From Prevent to "Predict & Prevent (PnP)": Optimizing oil and gas Asset integrity decisions

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Abstract Asset integrity decisions for (production) critical equipment are mostly qualitative and experience-driven. Preventive maintenance strategies are dominating in oil and gas asset management for many years. Record low oil prices compelled the industry to undergo major organizational and technical transformations. Companies need to find better and effective ways of improving preventive maintenance strategies. One of the main challenges include doing minimum maintenance, keeping maintenance budget low without compromising safety, availability and reliability requirements. Oil and gas industry is keen in finding innovative solutions to optimize maintenance strategies. As a result, organizations are adapting to intelligent life cycle analytical methods for running asset in optimal and smarter manner. Apply Sørco's Predict and Prevent (PnP) methodology uses equipment (As-is) condition, combined with maintenance history data analytics to precisely predict upcoming maintenance requirements. The results of PnP analysis provide decision basis for in-time asset decisions for repairs, inspections, spares, overhauling and equipment modifications. The methodology combines integrity-engineering expertise with life cycle predictive analytics. Results from business cases reveal useful output that provide basis for smarter asset integrity decisions.

Keywords Life Cycle predictive Analysis, historical data, equipment health assessment, Reliability and Availability forecasting

1 Introduction

High critical equipment is usually equipped with sophisticated monitoring capabilities on an offshore platform. Due to high costs for setting up physical and digital infrastructure, it is not feasible to monitor all the equipment. Offshore oil and gas operations are risky, remote and costly therefore efficient maintenance management

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is a continuous challenge. Many companies invest in sophisticated equipment aiming to maintaining availability and productivity targets for their assets. The decision-making problem concerns allocating right budget to the appropriate equipment or component. The objective is to minimize the total expenditure and to maximise availability of production resources (Riane, Roux et al. 2009). Predict and Prevent (PnP) methodology is a tailor made analytical platform targeting critical equipment lacking monitoring due to feasibility or other reasons. PnP aims to extract vital information from historical data combined with status of the equipment (or group of equipment). It uses principles of predictive analytics and interpretation of equipment health.

Predictive analytics in a well-known field of mathematics and statistics. It relies on factual quantitative data generated by machines in operation. The data when interpreted into useful information, can lead to smarter and proactive asset decisions. According to (Mobley 2002), predictive maintenance is a philosophy or attitude that uses the actual operating condition of plant equipment and systems to optimize total plant operation. It provides sufficient warning of an impending failure allowing equipment to be maintained when there is objective evidence of impeding failure (Liyanage, Lee et al. 2009). Preventive maintenance strategies are time/calendar-based whereas predictive are condition-based (Scheffer and Girdhar 2004). Increasing awareness on knowledge management for improved performance, with help from latest information & communication technology (ICT), preventive maintenance is being replaced with predictive maintenance (Parida and Kumar 2006).

Life cycle analysis is a methodology used to understand historical failure and repair data, how to obtain such information, and how to turn historical data into probability density function (PDF) and reliability function (Calixto 2016). Several analysis techniques, such as RCM (Reliability Centred Maintenance), FMEA (Failure Modes and Effects Analysis), RBI (Risk-Based Inspections), Failure Tree Analysis (FTA), Safety Integrity Level (Riane, Roux et al.) etc., are widely in use covering both project and operational phase of any asset.

Three basic groups of diagnostics can be *Model-based*, *Data-driven* and *Hybrid* (combination of model-based and data-driven approaches) (Liyanage, Lee et al. 2009). Predictive analytics can bring large value potentials contributing to continuous improvement in any organization. Offshore oil and gas industry need to rely more on predictive technologies to identify smarter ways for improving maintenance performance. Predict and Prevent (PnP) engages the power of life cycle predictive analytics of maintenance history data which is combined with equipment "as-is" condition data.

