can be quite challenging.

According to [6] the prognosis process has four main parts and should be developed as follows:

3.4.3.1 Pre-processing

First the failure modes and the way they interact shall be identified. This is done in the FMSA and explained in section 3.2.2. Then the alert, alarm and trip levels are defined. Later, possible future failure modes are determined and, lastly a suitable model for the failure modes is selected

3.4.3.2 Prognosis of failure modes detected

Once a failure or group of failures are detected, one should assess the severity of the failures and project the parameters onto the future using either projection or extrapolation methods, to predict their different ETTF. The failure with the shortest ETTF is considered as the critical one for the system at current state.

3.4.3.3 Prognosis of future failure modes

Some failure modes can be the cause of other problems. Based on current failure modes one should analyze the possible scenarios that could develop and select the future failure mode with the shortest ETTF as the critical one for future state.

3.4.3.4 Post action prognosis

Based on the critical failure modes found in the two previous steps, one should identify the maintenance actions or change in operational parameters that will eliminate or delay the effects of the failure modes in the system. Once the mitigation measures have been identified, the whole prognosis process should be repeated taking into consideration the mitigation actions as performed, to calculate the new ETTF of the system.

3.4.4 Models

The most common way to detect faults, determining the health and predict future degradation of a system or its components is by using models. Models for diagnosis can be knowledge-based or numerical and can be subdivided as shown in Figure 3-3.

The approaches presented here are some of the most widely used in fault detection, diagnosis and prognosis; there exist other types of models that could be used, especially for systems with unique characteristics. In the case of conventional subsea systems (without rotating equipment) the processes and components are usually simple and can be diagnosed with one or more of the models described below:

- **Models**
  - **Knowledge – based**
    - **Fault model**
      - **Fault/symptoms**
      - **Causal tree**
    - **First principles (PoF)**
  - **Numerical**
    - **Feature extraction and pattern recognition**
    - **Artificial Neural Network**
    - **Statistical**
    - **Fuzzy logic**
  - **Hybrid approach**

Figure 3-3 – Types of models

3.4.4.1 Knowledge-based models

Knowledge-based models are used to predict health state and faults using *a-priori* knowledge. This approach requires having a deep understanding of how the system works, how faults are generated and how they evolve over time. Knowledge-based models provide qualitative results and work by using rules, for instance: *IF condition A is met, THEN failure X occurs.*

Faults/symptoms models consist of creating fault hypotheses based on the evaluation of one or multiple symptoms present in the system at the time an anomaly is detected. The hypotheses are then confirmed and ranked by their probability of being accurate.

Causal tree approach provides more information about the fault and its propagation than fault/symptoms models. The goal of this method is to find the root cause of the failure by analyzing existing failure modes using fault-tree diagrams.

First principles models use mathematical simulation to predict the behavior of the equipment, regardless of the state (healthy or faulty) based on process physics, such as energy and mass balances. This type of model calculates physical quantities without the need for input parameters, but directly from the laws of physics of the system analyzed [40]. In condition monitoring this type of model is known as Physics of Failure (PoF).

3.4.4.2 Numerical models

Numerical methods use complex algorithms to diagnose faults and do not require in-depth knowledge of the failure mechanisms.

Feature extraction and pattern recognition algorithms compare a set of predefined reference signals with portions of the measured signal (feature extraction) then try to find similarities between them and finally classifying the measured signal accordingly (pattern recognition) [40].

Artificial Neural Networks are systems that emulate the way the human brain process the information. In any generic system, data is fed (input), then the information is processed; whereas in an ANN the inputs are detected and a desirable or target output is given, then based on this information the system calculates what combination of parameters yields the target output based on the current input. Neural networks are used in fault diagnosis when there is no much information about the process, the signals or the fault patterns [40].

Statistical models find changes in the mean or variance of the data measured based on assumed statistical distributions of the parameter measured. Failures usually follow a specific density function and therefore they can be detected early by using this process. Statistical models are good for systems with repetitive failures, since their failure distribution can be estimated relatively easy.

Fuzzy logic models are ruled-based (if-then) systems that use truth values ranging from 0 to 1 to describe conditions as opposed to binary (yes/no) values used in other methods. Fuzzy models are particularly useful when failure mechanisms analyzed are non-linear since it uses qualitative analysis that incorporate expert knowledge.

The main pros and cons of these models are shown in Table 3-1.

Table 3-1 - Comparison of most common models for fault detection, diagnosis and prognosis

Type of model	Advantages	Disadvantages
Knowledge-based		
Faults/symptoms	Does not require complex algorithms. Little knowledge about failure mechanisms required.	Does not provide in-depth information about the fault and its propagation.
Casual tree	Provides detailed information about the possible cause of the failure. Does not require complex algorithms. Good for fault isolation.	It cannot find all the possible failure causes. Not practical to use when failures are state dependent. In-depth process knowledge required to develop the model.
First principles (Physics of failure)	Limited amount of data required. Good for new designed complex equipment. The knowledge is not dependent of subjective human judgment. Good knowledge of the equipment behavior is obtained.	The model is just an approximation to the real process. Every piece of equipment requires a separate model. Signals measured must be highly accurate. In-depth process knowledge required to develop the model.
Numerical		
Neural network	Little influence by noise. Very fast even for complex systems. Little knowledge about process, signals and fault patterns is required.	Complex training of the neural network. Large measured data sets are required. Valid results are confined to the trained range.
Pattern recognition	Different faults can be detected independently from the same signal (in case of no correlation of faults). Little process knowledge required. Little influence by noise. Suitable when mathematical models for equipment are not available.	Fault measurements needed. In-depth knowledge of the sensor signal behavior required. Large effort needed to build the algorithms.
Statistical	Relatively easy to set-up. Provide accurate results for system with known mechanism of failure and reliability data.	Not good for detection of rare anomalies. Requires large historical data. Accuracy depends on parameter estimators chosen.
Fuzzy logic	Little knowledge about failure mechanisms required. Fast and robust implementation. Possibility to include a-priori knowledge into the model.	Every piece of equipment requires a separate model. Changes in the system require reprogramming of the model.

3.4.4.3 Hybrid models

When one type of model cannot predict the fault and state of health of a machine with the expected level of confidence, a combination of a numerical algorithm with a knowledge-based model is recommended. This hybrid approach can yield very accurate results, because it combines data trends with equipment behavior, but it must be noted that hybrid models require great level of expertise in both SPS operation and algorithm conception.

3.4.4.4 Model recommendation for Cameron subsea production systems

There exists large reliability data both within Cameron and outside the company (e.g. OREDA); therefore it seems logical to use statistical based models for failure detection and prediction. Nevertheless, many of the faults in a subsea system are sporadic, which makes trending difficult and require the use of other diagnosis/prognosis methods. The author recommends the two types of approaches depending on the nature of the failure, as described below.

For mechanical components is advisable to combine statistical models faults/symptoms diagnosis. The statistical method will cover those failures with slow degradation, whereas the fault/symptoms model will discover faults that are intermittent, but with known behaviors. For most mechanical components, the failure mechanisms are simple and known, which makes this diagnosis approach ideal. An example of mechanical failure is the degradation of a choke valve due to erosion; this problem can be noticed if the flow rate starts to increase but the pressure drop remains unchanged, such that it is necessary to close in the choke a few steps to maintain a set production rate.

Electrical failures have more complex behavior and therefore should be treated differently. Since the physics of failure are known for most electrical components it is advisable to use a statistical-PoF hybrid approach for fault diagnosis when statistical data is available. Conversely, if the distribution of the available data is not known or the amount of records is not sufficient (e.g. new design), the PoF model can be improved by combining it with ANNs which are ideal for machine learning when historical data is scarce. Lastly, in case that the failure mechanisms are not known, it is recommended to use a pattern recognition model instead of PoF.

These recommendations are for conventional subsea production systems. For more complex architectures such a subsea processing, compression or all-electrical systems, the use of other approaches might be necessary.

3.5 Advisory generation

After the diagnosis and prognosis have been made, the system should advise actions required to avoid total failure in the near future and/or to extend the lifetime of the equipment. The recommendations provided by the advisory generation system should be generated automatically, with the option of manual input from Cameron experts in case of complex failure mechanisms or combination of them.

A decision support system is the final result of CM and is key for asset management optimization because it provides the users with a solution in case of failure, i.e. *what to do when faults are detected?*

3.6 System display

Information about the condition of the SPS should be presented to the user all through the monitoring process, i.e. fault detection, diagnosis of faults, prediction of future degradation and/or failure, and maintenance/operational advisories. The information shall be presented in the simplest form to avoid confusion and guarantee the issues are spotted correctly and quickly without need for guessing.

4 Case studies

To illustrate the process of implementing a CM system in a conventional SPS, two case studies are presented hereafter. For each case study only the blocks of measurement, data acquisition and processing, and diagnosis and prognosis are studied individually because these are the only blocks that will present specific information for the system. The block of system classification is explained in section 3.1, and the block of advisory generation is presented at the end of the second case study, as this block is common for both cases, i.e. there is only one advisory generation system for the whole SPS.

An information display system for the SPS is recommended and described in section 4.4. Conclusively, some commercial options for integration of the CM system into a single software platform are compared and discussed.

4.1 Case study 1: Xmas tree gate valves with hydraulic actuators

4.1.1 Measurement

4.1.1.1 Identification of equipment and function

In this section gate valves and hydraulic actuators used in a subsea XTs will be studied. The purpose of these valves is to isolate and direct the flow of hydrocarbons or injection fluids. The majority of the valves in a subsea XT are of the gate type and they function either fully open or fully closed. These valves are of the fail-closed type, meaning that in case of system failure (e.g. loss of power) the valves move automatically to closed position to avoid flow through the system. An example of valves arrangement in a subsea XT is shown in Figure 4-1.

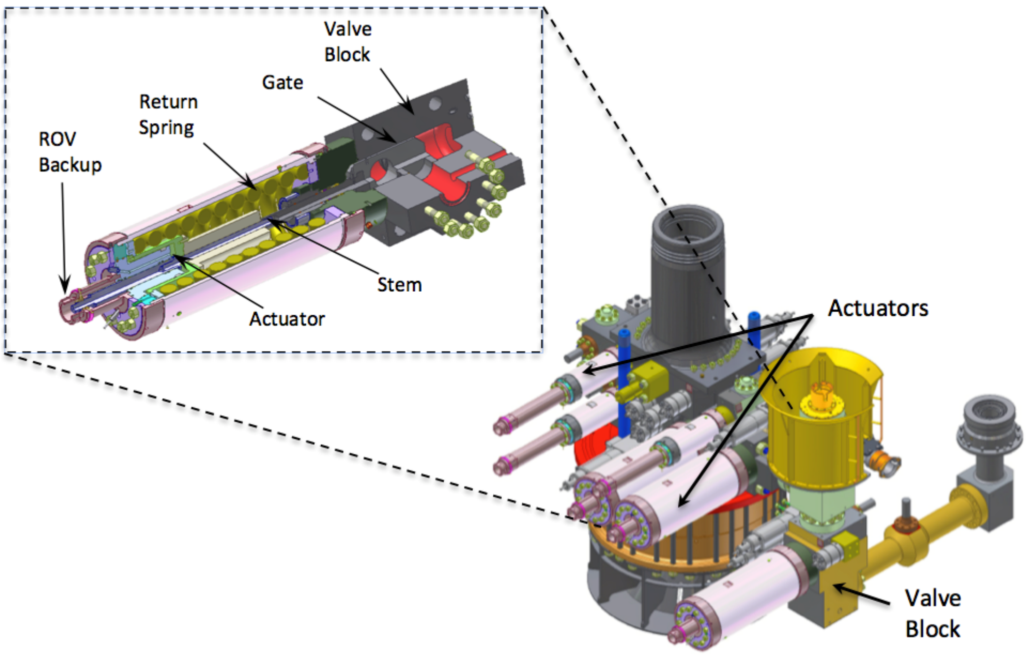
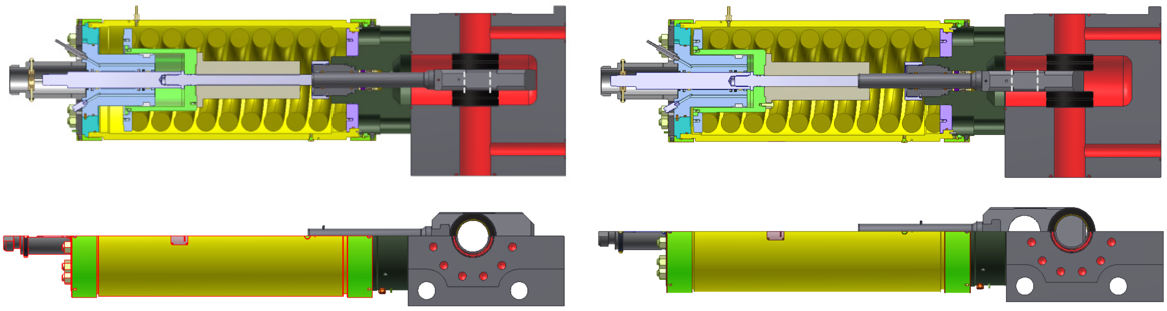


Figure 4-1 - Hydraulic valves and actuators installed on subsea XT (source: Cameron)

The valves and actuators described herein operate in the following manner: if the valve needs to be opened, pressurized hydraulic fluid is sent into the chamber to push the actuator. Once the force exerted by the actuator on the return spring overcomes the opposing forces, the stem moves inside the valve exposing an opening in the gate that matches the opening in the valve block, letting the fluid go through (see Figure 4-2a). To close the valve, the hydraulic pressure is released and the spring force moves the actuator back to its original position (see Figure 4-2b).



a) Valve open b) Valve closed

Figure 4-2 - Opening and closing of a hydraulic gate valve (source: Cameron)

4.1.1.2 FMSA

The failure modes and causes obtained from OREDA and Cameron internal reliability databases are listed in the FMSA in appendix B. For the purpose of this thesis the FMSA will be done at the subsystem level. This level of detail will provide enough information about the techniques needed to monitor the equipment.

