Use of MCDM and AI Techniques for Mechanization of In-Service Inspection Planning Process

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Abstract. The in-service inspection planning process for topside piping equipment of aging oil and gas (O&G) production and process facilities (P&PFs) involves personnel with different kinds of expertise, experience, and knowledge as well as a vast amount of data and information. To simplify the inspection planning process and increase the quality of an inspection program, various industrial organizations as well as researchers have been developing numerous techniques in an isolated fashion to address the challenges pertaining to different activities involved in the inspection planning process. In order to mechanize the overall inspection process, suitable techniques need to be identified for the different activities carried out in a generic inspection planning process. This manuscript discusses the potential use of multi-criteria decision analysis (MCDM) and artificial intelligence (AI) techniques. It also provides evidence about the suitability of AI techniques in relation to fuzzy logic and artificial neural networks for the mechanization of the inspection planning process in a dynamic manner.

Keywords: In-service inspection planning, AI techniques, MCDM techniques, Inspection programs, Aging O&G P&PFs.

1 Introduction

In offshore P&PFs, the topside piping equipment plays a vital role in the production of hydrocarbons (O&G). In this process, performing equipment maintenance at a level anticipated to comply with the standards and guidelines imposed by regulatory authorities (i.e. Petroleum Safety Authority (PSA), Norway) is a mandatory task for the aging O&G P&PFs operating in the North Sea. Therefore, the owner/operator companies of the P&PFs conduct inspections to identify the equipment's fitness for service and the level of required maintenance and modifications (Ratnayake, 2012a). In this context, the in-service inspection planning process, which consists of a series of subprocesses, for instance, preparation of inspection programs, carrying out inspections at plant level, evaluating inspection results and updating the risk level of equipment, feedback for operation and maintenance and evaluation of resource allocation for the next inspection cycle, is of major significance.

Researchers have identified the importance of inspection planning in various industrial settings, and reliability-based and risk-based approaches were developed from 1963 onwards, gradually establishing risk-based inspection (RBI) concepts for the planning of inspections over the last 25-30 years (Ratnayake et al., 2011; Straub & Faber, 2006). The application of RBI planning has been limited in the past due to the significant numerical effort required by these methods. The MCDM methods, such as the analytic network

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process (ANP), and the analytic hierarchy process (AHP) developed by Satty (1980), were applied by many researchers in different levels of the inspection planning process. Ratnayake (2012a, 2012b, 2013) and Ratnayake & Markeset (2010) used AHP in planning inspections for topside mechanical equipment. The views of the industry's professionals were considered in developing these AHP models to recommend critical thickness measurement locations (TMLs) (Ratnayake, 2012a, 2012b). The models were based on prioritizing the critical TMLs and optimising the cost for the inspections. Dey (2004) also used the AHP in hydrocarbon pipeline inspection planning, which was illustrated by case studies. The AI technique-based models were also developed to identify critical TMLs, considering the degradation mechanisms. The techniques, for instance fuzzy logic and artificial neural network (ANN), are used by Nesic et al. (2009), Singh and Markeset (2009), Zio (2012) in developing the models. Most of these models are based on empirical methods, in which planning personnel use these models together with their expertise for the planning purposes. The models which developed utilizing AI techniques are more able to incorporate expertise than the empirical models.

This manuscript discusses the advantages and disadvantages of the MCDM and AI approaches in the inspection planning process. The goal of this paper is to identify the sub-processes in the inspection planning process where it is possible to use the AI techniques for the mechanisation of the inspection planning process.

2 Background

The inspection planning work process is defined in several standards, for instance DNV RP G101 (2010) and API RP 581 (2008), and illustrates the sub-processes and flow of sub-processes. A generic inspection planning work process consisting of sub-processes that have been employed in the industry is illustrated in Fig. 1.

The main part of the inspection planning work process is the preparation of the inspection program. In planning inspection programs, the recommendation of critical TMLs for inspection is a primary task. A huge amount of data is gathered, and various techniques are used to identify TMLs by prioritization of criticality. In P&PFs, the topside piping equipment inspection planning personnel's primary concern is corrosion and erosion trends. However, there are other degradation trends, for instance, fatigue degradation, crack propagation due to fatigue, stress-induced cracking, slug effects, flow turbulence effects, stress generation, thermal effects, etc. In general, chemical and mechanical corrosion have been taken into consideration (i.e. CO_2 corrosion, H_2S corrosion, microbially-induced corrosion and sand erosion) during inspection planning. NORSOK M-506 (2005) and DNV RP O501 (2007) are examples of the models developed in standards to assist the inspection planning. The prioritization of identified critical TMLs is based on the thresholds provided by the governing documents, for instance plant strategy, RBI guidelines, piping standards (e.g. ASME B31.3), etc.