1.1 Cost of Data:

Lifeline of all predictive analytics is data. Maintenance management loop introduced by the Norwegian Petroleum Directorate (Oljedirektoratet 1998), emphasizes the use of data (qualitative and quantitative) from reliability databases, generic libraries, industrial experience, failure history, operations and maintenance. Organizations use already established maintenance and reliability databases or build their own, if they lack such sources. Costs are associated with capturing, registering, storing, managing and maintaining large amounts of (online/offline) databases. This require human experts, physical and non-physical resources (i.e. software, digital infrastructure etc.). These cost includes both direct (related with data storage activities, hardware integration & facilitation) and indirect costs (related with utilization, validating and analytics). These costs vary from project to operational phase. As per today, no published literature and/or data is available that provide estimated figures for oil and gas industry. There is a need for further research to highlight challenges related with realizing the return of investments. A conceptual view of costs associated with management of data in larger maintenance engineering projects from offshore oil and gas platforms is shown below.

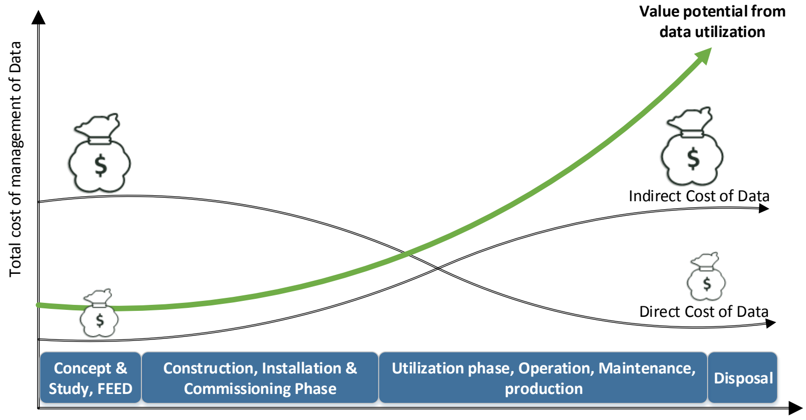

Figure 1. Cost vs. Value in Asset life cycle phases

Figure above elaborates cost and value potential of data management in life cycle of an offshore platform. Direct cost are usually higher due to investment in hardware, software and data acquisition, hosting facilities etc. Initial investments are therefore high in project early-life (start-up) and minimal in operation phase. In operation phase, indirect cost (related with use and interpretation of data) are on the rise. Indirect costs are on the rise in utilization and operation/maintenance phase. Simultaneously the potential for extracting valuable information from asset-generated data is seen as a continuously upward rising trend. With recent focus on digitalization, Internet of Things (IoT) and utilizing of big-data analytics, presents significant benefits for the industry.

Based on larger maintenance engineering projects, developing generic strategic reliability databases, customizing strategies, preparing integrity tasks require investment. These are necessary for life cycle planning, execution, maintenance reporting and continuous improvement of the asset. Once strategic maintenance plans are developed, history data (failure, uptime, downtime, repair time, repair cost etc.) is used for continuous improvement and life cycle management.

Maintenance and reliability engineer are responsible for quality, verification and ownership of collected data. It is important that the reporting structure is prepared by the reliability engineer using international reliability standard requirements, refereeing to relevant ISO and NORSOK standards (ISO 2016).

In new build/green field projects, criteria and premises for reporting must be defined early in the engineering phase. Failure to do so in early phase may kickback in form of re-structuring of the maintenance management system on later stages. This may incur unnecessary cost and challenges for maintenance and reliability organization. Data quality, as seen in the industry lacks structure and refinement. The industry needs a positive approach towards better management of history data. This data plays vital role in safety, asset performance and control of the asset.

1.2 Power of predictive analytics:

A general rule of thumb in data analytics, the nature of data determines what type of modelling technique is to deploy. A combination of statistical and mathematical techniques is applicable to solve a complex problem. In order to fully understand a system's performance this data is combined with predictive technologies are analysed to create additional value (Mobley, 2002 #1).

Weibull analysis is quite useful method in analysing maintenance history. It performs well in situations where less data is available or data quality is questionable.