4.1.1.3 Analysis

Based on the methods of detection selected and listed in the FMSA, there are 10 CM techniques that could be used to detect the possible failure modes. Some failure modes can be detected with more than one monitoring method; when this is the case the MPN should be used to select the technique with the highest ranking, hence the most efficient to detect the failure. At least one monitoring method per failure mode should be selected to ensure all the failures are covered. Some of the monitoring techniques required are typically used in Cameron SPS's, while other methods will have to be added to the system. The CM techniques with the highest MPN and covering all the failure modes found in the analysis are shown in Table 4-1.

For some of the failure modes two CM techniques with the same MPN are listed, these are flow metering of control and process fluids. Since both measurements are currently available in most SPS's, they both will be used to monitor the condition of the valves, increasing in this way the reliability of the monitoring system for these failures.

Table 4-1 - CM techniques required to detect valve failures

Methods of detection currently available	Additional methods of detection required
Process pressure monitoring	Periodic pressure testing of the barrier philosophy
Process fluid flow metering	Fluorescence leak detection system
Control fluid flow metering	Partial stroke testing
Control fluid pressure monitoring	Valve signature analysis

The monitoring techniques currently used in typical Cameron SPS's have been used extensively by Cameron and therefore will not be described here. The new methods proposed by this research work are explained below.

Periodic pressure testing of the barrier philosophy

This method is used to detect the integrity of the seals in the main blocking valves of the tree, which are the Production Master Valve (PMV), and the Production Wing Valve (PWV). To do the test both valves should be closed, then test fluid is introduced at a pressure equal to or slightly higher (max 10% higher) than the normal system operating pressure. The pressure is held and recorded for 10 minutes in case of oil fields or for 60 minutes in case of gas fields. If the seals are in good condition the pressure should remain constant during the whole testing time, otherwise a decay in the pressure will be observed (see example in Figure 4-3).

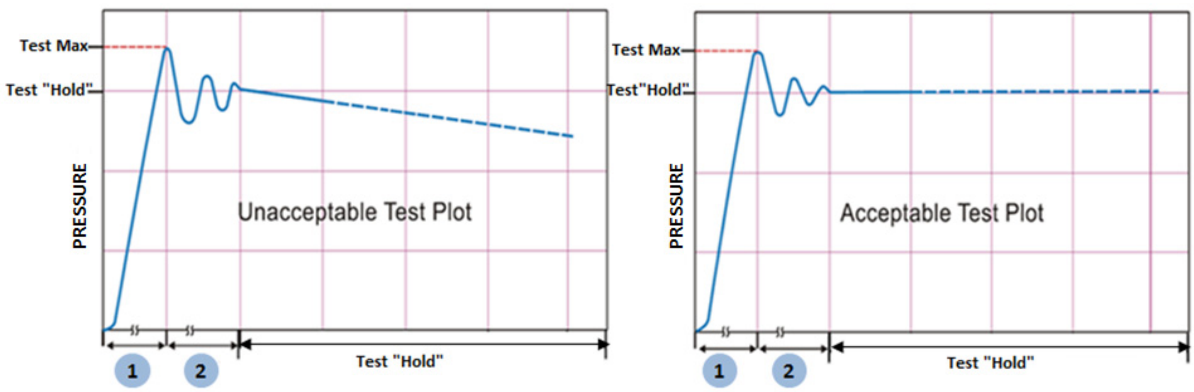


Figure 4-3 – Examples of pressure test plot [41]. 1: Pressurization, 2: Stabilization.

Support vessels are normally used to conduct the test. The vessel will connect the test line to the tree through an access valve located between the PMV and PWV as shown in Figure 4-4. When positive pressure is provided through the test line, the seals on the PWV are tested. This is because the pressure is acting on the upstream side of the valve emulating normal operating conditions, but for the PMV this positive pressure is acting on the downstream side, thus not representing a real scenario. To test the seals on the PMV a negative test should be conducted. This test is similar to the positive pressure test previously described, with the difference that the system is depressurized instead of pressurized, and leaks are detected if there is an increase in the pressure recorded, indicating that process fluid is passing through the PWV seals.

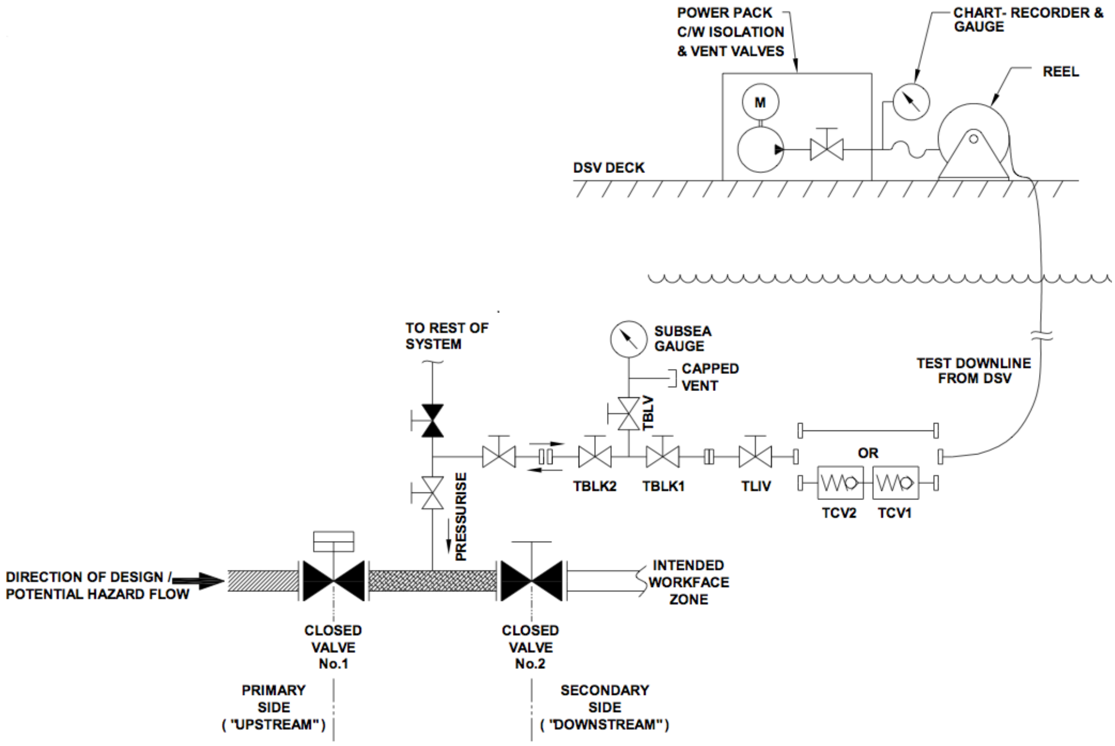


Figure 4-4 - Positive pressure test [41]

NORSOK standard D-010 [38] recommends to carry out this test once a month until three consecutive tests have been performed, then once every three months until three consecutive tests have been carried out and after that only once every six months. This could add significant operating costs to operators and one alternative is to do the test from the topside facility by using the chemical injection line, provided that this line connects to the tree between the PMV and PWV.

Fluorescence leak detection system

This system described in section 2.4 consists of use of fluorometers that detect different of wavelengths of light absorbed by seawater and hydrocarbons. In case of standalone trees one detector per tree is sufficient. When trees are grouped in templates, several sensors may be needed depending on the size of template, since the effective radius of detection is about 5m. A new design of fluorometers [42] promises a range of detection up to 10m.

An example of sensor arrangement in a template with 4 XTs is shown in Figure 4-5. This type of sensor is particularly efficient for oil detection, but not for gas. For the latter, acoustic leak detectors are recommended.

Figure 4-5- Fluorometers installed on subsea template

Partial stroke testing

The easiest way to verify if a valve fails to close on demand is by shutting the valve and then opening it again. This is done during the periodic pressure testing described previously; however, these tests are not carried out frequently enough to provide good indication of the valves over a long period of time. On the other hand, shutting the valve frequently for testing adds some disruption to the system such as temporary loss of production and stop/start procedures that should be done only when completely necessary. A solution for this is to do partial stroke testing, which consists in closing the valve only 20% and opening it again. By using this procedure one can detect if the valve is stuck or if there any issues preventing or slowing down the valve closure. The analysis of the parameters measured by partial stroke test can be done by comparing the signature of the valve as new with the signature of the partial stroke performed. This method of valve signature analysis is explained below.

Valve signature analysis

Valve signature or valve profile refers to the behavior of valve/actuator parameters with respect to each other, under specific operational conditions. Due to the mechanical nature and fabrication tolerances of the valves components, each valve will have its own unique signature. This behavior profile should be recorded before the tree is put into production when the valve is still in new condition, for example at the factory acceptance test. This original signature will represent the baseline and will be used later to compare the performance of the valve after many hours of operation.

For the valves analyzed in this case study the author recommends a valve signature of actuator *pressure vs. opening (or closing) time*. Even though this analysis might seem simple, a plot of pressure vs. actuating time can provide a lot of useful data. From this graph one can see the different stages of the valve opening or closing. The pressure is measured by a sensor installed in the low pressure line and the values are collected by the SCM.

A pressure-time plot has been created using real data from Cameron MCS, to exemplify the valve profile concept. The values listed in appendix C have been used to create the plot shown in Figure 4-6 by using spreadsheet/graphing software. The graph shows the operation of a valve in new condition (green curve) and a valve with some degradation or mechanical defect (red curve). The green curve is based on real values acquired by the SCM, while the red curve is just a simulation of the behavior of a defective valve. From this plot one can notice the valve coming off its seat, the breakaway point, the actuator spring compressing and the valve contact with the seat. The breakaway point is the moment in time when the actuator overcomes the opposing forces (spring resistance, friction, hydraulic pressure on return side, etc.) and starts moving.