In executing inspections, resource allocation is another major part of the planning process. The TMLs' accessibility, methods for inspection, manpower and working hours needed to be calculated. The feedback process performs by comparing the current measurements and historical data to identify the current risk level of TMLs. Furthermore, the annual inspection budget, the annual activity plan and the feedback PM plan are assigned according to the feedback provided by the risk level of the TMLs. Therefore, the inspection planning sub-processes consist of data analysis, forecasting, optimizing and prioritizing. Currently this is performed by using basic calculations and primary software tools.

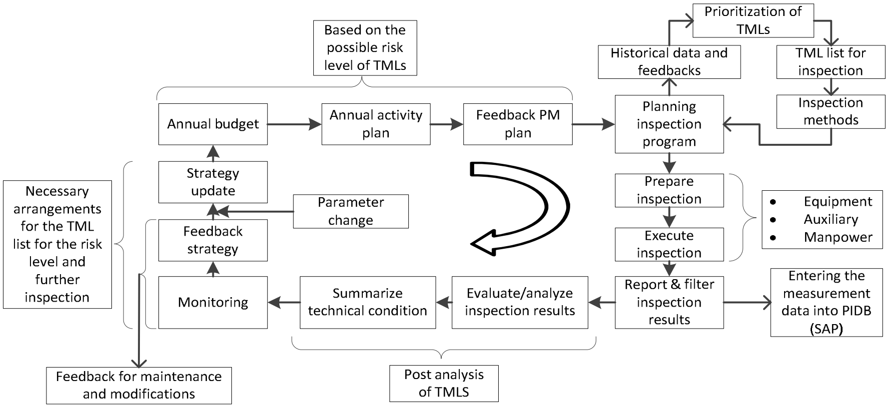

Fig. 1. Inspection planning work process

3 Static and Dynamic Modelling for Inspection Planning

The models developed in the condition based maintenance and monitoring paradigm, in particular to identify the inspection intervals and the prioritization of the inspections can be divided into static and dynamic models (Wang, 2003). Static models are driven by the fixed condition monitoring interval data, while dynamic models are driven by both fixed condition monitoring interval data and real-time condition monitoring data. Therefore, the dynamic model overrides the static model with real-time condition monitoring data, which keeps the equipment under close attention before an appropriate mitigation action takes place when it reaches a critical level (Wang, 2003). The currently developed static and dynamic models are less likely to connect to the real-time condition monitoring data (Jardine et al., 2006). However, the aging P&PFs are constantly affected by the changing production and process conditions where the deterioration and degradation trends are dramatically changing over time. Therefore, the dynamic behaviour of the models which can be connected to the condition monitoring data will be useful for the aging P&PFs to monitor the critical equipment regularly.

4 The Decision Support Modules in Inspection Planning

Different decision support modules (DSM) are developed based on the static and dynamic models to support the decision-making process of the sub-processes in inspection planning. DSMs are developed in an isolated fashion to address the different scenarios, such as the identification of different degradation trends for TMLs, the prioritization of TMLs, inspection methods, etc. However, a number of researchers have observed the difficulty in making proper decisions on the above analysing process and have suggested different approaches. The main model development is focused on degradation monitoring followed by the identification of critical TMLs. The techniques, for instance AHP, ANP, outranking, fuzzy logic, artificial neural networks and genetic algorithms, are used in developing the DSMs.