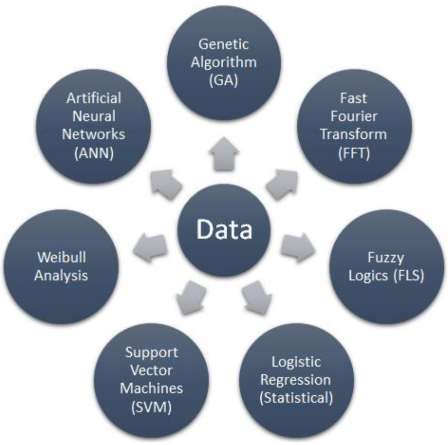

Figure 2. Data and predictive analytics methodologies choices

It has many advantages including simple graphical solution, highly useful for inadequate data, flexibility of working with small samples and its accuracy (Abernethy, Breneman et al. 1983). For other complex problem solving with large amounts of data, data-driven techniques such as Artificial Neural Networks (ANN), Fuzzy logics (FLS) and Genetic Algorithm are preferred. Predictive analytics provide opportunity for holistic system performance upgrade and overall process optimization.

2 Methodology and Toolbox

Methodology of predict and prevent (PnP) is quite simple in nature. Basic idea is similar to diagnostics in a medical examination. In medical, two main sources of information are:

- Patient's current condition by assessing vital signs (blood pressure, temperature, heartbeat etc.)
  And
- Patient's medical history

PnP technique aims to identify the most efficient maintenance strategy based on equipment's current condition and its maintenance history. Figure 3 represents the PnP methodology that starts with collecting data, analysing, validating and implementation of results.

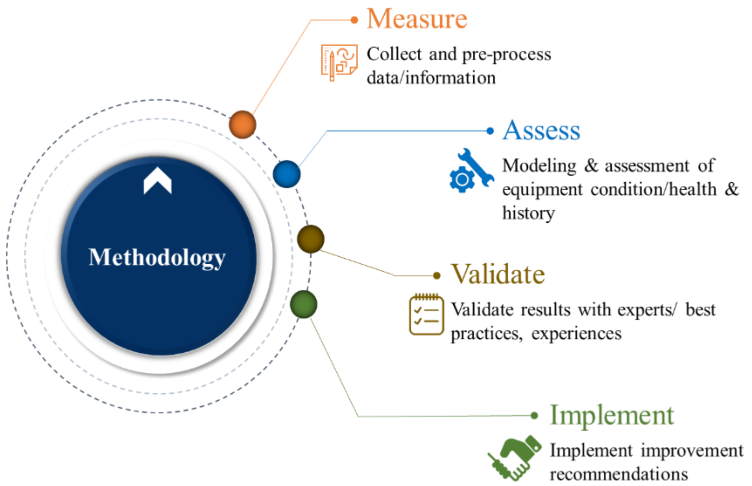

Figure 3. PnP Methodology

To identify upcoming failures with accuracy, plug-in Health Assessment & Reliability Toolkit (HART) is used. AligniT (Software) application performs Weibull and cost simulations.

HART interprets voltage & current patterns of the motor using model-based fault detection. Based on the patterns it generates condition assessment report, with warning levels, highlighting major electrical and mechanical, process & energy failures (with accuracy > 90%). The results provide useful input in energy saving, reduced OPEX, increased productivity and improved process safety.

AligniT is software application to identify failure distributions, simulate reliability, availability and predict upcoming failures. Cost simulations are performed to identify optimum preventive maintenance intervals.

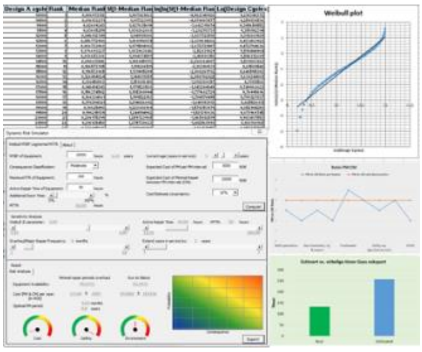

Figure 4a. AligniT - The Simulation software Module

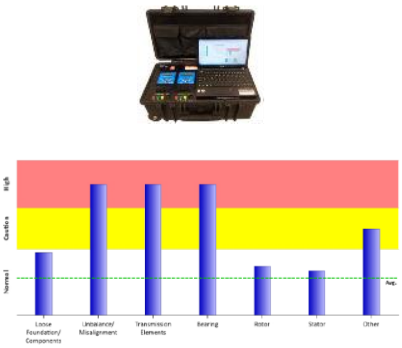

Figure 4b. HART - As-is health assessment hardware tool

Results, after validation from domain experts, are implemented into maintenance management systems. Such output is vital for planning preventive maintenance, corrective maintenance, life-cycle evaluations, overhauling, major repairs, modifications, selecting suitable operational strategy and spare parts etc.