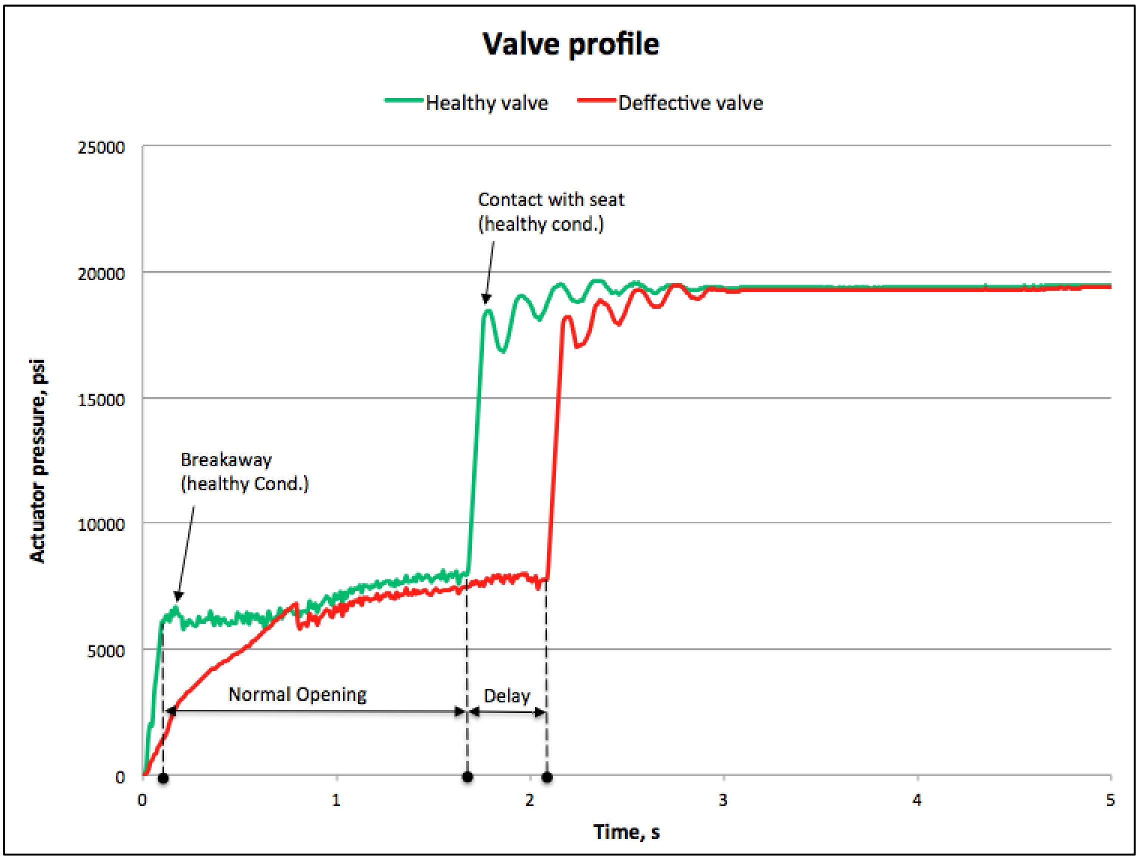


Figure 4-6 - Valve profile (opening)

Looking at the graph one can depict that it takes about 1.8 seconds to open the valve when it is in healthy state. Once the valve hits the seal, the pressure builds up rapidly until the maximum hydraulic pressure given by the system (ca. 19000 psi) is reached. A hypothetical failure has been plotted (red curve) to see the how the profile varies from a healthy condition. In the red curve, one can see slower pressure increase when the valve is being opened; it takes about 0.3 additional seconds for the valve to be fully open, which is an indication that something is wrong with the system, possibly an obstruction in the hydraulic line or a leakage in the piston seal.

Pressure-time behavior should be known for the most common failures and these patterns can be fed into the diagnosis algorithms to determine automatically the cause of failure.

4.1.2 Data acquisition and processing

4.1.2.1 Data acquisition

The physical properties measured by the sensors (e.g. pressure) are converted to electrical signals ranging from 4-20 mA, where 4 mA corresponds to the lowest limit of the range and 20 mA to the highest end. Then these electrical signals are converted to a discrete time digital value that represents the physical property measured. For instance in a pressure transmitter that has been calibrated to measure from 0 bar (4 mA) to 10 bar (20 mA), a signal of 12 mA (50% of the range) will be represent a pressure of 5 bar.

The analog data is collected and digitized by the subsea electronic module in the subsea control module and then transmitted to the master control station for further processing.

4.1.2.2 Data manipulation

In the instance of the parameters measured in this case study the raw data received by the MCS is in the proper form for further analysis; as a result there is no manipulation of data needed.

4.1.3 Models for fault detection, diagnosis and prognosis

4.1.3.1 Periodic pressure testing of the barrier philosophy

For the periodic pressure test of the PMV and PWV no complex model is necessary. The evaluation criterion simply consists on evaluating the hold pressure and visually detecting if the pressure varies. This process could be automated, but since pressure tests usually require witnessing of the procedure to create quality control records, a manual verification is sufficient.

4.1.3.2 Leak detection system

Detection of hydrocarbon by fluorescence or acoustic signals is done by detecting presence or not of hydrocarbons within the sensor range. Thus, the use of predictive models is not applicable for leak detection.

4.1.3.3 Partial stroke testing and valve signature analysis

A simple pattern recognition model is recommended for gate valves and hydraulic actuators. This model will be based on empirical results obtained when new valves are tested after assembly in the XT. The result of these tests is the original valve signature, which will be used during operation to compare the values in working conditions vs. the values of the original signature. It is worth to mention that in addition to internal forces of the actuator i.e. spring force, pressure on the return side or piston side, piston seal friction and stem packing friction; the wellhead pressure also adds resistance to the opening/closing of the valve during normal operation; however these forces are negligible when compared with the high force exerted by the actuator and will not be taken in consideration.

For partial stroke testing the analysis is similar to the one previously described, with the difference that the valve opens only for a short period of time with the purpose of obtaining approximately 20% of the closing span. Since the valves in question do not have position indicators, other methods should be used to estimate when the valve is 20% closed. The author suggests using the valve signature for reference of closing time. One can say for example that if a new valve takes 0.2 seconds for the gate to come off the seat (breakaway) and then 2 seconds to close fully from the breakaway point, it would take approximately 0.6 seconds (breakaway time + 20% closing time) to close 20%. This value is not exact since the closing of the valve is not linear due to the spring action, but in this case that is not so relevant because the accuracy of the closing range is not critical for the test. The objective of this partial stroke test is to plot the pressure decay of the valve closing up to 20% and compare it to the original signature, to see if there are any major discrepancies that could indicate some issues with the valve or actuator such as gate obstruction or spring failure.

4.1.4 Discussion

At first glance a subsea gate valve with hydraulic actuator might seem a relatively simple device, especially due to the lack of electronics and the limited range of motion. But when the analysis of failure modes was carried out, the results contradicted the initial estimation. The valve and actuator analyzed in this case study can have many failures of different nature. Consequently, the monitoring techniques necessary to ensure proper predictive maintenance can be many and represent a considerable capital investment.

The FMSA is probably the most important step in establishing a CM program. This document provides important and relevant information to determine the type of sensors to be used, crucial data for establishing a "best in class" CM program. It is very important to get input from experts with vast experience in fault management of subsea systems, as well as use reliable historical data.

The key for effective implementation (both economically and technically) of CM lies in using the sensors and equipment already available in existing SPS's in a smart way. This has been demonstrated with the valve signature analysis proposed earlier, where simple signals currently measured in any SPS are used to determine the health of the valves/actuators. There are many other ways to do signature analysis. For example, by using position detectors coupled with electronic valve position analyzers, but the question the designers of the CM system have to ask themselves are:

- Do we really need a new sophisticated system?
- Will this new system provide much more useful information than others?
- Can we determine the health of the equipment by other –and simpler- means?

Regardless of the simplicity of the valve profile analysis, the efficacy of this method relies on the quality of the original signature; if the latter cannot be trusted it will not be able to provide an accurate baseline to be compared against the valve profile during operation. This highlights the importance of having a good factory acceptance test of the trees when they are fabricated, so reliable valve signatures are generated for further use.

Another interesting finding is that in many cases there is no *one size fits all* solution available. That is the case of leak detectors. Even though subsea leak detection is a relatively small technology niche, there are a handful of different technologies that can be used in different scenarios depending on the type of fluid being monitored, leak rate detection sensitivity, and effective area of sensor coverage.

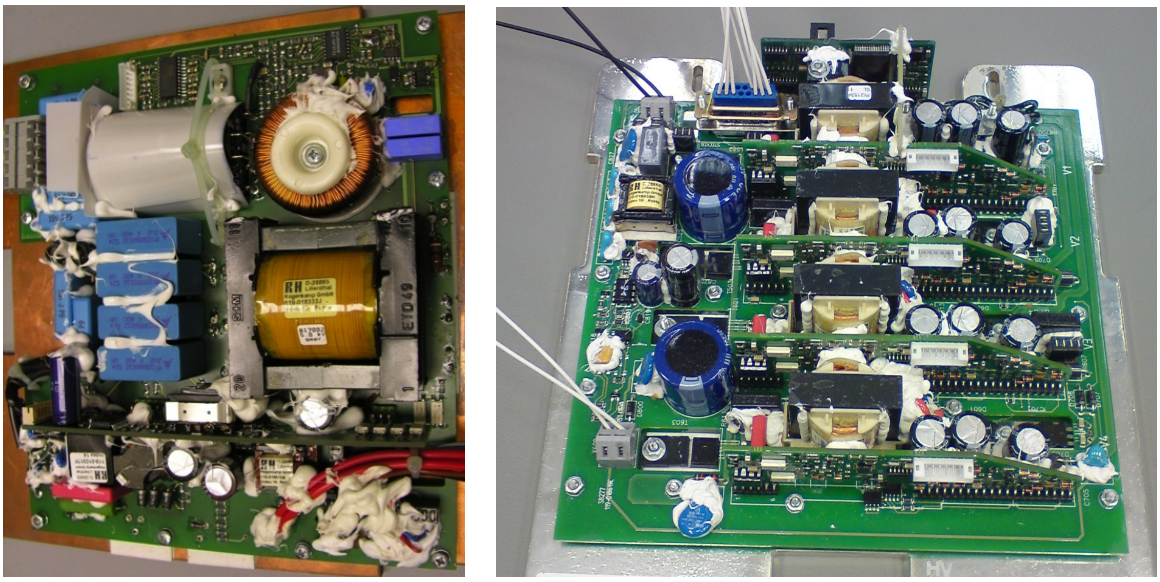
It is also significant to notice the importance of keeping to a minimum the equipment shutdowns for testing the integrity of the systems. One way to deal with this is by executing the partial stroke testing explained in the previous section, which allows for testing the opening and closing function of the valves without stopping production.

4.2 Case study 2: Power supply unit

4.2.1 Measurement

4.2.1.1 Identification of equipment and function

The Cameron Power Supply Unit (PSU) shown in Figure 4-7, is a device located inside the Subsea Electronic Module in the SCM and which main function is to convert the high input voltage to a low output voltage to supply the SEM/SCM internal electronics and all connected SCM external instruments with electric power.



a) Input module **b) Output module**

Figure 4-7 - Cameron Power Supply Unit (source: Cameron)

The PSU is composed of one input module (a) and one output module (b). A detail schematic of the PSU cannot be presented here due to proprietary information from Cameron and PSU supplier. However, a simple flow diagram (see Figure 4-8) has been created to describe how the unit works.

First, the input module receives Alternating Current (AC) power; next this power is filtered and rectified to convert it in Direct Current (DC). Then the current is limited to 350 VDC by a chopper, after that the power passes through a power factor correction circuit and is finally sent to the output module where 4 step-down converters transform the 350 VDC to 24 VDC output voltage which is the standard supply voltage for external instrumentation according to SIIS. The input voltage to the PS can be in DC or AC. In the case of input power in DC, the current does not need to be converted and the rectifier acts only as a conductor. Cameron PS can receive an input voltage ranging from 300 to 850 VAC or 400 to 1200 VDC.

The power supply unit depicted here is the latest model developed by Cameron and its supplier; it has the capability to be monitored extensively and it is expected to have better reliability than previous models.

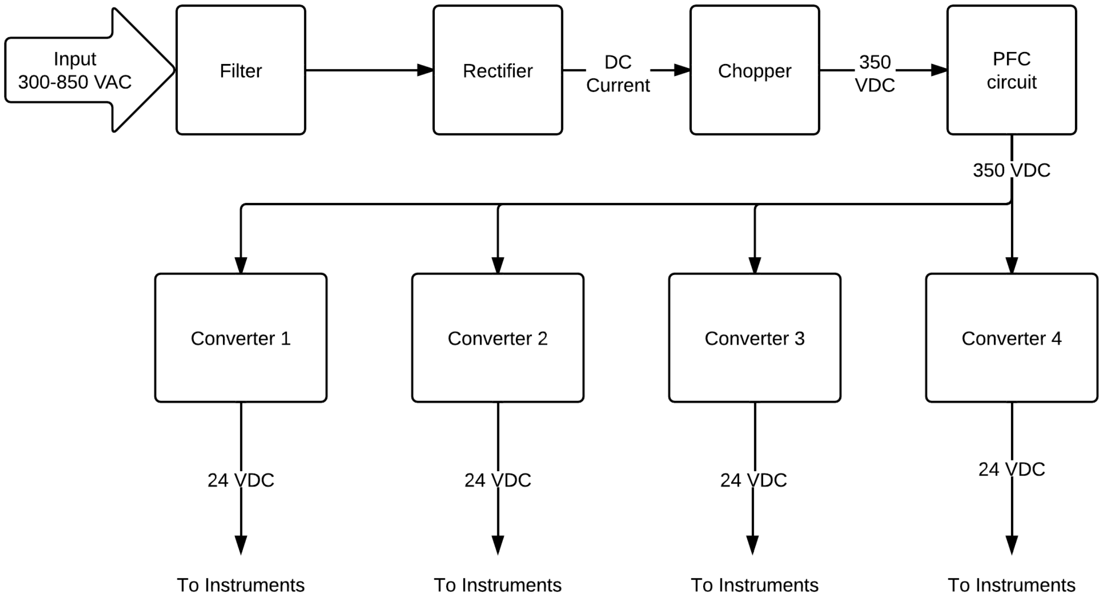


Figure 4-8 - Power supply unit flowchart

Each SCM has two SEMs for redundancy and there is one PSU in each SEM; this means that in case of a PSU failure in one of the SEMs, the other unit in the other SEM should take over as soon as the failure is detected to maintain functionality of the system.