The main contribution of the DSM in inspection planning is through degradation models. Ratnayake & Markeset (2010) and Singh & Markeset (2009) have reviewed the degradations and degradation models for O&G topside piping and hydrocarbon transportation pipelines. The O&G piping equipment is frequently subject to different degradation mechanisms, internally and externally. A number of manuscripts address specific types of corrosion behaviour: Ramsamooj and Shugar (2001) offer a detailed description of corrosion and fatigue modelling in unfavourable conditions; NORSOK M-506 (2005), Singh & Markeset (2009) and Valor et al. (2010) address $C0_2$-driven corrosion and the problems of pitting corrosion; Walton et al. (1996) deal with the problems of modelling marine corrosion damage, and DNV RP O501 (2007) illustrates the erosion behaviour of the equipment subjected to produced sand. A large amount of degradation modelling causes the problem to converge into one variable situation, by treating individual items of equipment independently. For large systems, such as those found in the O&G industry, this is a practical assumption that allows the modeller to handle potentially intractable modelling problems. However, this is not usually a realistic assumption since the systems are undergoing different degradation mechanisms in different locations at different times. Therefore, the application of different degradation models (i.e. based on different degradation mechanisms) in one system will enable the identification of different degradation tends in the TMLs. The results from the different models can be used for cumulative prioritization to identify the most critical TMLs in a system.

5 Use of MCDM and AI Methods in Inspection Planning

The MCDM and AI techniques are used in static as well as dynamic modelling of the stages of the inspection planning process. The main functions of the exploited models are optimization, forecasting and prioritization. In MCDM, there are two different approaches for problem solving. The first is to evaluate problems which consist of a known number of alternatives in the solution domain. The second approach is where the number of alternatives for the problem is unknown. However, in this situation, the problem is solved by mathematical modelling to identify the solution (Triantaphyllou, 2000). Therefore, in the inspection planning process of O&G topside piping equipment, the alternatives are limited and the first approach in MCDM is used by many researchers.

Outranking methods, ANP and AHP are the three most frequently used MCDM techniques for prioritization (Bozbura and Beskese, 2007). The outranking methods determine which alternatives are being preferred to the others by systematically comparing each criterion instead of building complex utility functions (Brans et al., 2005). In AHP, pair-wise comparisons are made in between elements at each level of the hierarchy by means of a nominal scale to establish a comparison matrix. The eigenvector of the matrix is derived as the weights' vector of elements at the hierarchy. Finally, overall priority can be obtained by synthesizing local and global weights. The fuzzy version of AHP is preferred in the prioritization of problems for the following reasons: no measurement scale needs to be explicitly defined for each criterion/attribute in pair-wise comparison; representation of uncertainties such as vagueness; non-specificity and discord can be incorporated in the models (Klir and Yuan, 1995). However, there are limitations in using fuzzy-AHP, and these are some of the problems: a high number of computational requirements; only triangular membership functions can be used;, difficulties with criteria and attribute addition and deletion and the number of pair-wise comparisons are increased with the number of criteria (Buyukozkan et al., 2004).

Table 1. Comparison of usage of MCDM/AI techniques in inspection planning

Method	Usage in inspection planning process modelling	Advantages	Disadvantages
MCDM methods (Brans and Mareschal, 2005)	Extensively used in inspection planning. Static modelling behaviour due to the fixed designed methods by designer. Decision selection is from fixed alternative domain.	Easy interpretation of the criteria and alternatives. Easy for designing the models. Flexibility in defining the threshold limits.	Static behaviour of the models. Reflects the designer's perspectives. Fixed boundaries in generating decisions.
Fuzzy logic (Buyukozkan et al., 2004)	Relatively well used in the inspection planning. Represents the process uncertainty parameters. Modelling is static. However, by incorporating other AI techniques, dynamic behaviour can be obtained. Utilizes vagueness and impression of parameters to design noise-tolerant models. Rule base inferencing.	Interpretation of expert knowledge, intuition and experience. Interprets the vague, noise and imprecise data and information. Rule base is used to mimic human-like reasoning by using suitable inferencing methods.	More toward static behaviour in the modelling. Limitations in interpreting human-like reasoning behaviour. Inability of self-learning capabilities.
Artificial neural network (Zhang et al., 2004; Caputo & Pelagagge, 2002)	Relatively well used in inspection planning. Dynamic behaviour is observed in the neural network models. Equipped with the self-learning abilities to adapt the problem-solving capabilities.	Dynamic and good in modelling nonlinear and unstable processes. Trained for complex input output modelling. Self-learning abilities (adaptively). Different types of architecture for different levels and different types of complex problems.	Selection and designing of ANN for solving a problem situation is complex. Identification of proper network design needs extensive effort and research. Training and validation of the designed ANN requires large amount of data.
Genetic algorithms (Cavory et al., 2001)	Limited use in inspection planning. Shows more static behaviour in the modelling. Dynamic behaviour can be adapted using fitness function.	Easy representation of criteria and fast generation of outputs. Simple designing of a model.	Depends on the designers perspectives. No flexibility for imprecise data. Rigid in model construction.
Bayesian networks (Lee et al., 2014)	Extensively used in inspection planning. Static in behaviour since the model uses the statistical methods (probability).	Able to represent the historical behaviour. Easy for designing models and generating desired output. Reduction of number of parameters by conditional probability distribution.	Static in behaviour and relies on the designer's intuition and knowledge. Limited representation of the new data in the system. Less adaptability to the system behaviour.
Petri nets (Ratnayake, 2012a)	Limited use in inspection planning Static behaviour (less adaptability). Dynamically used, but cannot change the parameters.	Easy to model.	Limited alternatives in the modelling process. Needs extensive understanding of the process for modelling.
Hidden Markov model (Lee et al., 2014)	Limited use in inspection planning. In between static and dynamic (has some level of adaptability). Less dynamic in nature. Dynamic as a hybrid model with unknown state space parameters.	Can be used for fault and degradation diagnosis on non stationary signals and dynamic systems. Appropriate for multi failure mode.	Not appropriate when the failure state is observable. Large amount of data is needed for accurate modelling.