Results from combined predictive analytics using ***AligniT*** & ***HART*** provide useful decision support for engineers to identify state of the equipment. Highlighting weaknesses in existing maintenance strategies and suggesting optimization opportunities. PnP analysis works well life cycle analysis of single equipment or group of equipment.

PnP analytics aims to:

- Identify optimal (safe and cost effective) maintenance strategies
- Predict upcoming overhaul/repair needs
- Prevent upcoming failures
- Provide input for more informed decisions regarding repair vs. replace
- Predict need for spares
- Assess equipment start-mid and late-life/End-life assessments with respect to maintenance requirements

3 Description of the model

In reliability engineering, data is collected from equipment, systems, and processes. Data is modelled and results are used to make asset decision for production design, manufacturing, reliability assessment and logistic support (Kapur and Pecht 2014). PnP model is shown in Figure 5.

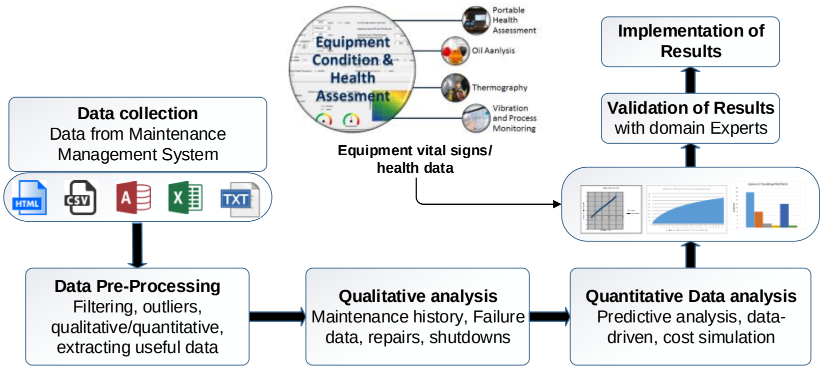

Figure 5. Generic Model PnP analytics

Data is collected from maintenance management system in different format and types. This data is pre-processed processed for classification, extracting associations, relationships and trending. Moreover to identify frequency distribution and statistical occurrence of the failure. Weibull plots from maintenance records are generated to identify probabilities. The two-parameter Weibull equation is simple and is suitable for many applications. Weibull is quite useful due to its flexibility and its capability to describe many physical modes. It is easy to gather required to carry out this analysis since time to failure and preventive replacement details for the failure modes are nearly all that we need (Narayan 2004). Weibull analysis is used for reliability and availability estimation. PnP benchmarks predictive preventive maintenance intervals. Validation of results is performed with input from domain experts.

4 PnP life cycle analysis Results

PnP analytics uses risk and reliability principles to identify most effective maintenance strategies. It helps understanding failures, distribution and how these occur over time. Failure modes, causes, down time and repair time are extracted from recorded maintenance history from maintenance management system. Quality of history is varying from case to case. In some cases, more quantitative information is recorded while in others, a mix of qualitative and abstract information. Suitable statistical techniques is selected to make more sense of the history data. It is further used to estimate reliability, availability, mean time to failure (MTTF). Preventive and corrective maintenance costs are simulated to identify most cost efficient intervals. In case of lacking history data, failure times are approximated, from the time they occurred.

Below are examples of extracting useful trends from data from an offshore platform. The collected data includes 5 years of operation and maintenance history with 15 failures observed failures.

Failure histogram of data highlights that most failures occur between 16000-24000 run-hours. Mean failure time is statistically calculated to be 15477 hours. Another important performance indicator is preventive vs. corrective work. In this case, the ratio of preventive to corrective work is 10:1. Which corresponds to high level of preventive maintenance activities.

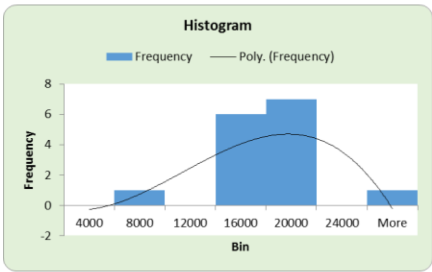

Figure 6. Histogram of failures from maintenance data

The Norwegian industry practice ratio of preventive to corrective work is 3:1 whereas according to world class standards, this ratio should be 6:1 (Imam, Raza et al. 2013). The ratio simply is an indication of balance between preventive and corrective work. Weibull Probability Density Function (PDF) represents proportion of cumulative failures. Weibull PDF and Predicted reliability at time (t) is shown below.