4.2.1.2 FMSA

Appendix E contains the failure modes, symptoms and appropriate monitoring techniques for the PSU. Since this PSU is a new model, there was no reliability data from field experience available. Hence, the FMSA study was based mostly on experts' advice. Another way to find the possible failure modes is by performing an accelerated test, where the unit is subjected to high stresses over a relatively short period of time to simulate the stresses expected over the lifetime of the equipment.

4.2.1.3 Analysis

The PSU described earlier has the capability for monitoring multiple variables, these are:

- Input voltage and current
- Output voltages and currents
- Various temperatures
- Circuit voltages
- Microcontroller status

These parameters will allow detection, diagnosis and prognosis of the failure modes listed in the FMSA. Some of these variables will require the use of algorithms to interpret the symptoms; these are explained in detail in section 4.2.3.

4.2.2 Data acquisition and processing

4.2.2.1 Data acquisition

Due to the electronic nature of the PSU, all the data collected is already digitized and it only needs to be time/quality stamped in the SCM and then sent to the MCS for further processing.

4.2.2.2 Data manipulation

When the input power is in AC, the effective current and voltage have to be calculated using the Root Mean Square (RMS) method. This conversion is necessary due to the sinusoidal form of the AC. As seen in Figure 4-9 the AC voltage (and current) fluctuates between a positive peak and a negative peak. Since most the time the voltage (or current) is somewhere in between the extremes, the peaks are not good representative values. That is why the voltage and current are expressed in RMS terms by applying the following formula:

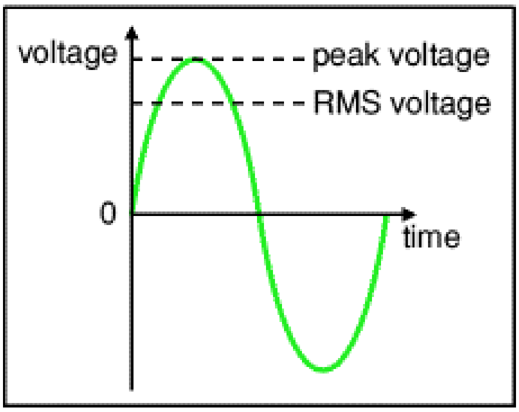


Figure 4-9 - AC peak voltage and RMS

$$V_{RMS} = 0.707 \times V_{peak} \quad (4)$$

Where:

V_{RMS} is the root mean square voltage

V_{peak} is the peak voltage

Equation (3) is also applicable for current. In the case of DC voltage it is not necessary to calculate RMS because the signal steady.

4.2.3 Models for fault detection, diagnosis and prognosis

Since the failure data is scarce because the PSU has not been yet in operation and also due to the nature of the failures, it is recommended to use a Physics of Failure approach. This method consists of estimating the state of the equipment and predicting its RUL by comparing current environmental and operational loads with a predictive model of degradation. Pecht (41) explains how this method is based on the assumption that the level of exposure (time and magnitude) of a system to external loads determines its degree of degradation. A PoF method is developed in the following manner [43]:

- Identify possible failure modes and the environmental and operational loads that could cause these failures (FMSA).
- Determine the dominant failure mechanism, by using accelerated test or expert's advice.
- Develop a behavioral model of the dominant failure mechanism.
- Create an algorithm for failure detection and calculation of RUL, based on the data obtained in accelerated tests and statistical distributions applicable to the failure mechanism.

Environmental loads are those conditions external to the function of the equipment that can affect its performance in one way or another. Environmental loads can be thermal, mechanical, chemical or physical. Operational loads are those factors inherent to the function of the equipment that can have an effect on its performance, such as voltage, current or resistance.

In the case of the PSU, the most important factors to develop the model and monitor the health of the system are the temperature of the PSU, the input and output voltages, and input and output currents.

4.2.3.1 PSU failure

To predict general failure of the PSU (item 1.1 in FMSA) caused by thermal cycling, it is recommended to use the Coffin Manson's model [44, 45], which requires an accelerated test to validate it. The model is defined by the following formula:

$$N_{fu} = N_{fa} \times \left(\frac{\Delta T_A}{\Delta T_u}\right)^2 \tag{5}$$

Where:

N_{fu} is the number cycles to failure at operating temperature change

N_{fa} is the number cycles to failure at accelerated temperature change

ΔT_a is the thermal cycle temperature change in accelerated environment (˚K)

ΔT_u is the thermal cycle temperature change in operating environment (˚K)

4.2.3.2 ESR estimation

According to Imam et al. [46], the most common cause of power supplies breakdown is attributed to the failure of electrolytic capacitors. These components are responsible for storing and filtering the electrical energy coming out of the converters.

The main symptoms of a degraded electrolytic capacitor are an increase in the Equivalent Series Resistance (ESR) and a decrease of the capacitance. The ESR cannot be measured directly, but it can be estimated by finding the relationship between the ESR and other variables available for diagnosis. There have several models developed to estimate this relationship based on PoF; two of these methods are explained below.

It has been demonstrated that an increase in the ESR generates elevates the ripple voltage of the converter. By finding the relation between ESR and ripple voltage the degradation state of the capacitor can be estimated. This is called the failure prediction method and can be summarized by the following formula derived by Chen et al. [47]:

$$\mathrm{ESR} = \frac{V_{O,ac}}{I_{L,ac}} \tag{6}$$

Where:

$V_{O,ac}$ is the output AC ripple voltage

$I_{L,ac}$ is the inductor current AC component

Another approach that can be used to estimate the ESR, is the life prediction method, which consists of calculating the temperature increase caused by the ripple current and relate this value with the ESR. This relationship has been defined by Kulkarni et al. [48] using this equation:

$$\frac{1}{ESR_t} = \frac{1}{ESR_0}\left(1 - k.t.e^{\left(\frac{-4700}{T+273}\right)}\right) \tag{7}$$

Where:

ESR_t is the equivalent series resistance ($m\Omega$) at time t

ESR_0 is the equivalent series resistance ($m\Omega$) at time $t=0$

k is capacitor constant, determined empirically and dependent on the capacitor size and geometry

t is the time in operation (hr)

T is operating temperature of the capacitor ($°C$)

According to Kulkarni et al. [48] an electrolytic capacitor will reach the end of its useful life when the ESR value is 2.8 higher than its initial value.

4.2.4 Discussion

Diagnosing and predicting failures of parts with no records of operation, such as the new PSU described in this case study, requires a different approach than for devices with long history of operation and maintenance. The author proposes using accelerated life tests coupled with PoF models for newly designed equipment or parts.

Even though the PSU analyzed is a complete new design, it still has several characteristics in common with its predecessor. This similarity of parts is normal not only for the PSU, but also for most of the novel equipment. One key to determine possible failure modes is to find those commonalities and check if there are old failure modes that could be present in the new design. For this, it is very important to involve engineers and technicians with vast experience in maintenance of the legacy system. Moreover, if the new part is designed and/or fabricated by a third party, the supplier should also be consulted because it might have some failure data of similar parts used in other applications.

Another important aspect if failure prediction of newly designed equipment is the corroboration and refinement of the models created for fault diagnosis and prognosis. When parts are replaced due to failure, the actual condition of the part should be compared with the degradation estimated by the model to see if the predictions are accurate. In the case of noticeable discrepancies, the model should be refined to provide better diagnosis/prognosis in the future.

4.3 Advisory generation system proposed for Cameron SPS

One of the most important features of a CM system is the ability to provide decision support for maintenance planning and equipment operation. The goal of the advisory generation system is to tell the operator what to do in case of presence of a fault or failure, without the need for expert input and with high level of confidence.

Recommended actions provided by the system are based on the results of the prognosis and could be one or more of the following:

- No action required
- Change operational parameters to reduce the strain on the affected part to extend its lifetime, at least until the next maintenance campaign.
- Reconfigure the system to bring it back to normal operation, for example by using parallel standby equipment.
- Perform further analysis, for instance visual inspection by ROV.
- Maintenance intervention required within a certain timeframe specified.
- Immediate maintenance intervention.
- Stop the equipment immediately to prevent irreversible damage or catastrophic failure.

The information conveyed by the system should be as specific as possible, for example:

> *Under current operating conditions of production, the choke valve tag # PCV-12 has a 95% probability of achieving a RUL of 400 hrs; or as a mitigating measure if flow is reduced by 50%, the RUL can be extended to 650 hrs with a probability of achievement of 90%*

The information can be presented as simple text or better yet in graphical form, such as the dashboard exemplified in appendix D.

Since Cameron access to information from the field operator is limited to the equipment and operating conditions, the actions/solutions proposed by the advisory system can provide recommended time for intervention based only on the RUL estimated and not on external factors, such as availability of support vessel/rig, maintenance personnel, spare parts; opportunity cost; maintenance campaign scheduled for the same field; etc. Consequently field operators should consider all other factors that will affect positively or negatively their production strategy if the recommended action is taken as it is.

In order to integrate decision support systems with the end user operator's asset management system, there has to exist some kind of standardization in the way the data is saved, formatted and transmitted. A non-profit organization has been created to deal with this standardization issue: the Machinery Information Management Open System Alliance (MIMOSA).

MIMOSA has developed a vendor-neutral open information exchange standard that provides open system architecture for condition monitoring, as well as rules for integration of the monitoring system with enterprise applications for asset management [49].

The actions suggested by the advisory system are not necessarily absolute. If the user needs to make a change in the maintenance strategy proposed by the system, it could probably be done, but they should contact Cameron for further discussion and risk evaluation of alternative solutions.

4.4 Display system for Cameron SPS

The purpose of the CM display system is to provide audiovisual information about the condition of the subsea production system, including presence of faults, alerts/alarms related to equipment faults, state of the equipment, estimated RUL, possible future failures, and provide recommendation for equipment intervention when needed.

Taking human factors into consideration, the system should be designed as *ruled-based*, i.e. operators are not required to have interaction with the system to detect any anomalies, unless and alert, alarm or trip goes off. Once a fault is detected, the operator should follow a set of predetermined rules to get more information about the problem and how to proceed. This process can be illustrated with a simple example:

A SPS is currently working normally without need for operator's surveying of the system, other than process monitoring. An alert is then generated**:**

Alert! ΔP across choke valve PCV-12 is X bars under the normal operational limit

At that point the first rule is activated; the operator should check if there have been any changes in the operation condition that may have triggered the alert or if this could be a real sign of choke degradation.

There are many ways to present the information. The author recommends the use of **dashboards** to convey the information to the operator in a way that is easy to understand and with minimum room for misinterpretation of information*. Dashboards are commonly used to monitor production or business processes and have been adopted by many industries. Dashboards should have a simple design; these are some basic rules for process representation (88):

- Bright saturated colors should be used only to indicate abnormal conditions.
- Avoid 3D or complex representation of equipment.
- Data is not information, unless that is presented in the proper form.
- Visual indicators are most effective than just values.
- Trends in equipment operational parameters should be included.
- Avoid process representation by Piping and Instrumentation Diagrams (P&ID).
- Displays should be organized by hierarchy for proper navigation.

The last point above denotes that the system should contain one main display showing the overall health information of the whole system and a set of sub-displays with more detailed information about the subsystems and even down to the component level. When a fault is detected, the user should be able to look deeper into the more specific displays to find information about the root cause.