In recent years artificial intelligence techniques have also been used successfully in condition based maintenance planning. The earliest works made use of expert systems (Medsker, 1994); then came a number of studies using ANN (Caputo & Pelagagge, 2002). Jang (1993) proposed the adaptive network-based fuzzy inference system (ANFIS), a hybrid learning algorithm extensively used in forecasting problems. The ANN model is also used with a back propagation algorithm for predicting failure rates (Al-Garni et al., 2006). Ciarapica and Giacchetta (2006) experimentally used ANN and neuro-fuzzy systems to forecast activities in the rotating machinery preventive maintenance cycles. Genetic algorithms are used in optimizing the maintenance schedule tasks in production environments by Cavory et al. (2001). These are also used by Sortrakul et al. (2005) to solve an integrated optimization model for production scheduling and preventive maintenance planning. More recently, several works have employed fuzzy logic systems in the identification of critical TMLs (Ratnayake, 2014a, 2014b; Seneviratne & Ratnayake, 2013). However, the neuro-fuzzy approach integrates the neural networks and fuzzy logic to create powerful expert decision systems. Many authors have proposed various neuro-fuzzy models and complex training algorithms in inspection and maintenance planning (Zhang et al., 2004). Table 1 illustrates the usage of different methods for inspection planning process modelling in various industries with their advantages and disadvantages.

Although different models have been developed using different techniques, full mechanization of the inspection planning process has not yet been achieved. Researchers address the mechanization of some of the sub-processes illustrated in Fig. 1. To achieve total mechanization, as short-term goals, correct techniques for modelling the sub-processes needed to be identified. As middle-term goals, the knowledge bases for the models needed to be created. For long-term goals, full mechanization can be achieved by the integration of models, developed knowledge bases and the connection of condition monitoring sensors to the models.

6 Discussions and Conclusions

The planning process consists of several stages with different levels of data analysis. In this analysis the experience, knowledge and intuition of the field experts is extensively used. In the mechanization of the inspection planning process, prioritization techniques which can incorporate human-like abilities need to be used. The techniques, for instance fuzzy logic and ANN, demonstrate human-like reasoning abilities. However, referring to the advantages and disadvantages illustrated in Table 1, individual AI techniques show only a limited number of reasoning behaviours. Therefore, the use of multiple AI techniques in a model as hybrid AI techniques will enable human-like reasoning abilities to be embedded into the DSMs.

In the O&G P&PFs, the product and process condition variations cause the arbitrary degradation trends of aged equipment which are reaching critical levels. However, the financial productivity is less in aged P&PFs. Therefore, owner/operator companies face difficulties in performing inspections regularly to monitor the critical equipment. Hence, the dynamic modelling approach is necessary for the aged O&G P&PF inspection planning, where the condition monitoring data can be linked to the DSMs to identify the critical TMLs in a dynamic manner.

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