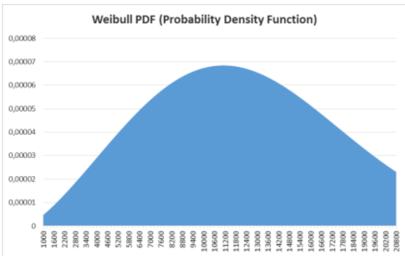

Figure 7a. Weibull PDF

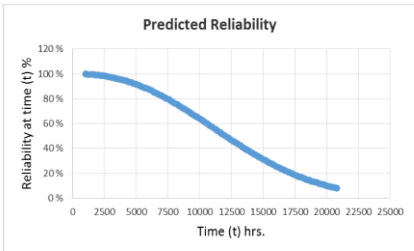

Figure 7b. Predicted Reliability

PDF (Figure 7a) of failure data shows peak at 5000 hours, cumulative failure probability is 8%. This correspond to chance of only one failure in 5000 hours. As a result, predicted reliability of the system @5000 hours is 92%. The reliability gradually reduces with time at 10000 hours, the reliability it reduced to about 60%. Decrease in reliability means that probability of failure is increasing; it does not mean that equipment will fail at 10000 hours. This requires identification of suitable preventive tasks and intervals to keep reliability to higher levels. Weibull plot was developed to determine two important parameters. Shape parameter, Beta (β), determines which member of family of Weibull failure distributions best fit or describes the data. Whereas characteristic life or scale parameter (α) is percentile of the failure, also denoted as MTTF. For the case β is calculated to be 2,35 whereas α 14058 hours. Beta (β) of 1 is regarded as useful life with constant failure rate. In the case under observation, high value of Beta shows that the equipment has passed its useful life period.

These two parameters are used to calculate reliability of the equipment and simulate preventive and corrective cost. The real cost figures were not available; therefore estimated costs are used based on experience. Corrective cost are assumed to be twice as preventive cost in this case. In other cases, corrective cost can be 5 or even 10 times higher than the preventive cost.

Visualized results from the case suggest the best cost-effective preventive maintenance strategy based on all inputs. Such graphical presentation is easy to explain and shows when the best time for maintenance intervention is.

Figure 7. Graphical representation of PnP results from a case

In this scenario, the two straight lines represent the accept criteria for reliability. The upper reliability limit is set to be 95% whereas lowest at 70%. These limits can be set according to desired reliability targets. Availability of the equipment is quite high, close to 100% which is not an issue in this case. Beyond an interval of 12 months, the reliability drops drastically. Considering cost, the best maintenance intervention interval is suggest to be between 6-9 months. These results are validated with team of domain experts. Based on health data from the equipment, the upcoming failures are bearing failure and misalignment. Further is to review the current maintenance strategies and identifying how to optimize the maintenance intervals in a manner without sacrificing safety and risk.

5 Conclusions

Optimizing maintenance strategies is a living process. In order to systematically target the real issues and take correct in-time decisions, sophisticated tools and methodologies to be employed. Prevent and Predict (PnP) method is a more pragmatic analytical platform combining equipment health and maintenance history to aid critical preventive and corrective maintenance decisions. In most cases from offshore oil and gas industry maintenance history and collected data is not fully utilized. Weibull analysis is used in PnP for analysing maintenance data that provides useful insights about equipment age, shape and characteristic. Outcome of Weibull analysis are reliability, availability and cost predictions. The results recommend an effective maintenance strategy. When combined with equipment health (as-is) upcoming failures are predicted with high accuracy. The case presented in this paper, created a potential of more than 40% savings per annum in preventive maintenance cost by optimizing existing maintenance strategies. PnP helps in predictive benchmarks that forms basis for smarter maintenance decisions. It also fits well with online remote predictive analytics using data from cloud, which is one of the emerging challenges in the industry.

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