Due to the remote nature of a SPS system, the graphical representation of the equipment is not so relevant. What is more important is that the data presented provides the user with useful information about the condition and possible faults/failures of the SPS and its different elements; hence there is no need to display fancy pictures of the equipment or detailed field layouts. The user should be able to get the following information at a glance:

- Is there anything wrong with the condition of the equipment? If so,
- What is wrong?
- What is the current condition of the equipment?
- How long can the equipment continue working without breaking down or having a catastrophic failure?
- Will this problem cause other faults?
- What can be done to mitigate and/or fix the problem?

4.5 Integrated solutions for fault detection, diagnosis and prognosis

There exist several interesting software packages in today's market for condition monitoring. These programs provide a common platform for the different conditions monitored in an industrial system, analyzing the data and presenting it to the user in a friendly format. The extent of the information provided varies among the different packages, some offer fault detection and diagnosis while others include also

* Please note: The design of system displays or Human Machine Interface (HMI) is a field of study on its own and it is not covered here in detail. The aim of this thesis is by no means to provide detailed guidelines for HMI design.

estimation of remaining useful life; some are experienced in subsea systems while others are not.

The author has studied several of the software packages available and has chosen the three more suitable for SPS's to evaluate them and propose the best alternative for Cameron to use in the CM of subsea equipment.

The packages studied and the companies that make them have been named A, B and C for simplicity and to avoid commercial issues. Since the information available over the Internet about these software is scarce and of marketing nature, all three suppliers have been contacted directly to obtain as much information as possible about their products.

Company A/Software A have been in the business of equipment surveillance for many years and has proven experience in monitoring aerospace vehicles, land transportation, sea transportation, power generation, healthcare. This software offers fault detection, diagnostics and trending; it seems very complete, but the company weakness is their lack of experience and knowledge in subsea systems and oil/gas production. Company A has expressed their interest in developing a software solution for Cameron based on their broad experience, provided that Cameron supports them with the knowledge necessary, such as failure modes, operational procedures, maintenance history, equipment drawings and manuals, etc.

Company B started by developing CBM software for the maritime industry and they have extended and adapted their product range to oil/gas production, specifically to subsea systems. The system is based on the technical condition index described in section 2.3.1.

Company C offers a software platform for remote monitoring and diagnosis that has been proven in oil and gas production, including a subsea installation in the Norwegian Sea. The current product does not have the capability for prognosis of future degradation or failure; however, company C has extensive experience in advanced algorithms including NN and fuzzy logics, and they are willing to develop a prognosis system specifically for Cameron.

The main features of each company/software are presented in Table 4-2.

It is clear that the three software solutions presented hereinbefore are quite competitive. Based on this preliminary information, the author believes that company "A" provides the best solution; they seem to have the most mature system and algorithms. Even though company "A" does not have experience with subsea systems, they have the potential to develop a customized solution for Cameron, as long as they are given support and necessary data. This recommendation is based on the information about the companies available over the Internet and various communications held with each supplier.

The author further recommends having formal technical and commercial evaluation of the three competitors. One way to make the assessment as fair as possible is to present all three companies with a base case study, including a sample data set for them to develop a solution and provide a technical and commercial proposal. This way it would be easier to compare the different options presented.

Table 4-2 - Software comparison

Feature	Software A	Software B	Software C
Years in business	19	17	N/A*
Experience in oil and gas	No	Yes	Yes
Experience in subsea	No	Yes	Yes
Fault detection	Yes	Yes	Yes
Diagnosis	Yes	Yes	Yes
Prognosis	Yes	No	No
Mobile alert capability	Yes	No	Yes
Web access capability	Yes	Yes	Yes
Other features	Software hosting, i.e. the supplier can run/maintain the software, analyze the data and provide decision support.	Traffic light alert system. System based on TCI.	Based on expert diagnostic knowledge

* N/A: no public information was available by the time this report was written

5 Recommendations for further work

Due to the time and resource constraints inherent of this type of research, it was not possible to do a full analysis of all the monitoring techniques needed in a SPS. Since the architecture of subsea systems differ from field to field, the author recommends Cameron to develop a CM system based on a SPS currently in operation, that reflects the aspects most commonly found in today's subsea fields. An example will be a system with multiplex electro-hydraulic control system; combination of standalone trees, manifold clusters and templates; gas/water injection; and retrievable chokes. The next step to be carried out by Cameron is to apply this methodology for the SPS chosen to define fault management models, monitoring techniques/sensors required and an advisory generation system for the whole system. This generic CM program based on a typical subsea field could then be used as a model for other field architectures.

The guidelines presented in this research were developed specifically for conventional SPS's; however, they could be easily adapted to more complex systems such as subsea processing or all-electrical control systems. In the field of subsea rotating equipment (pumps and compressors) there has been some research done with respect to condition monitoring that could be used as a starting point.

The way valve signatures are recorded in Cameron projects is not very clear. It is advisable for Cameron subsea controls division to gather the teams responsible for valve fabrication, test and installation on the trees/manifolds, to develop a common procedure for recording the valve signature during factory acceptance test of the equipment. Cameron should take advantage of its vast experience in design and fabrication of hydraulic operated gate valves, and use this knowledge to develop examples of how typical failure modes are reflected in the valve profile.

This thesis did not cover communication and data transmission between the MCS and Cameron onshore support center. Further research should determine the best options for interaction between the offshore facility and onshore operation centers. At a minimum, the following aspects should be defined for both the operator's and Cameron's onshore operation centers:

- Frequency of data transmission.
- Reduction (e.g. averaging) and compression of data.
- Type of access by Cameron and third parties to the CM system and other.
- Access to the operator's asset management system by Cameron to support advisory generation system (optional).

The scope of this thesis was centered on the measurement part of the CM process; therefore, diagnosis and prognosis should be studied more in depth. For this, Cameron could partner up with a CM software provider to generate comprehensive models for fault diagnosis and prognosis without compromising Cameron's internal human resources. The alternatives for this partnership should be studied carefully to select the most suitable option, taking into consideration both the needs of the customer and Cameron.

Lastly, condition monitoring programs could be extended to downhole equipment, umbilicals, pipelines, flowlines and risers, and flow assurance and production optimization could be included as part of the advisory generation system, to offer a full equipment/process monitoring solution to the end users.

6 Conclusive remarks

This thesis aimed to fulfill a gap in the information available on how to a carry out surveillance of subsea equipment in a systematic way. CM methodologies described in industry standards such as ISO and IEC are tailored for rotating equipment and some static machines for surface facilities, and therefore not so useful for static subsea equipment. The main difference between surface and subsea equipment lies on their maintainability. Components that are considered noncritical in surface applications (e.g. gate valves) become critical equipment when they are installed in equipment operating on the seabed. The development of subsea specific CM methodologies like the one presented in this thesis are a great tool for subsea equipment suppliers or operators who want to implement a CM program systematically.

Despite the many advances in sensor technology achieved in the last two decades, the subsea business still lags behind other industries with regards to condition monitoring. This is caused mainly by: 1) The lack of advanced sensors designed and qualified for subsea applications and, 2) The passive nature of many of the components found in conventional SPS's. But, with the increasing demand for efficiency driven by high operating costs associated with subsea intervention, development of new subsea fields in remote locations, and introduction of new complex systems to the seafloor (such as subsea compression, multiphase boosting and all-electric control systems); the subsea industry has been forced to develop modern sensors to keep up with these requirements.

The current scheme for SPS providers' integration with field operators system is limited. Subsea OEMs only have access to the SPS system via the MCS only when the field operators have operational issues and require input from the SPS supplier. Moreover, the OEMs do not have access to the client's production and asset management systems. As a result, the advisory generation system depicted here is only based on the condition of the equipment. A truly integrated operations system, should integrate equipment data with the field data related to life cycle asset management. An ideal advisory system should be able to generate an intervention recommendation based on:

- Condition of the equipment and its RUL.
- Availability of spare parts.
- Availability of maintenance personnel.
- Availability of intervention vessel/rig.
- Economical risks associated with loss of opportunity based on maintenance performed at the optimum time according to the prognosis.
- HSE, economical and operational risks associated with deferred maintenance due to production requirements, lack of intervention vessel/rig or need to wait for next scheduled maintenance campaign.
- Weather forecast, especially in arctic regions or areas with harsh weather.

Despite the efforts claimed by major O&G operators in IO, the fully integration of OEMs with the operators' system is still quite limited, driven by the sensitivity of the data. Oil companies have to open up to suppliers and provide access to their operational and asset management systems, so the latter can provide better solutions for the operators, such as comprehensive maintenance recommendations. In return, OEMs will also be more open with operators and share important information related to design and fabrication of subsea equipment that will allow both parties to achieve better RAMS levels.

Lastly, periodic revision of the CM system is of utmost importance for guaranteeing precise accuracy of the health assessment of the assets. Alarms and alert set points should be refined as well as baselines, if there are any changes in the equipment, such as modification of parts or operational parameters. Likewise Cameron engineers have to stay up to date with the latest monitoring technologies, so modern and more accurate sensors can be used in future applications and outdated methods replaced.

7 References list

1. Anon, *Subsea wells produce most*, 2011, Norwegian Petroleum Directorate: Stavanger, Norway.
2. Anon, *Petroleum Resources On The Norwegian Continental Shelf*, 2011, Norwegian Petroleum Directorate: Stavanger, Norway.
3. Langli, G., et al., *Ensuring Operability and Availability of Complex Deepwater Subsea Installations: A Case Study*. In *Offshore Technology Conference* 2001: Houston, Texas.
4. Hill, A., *Increased recovery from subsea wells*, in *PennEnergy* 2010, PennWell Corporation.
5. *ISO 17359: Condition monitoring and diagnostics of machines - General guidelines*, 2011, International Organization for Standardization: Geneva, Switzerland.
6. *ISO/FDIS 13381-1:2004: Condition monitoring and diagnostics of machines — Prognostics — Part 1: General Guidelines*, 2004, International Organization for Standardization: Geneva, Switzerland.
7. *ISO/FDIS 13379:2002(E): Condition monitoring and diagnostics of machines — Data interpretation and diagnostics techniques which use information and data related to the condition of machines — General guidelines*, 2002, International Organization for Standardization: Geneva, Switzerland.
8. *ISO 13374-1: Condition monitoring and diagnostics of machines — Data processing, communication and presentation — Part 1: General guidelines*, 2003, International Organization for Standardization: Geneva, Switzerland.
9. *ISO 13374-2: Condition monitoring and diagnostics of machines — Data processing, communication and presentation — Part 2: Data-processing*, 2005, International Organization for Standardization: Geneva, Switzerland.
10. Lewis S. Edison, J.D.B., Steve Edwards, *The value of smarter oil and gas fields*, 2011, IBM Center for Applied Insights: Armonk, NY.
11. Anon. *Benefits of Integrated Operations*. 2011 [Accessed 12 March 2012]; Available from: http://www.kongsberg.com/en/kog/news/featurestories/benefitsofintegratedoperations/.
12. Anon, *Verdipotensialet for Integrerte operasjoner på Norsk Sokkel*, O. Landsforening, Editor 2006, Oljeindustriens Landsforening (OLF).
13. Sätra, U.S.a., et al., *Proactive Maintenance in the Context of Integrated Operations Generation 2.* 2011(2): p. pp. 102-108.
14. Böhm, T. and K. Gutsche. *Diagnosis and Prediction for a Successful Management of Railway Infrastructure*. In *Proceedings of the 24th International Congress on Condition Monitoring and Diagnostics Engineering Management*. 2011.

15. Anders, V., D. Erik, and H. Jørn. *Transfer of Methods and Experiences from Operation and Maintenance in other Industries to Offshore Wind Farms*. In *Proceedings of the 24th International Congress on Condition Monitoring and Diagnostics Engineering Management*. 2011.

16. Anon. *CPM Condition and Performance Monitoring*. n.d. [Accessed 16 March 2012]; Available from: http://www.fmctechnologies.com/subsea.

17. Anon, *TeCoMan Fact Sheet*, 2011, MARINTEK: Trondheim, Norway.

18. Lagnebäck, R., *Evaluation of wayside condition monitoring technologies for condition-based maintenance of railway vehicles*. *Department of Civil, Mining and Environmental Engineering* 2007, Luleå, University: Luleå,.

19. Camargo, L.F.M., J.R. Edwards, and C.P.L. Barkan. *Emerging Condition Monitoring Technologies for Railway Track Components and Special Trackwork*. In *2011 ASME/ASCE/IEEE Joint Rail Conference*. 2011. Pueblo, CO, USA.

20. Pasteur, O., R. Chevalier, and R. Seraoui. *An Incremental Training Algorithm to Improve Condition Monitoring of Power Plant Parameters*. in *Proceedings of the 24th International Congress on Condition Monitoring and Diagnostics Engineering Management*. 2011.

21. Cerri, G., et al. *Automatic Operator Support System Based on a Neural Network Monitoring System*. In *Proceedings of the 24th International Congress on Condition Monitoring and Diagnostics Engineering Management*. 2011. Stavanger, Norway.

22. Turner, J. *Hybrid Modeling Improves Health and Performance Monitoring*. 2011 [Accessed 15 April 2012 15]; Available from: http://spinoff.nasa.gov/Spinoff2007/ct_3.html.

23. Anon, *VetcoGray SmartCenter*, G.E. Company, Editor 2010: Nailsea, UK.

24. Phillips, R. and S.G. Holley, *Creating Value and Enhancing Operational Efficiency With the Subsea E-Field*. In *SPE Intelligent Energy Conference and Exhibition* 2010, Society of Petroleum Engineers: Utrecht, The Netherlands.

25. Nilsen, F.P. *Integrated Operational Support & Preventive Maintenance*. In *Underwater Technology Conference*. 2010. Bergen, Norway.

26. Anon, *Subsea Systems Provides Fieldwide Production Monitoring and Control*, Schlumberger, Editor 2008.

27. Machin, J., *Parallel Subsea Monitoring and Control Solutions*, 2009, Society of Underwater Technology: Perth, Australia.

28. Neri, R. and K. Falk, *Subsea Architectures to Facilitate Increased Recovery from Reservoirs: Subsea Processing, Condition Monitoring and Process Optimisation in a Modern Subsea Control System*, 2006, The Society for Underwater Technology.

29. Moodie, D., L. Costello, and D. McStay, *Optoelectronic Leak Detection System For Monitoring Subsea Structures*, 2010, Society of Underwater Technology.

30. Moodie, D. and D. McStay *New sensor allows leak detection for subsea structures*. E&P Magazine, 2011.

31. *Cathodic protection for deep-water production equipment*. 2011 [Accessed 07 May 2012]; Available from: http://www.stoprust.com/deepwatercp.htm.

32. Midtun, B., *Evaluation of hydro acoustic condition monitoring of subsea processing equipment*, 2011, University of Stavanger: Stavanger.

33. Anon. *NAXYS*. n.d. [Accessed 9 May 2012]; Available from: http://www.naxys.no/.

34. Thivend, G. and N.M. Murray, *Subsea Sensors for Non-Intrusive Monitoring of Temperature, Pressure and Asset Integrity*. In *Offshore Technology Conference* 2010: Houston, Texas, USA.

35. Roberts, I., A. Albert, and M.S.U. Rossi, *Innovative Intelligent Technologies used for Production Optimization and Infrastructure Integrity Surveillance*. In *SPE Intelligent Energy International* 2012, Society of Petroleum Engineers: Utrecht, The Netherlands.

36. *ISO 13628-1: Design and Operation of Subsea Production Systems—General Requirements and Recommendations*, 2005, International Organization for Standardization: Geneva, Switzerland.

37. *IEC 60812: Analysis techniques for system reliability – Procedure for failure mode and effects analysis (FMEA)*, 2006, International Electrotechnical Commission: Geneva, Switzerland.

38. *NORSOK D-010: Well integrity in drilling and well operations*, 2004, Standards Norway: Lysaker, Norway.

39. Isermann, R., *Fault-Diagnosis Systems: An Introduction From Fault Detection To Fault Tolerance*2006: Springer.

40. Grimmelius, H.T., et al., *Three state-of-the-art methods for condition monitoring.* IEEE Transactions on Industrial Electronics, 1999. **46**(2): p. 407-416.

41. Anon, *Guidelines for Isolation and Intervention: Diver Access to Subsea Systems*, 2009, International Marine Contractors Association.

42. Anon, *MKlll Long Ranger Subsea Leak Detection System*, N.O. Ltd, Editor n.d.: Charlbury, UK.

43. White, M. and J.B. Bernstein, *Microelectronics Reliability: Physics-of-Failure Based Modeling and Lifetime Evaluation*2008, Pasadena, CA: NASA.

44. Pecht, M., *Prognosis and Health Management of Electronics*2008, Hoboken, New Jersey: Wiley.

45. Weglinski, R., *Highly Accelerated Stress Screening for air-cooled switching power supplies* 2007, TDI Power.

46. Imam, A.M., et al. *Condition Monitoring of Electrolytic Capacitor in Power Electronic Circuits using Adaptive Filter Modeling*. In *Power Electronics Specialists Conference, 2005. PESC '05. IEEE 36th*. 2005.

47. Chen, Y.-M., M.-W. Chou, and H.-C. Wu. *Electrolytic Capacitor Failure Prediction of LC filter for Switching-Mode Power Converters*. In *Industry Applications Conference, 2005. Fourtieth IAS Annual Meeting*. 2005.

48. Kulkarni, C., et al., *Physics of failure models for capacitor degradation in dc-dc converters*. In *The Maintenance & Reliability Conference, MARCON 2010*, MARCON: Knoxville, TN.

49. Johnston, A.T. *MIMOSA and OpenO&M™ Executive Overview*. 2004. Machinery Information Management Open System Alliance.]

Appendix A – Subsea Production System Architecture

System	Subsystem / Component			
Level 0	**Level 1**	**Level 2**	**Level 3**	**Level 4**
SPS	**Control system**	SCM (note 1)	Baseplate	
			Electric/hydraulic couplers	
			Compensators	
			SEM	Power supply
				Transformer
				Programmable integrated controller
				Pressure transducer
				Diplexer
				Modem
				Internal VEM
				DHPT
				IsoBoards
				Connector board
			Function blocks	Solenoid driver module
			Filter blocks	
			Digital transducer module	
			Selector valves	
			Pressure transmitters	
			Dump valve	
			Couplings	
			Lockdown mandrel	
		HPU (note 2)		
		EPU (note 2)		
		MCS (note 2)		
		SDU		
		Dynamic umbilical	Bend restrictor	
			Buoyancy device	
			Hydraulic/chemical line	
			J/I-tube seal	
			Power/signal line	
			Sheath/armour	
			Stabilizing & guidance equipment (note 2)	

System	Subsystem / Component			
Level 0	**Level 1**	**Level 2**	**Level 3**	**Level 4**
SPS (cont.)	**Control system (cont.)**	Dynamic umbilical (cont.)	Subsea umbilical termination unit	
			Topside umbilical termination unit (note 2)	
			Tension and heave compensation system (note 2)	
		Static umbilical	Hydraulic/chemical line	
			Power/signal line	
			Subsea umbilical termination unit	
			Topside umbilical termination unit (note 2)	
		Sensors	Pressure sensor	
			Temperature sensor	
			Flow sensor	
			Fluid level sensor	
			Leak detector	
			Sand detection sensor	
			Valve position sensor	
			Corrosion sensor	
			PIG detection sensor	
			Others	
	XT	On/off Valves and actuators	Valve	
			Actuator	
		Choke module	Hydraulic/chemical flying lead connection	
			Electrical/communication flying lead connection	
			Connector	
			Flow loop	
			Frame	
			Hose (flexible piping)	
			Piping (hard pipe)	
			Valve, check	
			Valve, choke	
			Valve, control	
			Valve, other	
		Sensors	See control system	

System	Subsystem / Component			
Level 0	**Level 1**	**Level 2**	**Level 3**	**Level 4**
SPS (cont.)	**XT (cont.)**	Tubing hanger	Chemical injection coupling	
			Hydraulic coupling	
			Power/signal line	
			Tubing hanger body	
			Tubing hanger isolation plug	
		Jumper connection		
		Tree cap (internal or external)		
		Debris cap		
		Insulation		
		Piping/couplings	Chemical injection coupling	
			Hose (flexible piping)	
			Hydraulic coupling	
			Piping (hard pipe)	
		Tree-wellhead connector		
		ROV Panel		
		Cathodic protection		
	Wellhead system	Casing strings /hangers		
		Annulus seal assemblies (packoffs)		
		Conductor housing		
		Permanent guidebase (PGB)		
		Temporary guidebase (TGB)		
		Wellhead housing		
	Manifold	On/off Valves and actuators	Valve	
			Actuator	
		Sensors	See control system	
		HIPPS module		
		SCM		
		SDU		
		Connectors		
		Insulation		
		Piping/couplings		
		ROV Panel		
		Structure		
		Cathodic protection		
		Foundation		
		Mud mat		

System	Subsystem / Component			
Level 0	**Level 1**	**Level 2**	**Level 3**	**Level 4**
SPS (cont.)	**Template**	On/off Valves and actuators	Valve	
			Actuator	
		Sensors	See control system	
		HIPPS module		
		SCM		
		SDU		
		Connectors		
		Insulation		
		Piping/couplings		
		ROV Panel		
		Structure		
		Cathodic protection		
		Foundation		
		Mud mat		
	EFL	Cable		
		Hose		
		Connector		
	HFL	Hose		
		Connector		
	Individual well HIPPS			
	Flowlines and tie-in spools	Heating system		
		Cathodic protection		
		Connector		
		Insulation		
		Valve, process isolation		
		Structure (protective or support)		
		Safety joint		
	Risers	Accessories	Bend restrictor	
			Buoyancy device	
			J/I-tube seal	
			Stabilizing & guidance equipment	
			Tension and heave compensation system	
		Heating system		
		Cathodic protection		
		Riser base	Gas lift system	
			Structure	
			Valves	
		Connectors		

System	Subsystem / Component			
Level 0	**Level 1**	**Level 2**	**Level 3**	**Level 4**
SPS (cont.)	**Subsea processing systems**	Subsea compressor		
		Subsea separator		
		Subsea booster pump		

Notes:

1- The SCM system described here is for Electro-Hydraulic Multiplexed control system, which is by far the most common type used by the time this report was written.
2- Located topside

Appendix B – FMSA of hydraulic valve and actuator

System Functions: Isolating and directing the flow of hydrocarbons or injection fluids

Item	Failure Mode	Failure Causes	Failure symptoms	Method of detection	Measurement location	Frequency of monitoring	Det	Sev	Dgn	Pgn	MPN
1.1	**Internal leakage at gate & seat**	Erosion, corrosion or mechanical damage to the valve sealing surfaces (seal or gate)	Dormant failure until the valve is shut. If leak is large enough indication of tubing head shut in pressure downstream when valve is shut	Pressure test (see note 1)	Upstream and downstream the valve	See note 2	3	3	4	4	**144**
1.2	**External leakage of production into the sea**	Failure of bonnet/stem seals assembly	Changes in pressure of the tree production flowline	Pressure transmitter in the flowline	Tree production flowline, as close as possible to the valve	Continuous	2	4	2	N/A	16
			Presence of leaked product in the surroundings	Acoustic leak detector	On top of the tree/template	Continuous	3	4	4	N/A	48
				Fluorescence leak detection system	On top of the tree/template	Continuous	4	4	4	N/A	**64**
				Visual detection by ROV	Around the tree	Periodic	3	4	5	N/A	60
		Failure of body/bonnet connection gasket	Changes in pressure of the tree production flowline	Pressure transmitter in the flowline	Tree production flowline, as close as possible to the valve	Continuous	2	4	2	N/A	16
			Presence of leaked product in the surroundings of the tree	Acoustic leak detector	On top of the tree/template	Continuous	3	4	4	N/A	48
				Fluorescence leak detection system	On top of the tree/template	Continuous	4	4	4	N/A	**64**
				Visual detection by ROV	Around the tree	Periodic	3	4	5	N/A	60

Item	Failure Mode	Failure Causes	Failure symptoms	Method of detection	Measurement location	Frequency of monitoring	Det	Sev	Dgn	Pgn	MPN
1.3	**Valve fails to open on demand from the closed position**	Actuator failure	Indication of zero production flow from tree instrumentation	Process flow meter	Process line	Continuous	4	3	4	N/A	**48**
			No flow of control fluid if valve or actuator is jammed	Control fluid flowmeter	Control fluid LP line	Continuous	4	3	4	N/A	**48**
		Leakage of hydraulic fluid from pipe / actuator / SCMMB.	Indication of zero production flow from tree instrumentation	Process flow meter	Process line	Continuous	4	3	4	N/A	**48**
			No flow of control fluid if valve or actuator is jammed	Control fluid flowmeter	Control fluid LP line	Continuous	4	3	4	N/A	**48**
			Continuous control fluid flow	Control fluid flowmeter	Control fluid LP line	Continuous	4	3	4	N/A	**48**
			Drop in topside control fluid reservoir level	Level transmitter in reservoir (low level alarm)	Control fluid reservoir topside	Continuous	4	3	3	N/A	36
		Blocked / Plugged control lines	Indication of zero production flow from tree instrumentation	Process flow meter	Process line	Continuous	4	3	4	N/A	**48**
			No flow of control fluid	Control fluid flowmeter	Control fluid LP line	Continuous	4	3	4	N/A	**48**
1.4	**Spurious closure**	Leakage of hydraulic fluid from pipe / actuator / SCMMB	Indication of zero production flow from tree instrumentation	Process flow meter	Process line	Continuous	4	3	4	N/A	**48**
			Continuous control fluid flow	Control fluid flowmeter	Control fluid LP line	Continuous	4	3	4	N/A	**48**
			Drop in topside control fluid reservoir level	Level transmitter in reservoir (low level alarm)	Control fluid reservoir topside	Continuous	4	3	3	N/A	**36**

Item	Failure Mode	Failure Causes	Failure symptoms	Method of detection	Measurement location	Frequency of monitoring	Det	Sev	Dgn	Pgn	MPN
1.5	**Valve fails to close on demand**	Blocked / Plugged control lines or valve	Dormant failure until the valve is shut. If leak is large enough indication of tubing head shut in pressure downstream when valve is shut	Partial stroke testing with valve signature analysis	At valve	See note 2	4	4	3	4	**192**
1.6	**Slow operation to the closed position**	Mechanical degradation in actuator or valve	Very slow pressure decay after valve is closed	Process flow meter	Process line	Continuous	3	2	3	3	54
			Slow valve closing reading in valve signature	Valve signature analysis	Valve positioners in the valve block (optional). Control fluid flowmeter in LP line. Pressure transmitter in LP line	During valve operation	4	2	4	4	**128**

Item	Failure Mode	Failure Causes	Failure symptoms	Method of detection	Measurement location	Frequency of monitoring	Det	Sev	Dgn	Pgn	MPN
1.7	**Slow operation to the open position**	Mechanical degradation in actuator or valve	Very slow pressure increase after valve is closed	Process flow meter	Process line	Continuous	3	1	3	3	27
			Slow valve opening reading in valve signature	Valve signature analysis	Control fluid flowmeter in LP line. Pressure transmitter in LP line. Valve positioners in the valve block (optional)	During valve operation	4	1	4	4	**64**
		Partial blockage of the supply control line	Very slow pressure increase after valve is closed	Process flow meter	Process line	Continuous	3	1	3	3	27
			Slow valve opening reading in valve signature	Valve signature analysis	Control fluid flowmeter in LP line. Pressure transmitter in LP line. Valve positioners in the valve block (optional)	During valve operation	4	1	4	4	**64**

Notes:

1. Only applicable for Production Master Valve (PMV) and Production Wing Valve (PWV)
2. Per NORSOK D-010: *The principal valves acting as barriers in the production tree shall be tested at regular intervals as follows:*
• test duration shall be 10 min,
• monthly, until three consecutive qualified tests have been performed, thereafter -
• every three months, until three consecutive qualified tests have been performed, thereafter –
• every six months.

Appendix C – Valve profile data

scan offset time [sec] 0.000
measure time [sec] 6.000
sample interval [sec] 0.012
recorded measure points 1000
valve command open

#	Opening Time (s)	Healthy (real data)	Defective (assumed data)	#	Opening Time (s)	Healthy (real data)	Defective (assumed data)
		Press. (psi)	Press. (psi)			Press. (psi)	Press. (psi)
1	0.012	390	50	35	0.42	6180	4200
2	0.024	1570	200	36	0.432	5940	4250
3	0.036	2040	500	37	0.444	6250	4300
4	0.048	1980	600	38	0.456	6270	4350
5	0.06	3250	800	39	0.468	5960	4400
6	0.072	3930	900	40	0.48	6160	4450
7	0.084	4650	1110	41	0.492	6210	4500
8	0.096	5440	1200	42	0.504	6060	4550
9	0.108	6080	1375	43	0.516	5980	4600
10	0.12	6080	1450	44	0.528	5960	4650
11	0.132	6310	1600	45	0.54	6090	4700
12	0.144	6330	1800	46	0.552	6040	4750
13	0.156	6090	2100	47	0.564	6020	4800
14	0.168	6520	2300	48	0.576	6430	4850
15	0.18	6330	2600	49	0.588	6230	4900
16	0.192	6660	2700	50	0.6	6330	4950
17	0.204	6450	2800	51	0.612	6040	5000
18	0.216	6310	2900	52	0.624	6180	5050
19	0.228	6250	3000	53	0.636	6430	5100
20	0.24	5770	3100	54	0.648	5980	5140
21	0.252	6060	3175	55	0.66	6370	5210
22	0.264	5940	3250	56	0.672	6230	5280
23	0.276	6140	3325	57	0.684	6210	5350
24	0.288	6080	3400	58	0.696	6370	5420
25	0.3	5960	3475	59	0.708	6210	5490
26	0.312	5920	3550	60	0.72	6060	5560
27	0.324	5940	3625	61	0.732	6250	5630
28	0.336	6270	3700	62	0.744	5800	5700
29	0.348	6080	3775	63	0.756	6000	5770
30	0.36	6090	3850	64	0.768	6470	5840
31	0.372	6090	3925	65	0.78	6310	5910
32	0.384	6200	4000	66	0.792	6060	5980
33	0.396	6180	4075	67	0.804	6120	6050
34	0.408	6490	4150	68	0.816	6270	6120

#	OpeningTime (s)	Healthy(real data) Press. (psi)	Defective(assumed data) Press. (psi)	#	Opening Time (s)	Healthy (real data) Press. (psi)	Defective (assumed data) Press. (psi)
69	0.828	6310	6190	110	1.32	7380	6880
70	0.84	6600	6260	111	1.332	7510	7010
71	0.852	6210	6330	112	1.344	7240	6740
72	0.864	6470	6400	113	1.356	7530	7030
73	0.876	6430	6470	114	1.368	7490	6990
74	0.888	6560	6540	115	1.38	7510	7010
75	0.9	6540	6610	116	1.392	7410	6910
76	0.912	6520	6680	117	1.404	7490	6990
77	0.924	6370	6750	118	1.416	7470	6970
78	0.936	6370	6820	119	1.428	7550	7050
79	0.948	6520	6020	120	1.44	7670	7170
80	0.96	6290	5790	121	1.452	7430	6930
81	0.972	6470	5970	122	1.464	7490	6990
82	0.984	6520	6020	123	1.476	7630	7130
83	0.996	6500	6000	124	1.488	7610	7110
84	1.008	6410	5910	125	1.5	7680	7180
85	1.02	6890	6390	126	1.512	7680	7180
86	1.032	6680	6180	127	1.524	7530	7030
87	1.044	6620	6120	128	1.536	7610	7110
88	1.056	6790	6290	129	1.548	7490	6990
89	1.068	6450	5950	130	1.56	7740	7240
90	1.08	6690	6190	131	1.572	7550	7050
91	1.092	6740	6240	132	1.584	7630	7130
92	1.104	6870	6370	133	1.596	7650	7150
93	1.116	6970	6470	134	1.608	7700	7200
94	1.128	7070	6570	135	1.62	7900	7400
95	1.14	6970	6470	136	1.632	7650	7150
96	1.152	6790	6290	137	1.644	7680	7180
97	1.164	6760	6260	138	1.656	7670	7170
98	1.176	7160	6660	139	1.668	7840	7340
99	1.188	6970	6470	140	1.68	7680	7180
100	1.2	7030	6530	141	1.692	7960	7300
101	1.212	7260	6760	142	1.704	7940	7200
102	1.224	6810	6310	143	1.716	7740	7240
103	1.236	7240	6740	144	1.728	7820	7320
104	1.248	7030	6530	145	1.74	7840	7340
105	1.26	7260	6760	146	1.752	7920	7200
106	1.272	7360	6860	147	1.764	7800	7150
107	1.284	7220	6720	148	1.776	7650	7150
108	1.296	7390	6890	149	1.788	7760	7260
109	1.308	7410	6910	150	1.8	7860	7360

#	Opening Time (s)	Healthy (real data)	Defective (assumed data)	#	Opening Time (s)	Healthy (real data)	Defective (assumed data)
		Press. (psi)	Press. (psi)			Press. (psi)	Press. (psi)
151	1.812	7840	7300	192	2.304	18870	7800
152	1.824	7900	7250	193	2.316	18960	7900
153	1.836	7780	7280	194	2.328	19030	7950
154	1.848	8110	7300	195	2.34	19030	8000
155	1.86	7800	7350	196	2.352	18960	7950
156	1.872	7700	7300	197	2.364	18940	8000
157	1.884	7940	7350	198	2.376	18870	7740
158	1.896	7990	7400	199	2.388	18710	7790
159	1.908	7860	7360	200	2.4	18560	7660
160	1.92	7940	7440	201	2.412	18340	7740
161	1.932	8070	7370	202	2.424	18200	7870
162	1.944	7590	7200	203	2.436	18180	7390
163	1.956	7860	7360	204	2.448	18100	7660
164	1.968	7970	7470	205	2.46	18260	7770
165	1.98	7960	7460	206	2.472	18390	7760
166	1.992	7940	7440	207	2.484	18560	7740
167	2.004	7970	7470	208	2.496	18790	7770
168	2.016	9240	7500	209	2.508	18960	9040
169	2.028	10510	7650	210	2.52	19160	10310
170	2.04	11780	7550	211	2.532	19330	11580
171	2.052	13050	7700	212	2.544	19400	12850
172	2.064	14320	7600	213	2.556	19480	14120
173	2.076	15590	7500	214	2.568	19480	15390
174	2.088	16860	7650	215	2.58	19500	16660
175	2.1	18130	7500	216	2.592	19430	17930
176	2.112	18340	7700	217	2.604	19350	18140
177	2.124	18410	7800	218	2.616	19250	18210
178	2.136	18410	7700	219	2.628	19100	18210
179	2.148	18270	7650	220	2.64	18960	18070
180	2.16	17950	7900	221	2.652	18870	17750
181	2.172	17570	7800	222	2.664	18830	17370
182	2.184	17180	7900	223	2.676	18810	17000
183	2.196	16950	7955	224	2.688	18790	17050
184	2.208	16870	7700	225	2.7	18830	17080
185	2.22	16820	7650	226	2.712	18870	17100
186	2.232	16950	7900	227	2.724	19030	17200
187	2.244	17180	7800	228	2.736	19180	17300
188	2.256	17490	7900	229	2.748	19330	17500
189	2.268	17870	7700	230	2.76	19480	17700
190	2.28	18260	7650	231	2.772	19580	18060
191	2.292	18620	7900	232	2.784	19630	18420

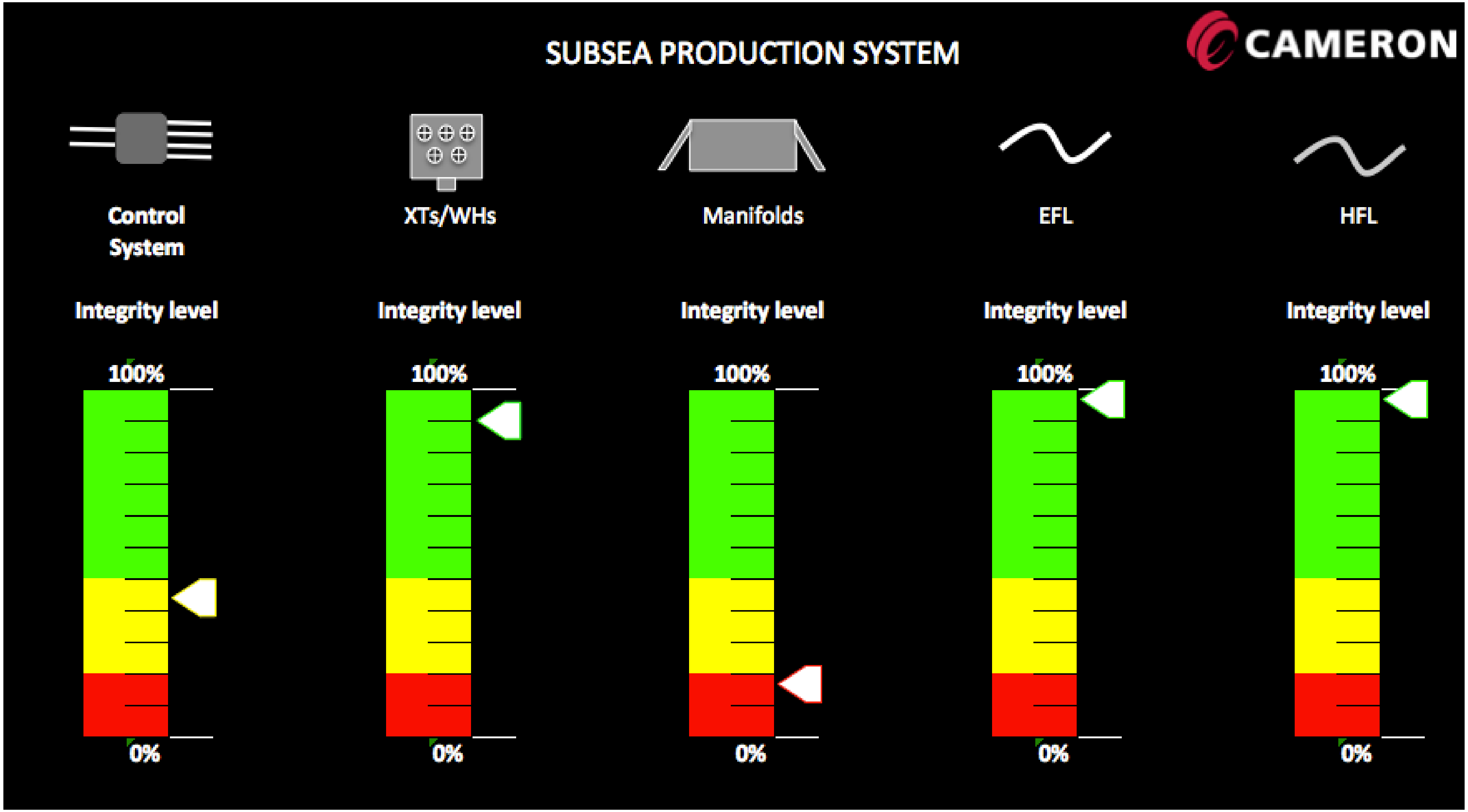
#	Opening Time (s)	Healthy (real data)	Defective (assumed data)	#	Opening Time (s)	Healthy (real data)	Defective (assumed data)
		Press. (psi)	Press. (psi)			Press. (psi)	Press. (psi)
233	2.796	19630	18670	274	3.288	19480	19430
234	2.808	19650	18760	275	3.3	19480	19450
235	2.82	19630	18830	276	3.312	19480	19430
236	2.832	19630	18830	277	3.324	19430	19430
237	2.844	19560	18760	278	3.336	19400	19360
238	2.856	19480	18740	279	3.348	19330	19280
239	2.868	19360	18670	280	3.36	19330	19160
240	2.88	19290	18510	281	3.372	19290	19090
241	2.892	19180	18360	282	3.384	19250	18980
242	2.904	19160	18140	283	3.396	19250	18960
243	2.916	19200	18000	284	3.408	19290	19000
244	2.928	19140	17980	285	3.42	19250	18940
245	2.94	19100	17900	286	3.432	19270	18900
246	2.952	19180	18060	287	3.444	19330	18980
247	2.964	19250	18190	288	3.456	19350	19050
248	2.976	19330	18360	289	3.468	19380	19130
249	2.988	19400	18590	290	3.48	19400	19200
250	3	19460	18760	291	3.492	19400	19260
251	3.012	19520	18960	292	3.504	19400	19320
252	3.024	19480	19130	293	3.516	19400	19280
253	3.036	19560	19200	294	3.528	19400	19360
254	3.048	19500	19280	295	3.54	19400	19300
255	3.06	19560	19280	296	3.552	19400	19300
256	3.072	19480	19300	297	3.564	19400	19300
257	3.084	19480	19230	298	3.576	19400	19300
258	3.096	19400	19150	299	3.588	19350	19250
259	3.108	19330	19050	300	3.6	19350	19250
260	3.12	19290	18900	301	3.612	19330	19230
261	3.132	19250	18760	302	3.624	19330	19230
262	3.144	19230	18670	303	3.636	19330	19230
263	3.156	19180	18630	304	3.648	19330	19230
264	3.168	19180	18610	305	3.66	19330	19230
265	3.18	19210	18590	306	3.672	19330	19230
266	3.192	19250	18630	307	3.684	19330	19230
267	3.204	19330	18670	308	3.696	19400	19300
268	3.216	19360	18830	309	3.708	19400	19300
269	3.228	19400	18980	310	3.72	19400	19300
270	3.24	19480	19130	311	3.732	19400	19300
271	3.252	19480	19280	312	3.744	19400	19300
272	3.264	19480	19380	313	3.756	19400	19300
273	3.276	19480	19430	314	3.768	19400	19300

#	Opening Time (s)	Healthy (real data)	Defective (assumed data)	#	Opening Time (s)	Healthy (real data)	Defective (assumed data)
		Press. (psi)	Press. (psi)			Press. (psi)	Press. (psi)
315	3.78	19400	19300	356	4.272	19360	19260
316	3.792	19400	19300	357	4.284	19360	19260
317	3.804	19400	19300	358	4.296	19350	19250
318	3.816	19400	19300	359	4.308	19380	19280
319	3.828	19400	19300	360	4.32	19360	19260
320	3.84	19400	19300	361	4.332	19400	19300
321	3.852	19400	19300	362	4.344	19350	19250
322	3.864	19400	19300	363	4.356	19360	19260
323	3.876	19400	19300	364	4.368	19380	19280
324	3.888	19400	19300	365	4.38	19360	19260
325	3.9	19400	19300	366	4.392	19360	19260
326	3.912	19400	19300	367	4.404	19380	19280
327	3.924	19400	19300	368	4.416	19400	19300
328	3.936	19400	19300	369	4.428	19360	19260
329	3.948	19400	19300	370	4.44	19380	19280
330	3.96	19400	19300	371	4.452	19380	19280
331	3.972	19400	19300	372	4.464	19360	19260
332	3.984	19400	19300	373	4.476	19400	19300
333	3.996	19400	19300	374	4.488	19360	19260
334	4.008	19400	19300	375	4.5	19360	19260
335	4.02	19400	19300	376	4.512	19350	19250
336	4.032	19400	19300	377	4.524	19380	19280
337	4.044	19400	19300	378	4.536	19360	19260
338	4.056	19400	19300	379	4.548	19380	19280
339	4.068	19400	19300	380	4.56	19360	19260
340	4.08	19400	19300	381	4.572	19400	19300
341	4.092	19400	19300	382	4.584	19380	19280
342	4.104	19400	19300	383	4.596	19400	19300
343	4.116	19380	19280	384	4.608	19380	19280
344	4.128	19400	19300	385	4.62	19400	19300
345	4.14	19400	19300	386	4.632	19400	19300
346	4.152	19380	19280	387	4.644	19400	19300
347	4.164	19380	19280	388	4.656	19400	19300
348	4.176	19400	19300	389	4.668	19400	19300
349	4.188	19400	19300	390	4.68	19400	19300
350	4.2	19400	19300	391	4.692	19400	19300
351	4.212	19360	19260	392	4.704	19380	19280
352	4.224	19380	19280	393	4.716	19400	19300
353	4.236	19400	19300	394	4.728	19400	19300
354	4.248	19400	19300	395	4.74	19400	19300
355	4.26	19380	19280	396	4.752	19400	19300

#	Opening Time (s)	Healthy (real data)	Defective (assumed data)	#	Opening Time (s)	Healthy (real data)	Defective (assumed data)
		Press. (psi)	Press. (psi)			Press. (psi)	Press. (psi)
397	4.764	19400	19300	438	5.256	19400	19300
398	4.776	19400	19300	439	5.268	19400	19300
399	4.788	19400	19300	440	5.28	19400	19300
400	4.8	19400	19300	441	5.292	19400	19300
401	4.812	19400	19300	442	5.304	19400	19300
402	4.824	19400	19300	443	5.316	19400	19300
403	4.836	19400	19300	444	5.328	19400	19300
404	4.848	19400	19300	445	5.34	19400	19300
405	4.86	19400	19300	446	5.352	19400	19300
406	4.872	19400	19300	447	5.364	19400	19300
407	4.884	19400	19300	448	5.376	19400	19300
408	4.896	19400	19300	449	5.388	19400	19300
409	4.908	19400	19300	450	5.4	19400	19300
410	4.92	19400	19300	451	5.412	19400	19300
411	4.932	19400	19300	452	5.424	19400	19300
412	4.944	19400	19300	453	5.436	19400	19300
413	4.956	19400	19300	454	5.448	19430	19330
414	4.968	19400	19300	455	5.46	19400	19300
415	4.98	19400	19300	456	5.472	19400	19300
416	4.992	19400	19300	457	5.484	19400	19300
417	5.004	19400	19300	458	5.496	19400	19300
418	5.016	19400	19300	459	5.508	19430	19330
419	5.028	19400	19300	460	5.52	19400	19300
420	5.04	19400	19300	461	5.532	19400	19300
421	5.052	19400	19300	462	5.544	19400	19300
422	5.064	19400	19300	463	5.556	19430	19330
423	5.076	19400	19300	464	5.568	19400	19300
424	5.088	19400	19300	465	5.58	19450	19350
425	5.1	19400	19300	466	5.592	19430	19330
426	5.112	19400	19300	467	5.604	19430	19330
427	5.124	19400	19300	468	5.616	19450	19350
428	5.136	19400	19300	469	5.628	19430	19330
429	5.148	19400	19300	470	5.64	19450	19350
430	5.16	19400	19300	471	5.652	19450	19350
431	5.172	19400	19300	472	5.664	19460	19360
432	5.184	19400	19300	473	5.676	19480	19380
433	5.196	19400	19300	474	5.688	19460	19360
434	5.208	19450	19350	475	5.7	19450	19350
435	5.22	19400	19300	476	5.712	19460	19360
436	5.232	19400	19300	477	5.724	19480	19380
437	5.244	19400	19300	478	5.736	19450	19350

#	Opening Time (s)	Healthy (real data) Press. (psi)	Defective (assumed data) Press. (psi)
479	5.748	19460	19360
480	5.76	19460	19360
481	5.772	19460	19360
482	5.784	19460	19360
483	5.796	19460	19360
484	5.808	19480	19380
485	5.82	19480	19380
486	5.832	19480	19380
487	5.844	19480	19380
488	5.856	19480	19380
489	5.868	19480	19380
490	5.88	19480	19380
491	5.892	19480	19380
492	5.904	19480	19380
493	5.916	19480	19380
494	5.928	19480	19380
495	5.94	19480	19380
496	5.952	19480	19380
497	5.964	19480	19380
498	5.976	19480	19380
499	5.988	19480	19380
500	6	19480	19380

Appendix D – Dashboard



Appendix E – FMSA of power supply unit

System Functions: convert the high input voltage to a low output voltage

Item	Failure Mode	Failure Causes	Failure symptoms	Method of detection	Measurement location	Frequency of monitoring	Det	Sev	Dgn	Pgn	MPN
1.1	**Loss of output from PSU all supply voltages**	PSU Failure	Loss of power in the SEM affected.	Combination model temperature, I/O voltage and I/O current measurement	Input and output modules	Continuous	4	1	4	3	**48**
1.2	**Loss of output from one of the PSU supply voltages**	Converter failure - Electrolytic capacitor deterioration	Increase in capacitor's Equivalent Series Resistance (ESR) and decrease in capacitance	Small ripple voltage and ripple current increase	Electrolytic capacitor	Continuous	4	1	4	4	**64**
				Raising temperatures in the capacitor core	Electrolytic capacitor	Continuous	4	1	3	3	**36**
1.3	**High output voltage**	Converter failure - Electrolytic capacitor deterioration	Increase in capacitor's Equivalent Series Resistance (ESR) and decrease in capacitance	Small ripple voltage and ripple current increase	Electrolytic capacitor	Continuous	4	1	4	4	**64**
				Raising temperatures in the capacitor core	Electrolytic capacitor	Continuous	4	1	3	3	**36**
1.4	**Low output voltage**	Converter failure - Electrolytic capacitor deterioration	Increase in capacitor's Equivalent Series Resistance (ESR) and decrease in capacitance	Small ripple voltage and ripple current increase	Electrolytic capacitor	Continuous	4	1	4	4	**64**
				Raising temperatures in the capacitor core	Electrolytic capacitor	Continuous	4	1	3	3	**36**