Nuclear Power Plant Maintenance Optimisation: Models, Methods & Strategies

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Abstract. Maintenance activities are very important for the complex and high-risk installations, especially for Nuclear Power Plant. Good maintenance will be able to minimise loss of production, reducing the cost of the electricity generation, and/or reducing the risk. However, there are many issues to make a good maintenance program, such as regarding limitation of reliability data, the complexity of the system, (in)dependency failure mechanism, unpredictable spare parts supply chain, accessibility for maintenance and repair, environmental limitation, human resources, management, regulation, etc. Many studies have been done by researchers and engineers from various sectors to optimising maintenance activities. We have studied several kinds of available literatures, especially that can be used for the nuclear industry. By using proposed maintenance framework, we would like to describe Nuclear Power Plant maintenance optimisation studies that have been done systematically. We also did a critical review and gap identification between scholar studies and real applications and then classified them to provide more easy understanding information that can be used as an information for the future development. Based on our study, there is a wide gap between academic study and implementation. Although many models, methods, and strategies have been proposed, most of the NPPs in the world are using traditional approach by following time-based and breakdown maintenance strategies. There are such kinds of factors, such as because of the regulatory framework barrier, weak relationships between stakeholders and regarding data availability. Future studies to explore those problems are needed.

Keywords: Nuclear Power Plant, maintenance, optimisation, model, method, strategy

1. Introduction

Nuclear Power Plant (NPP) is one of the most reliable carbon-free energy supply in the world. NPP can compete for head to head with fossil-fuelled power plant regarding their reliability, the amount of energy generation and also cost of generation [1]. By 2015, NPP supplied about 4% of the world's energy demand [2]. It has decreased significantly due to the decommissioning of some ageing NPPs as well as the impact of the Fukushima Daiichi accident that forced several nuclear reactors in Japan were suspended from their operation. Considering the change in energy development roadmap in China and Arabian countries, the number of interesting countries on nuclear energy, and also the expectation that Japan will re-operate their NPP, British Petroleum (BP) estimated that the energy mix from nuclear will grow to 5% by 2035 [2].

As a high risks installation, both operator and regulatory body have special attention to ensure that NPPs can be operated safely [3]. The regulatory body has an interest in providing protection to the
public and the environment for any negative consequences that may result from potential accidents in operation. While the operator must ensure that catastrophic accidents will not happen since it can stop their business continuity. But on the other hand, the improvement of safety aspects is also limited by several business factors, such as the ability to compete with other types of power plants and how operators can optimise their revenues.

Operation and maintenance activities contribute to the second largest cost for the entire NPP lifetime [4]. Based on the power generation costs assessment that has been done by Matsuo et al., maintenance activities become the biggest cost of NPP operation & maintenance activities in Japan [5]. If the effort for the new NPP can be done by reducing all the cost compositions including capital costs, however, that is not possible for the existing NPP. Competitiveness of existing NPP probably can be archive by reducing operation & maintenance costs, optimising electricity generation and extending plant operation. Since maintenance is become one of the biggest cost but on the other side also strongly correlated for safety, operation factor, availability etc., then maintenance has become an interesting topic for many researchers.

![Figure 1. Number of publication regarding NPP maintenance](image)

The research interest regarding maintenance strategy to optimising availability/reliability, minimising risk and cost has been growing up time by time. According to Web of Knowledge since 1987, there have been more than 19,000 journals and articles discussing the maintenance from various fields. As shown in Fig. 1, focusing on the nuclear power industry, there are about 1,220 correlated publications have been published. From that data, we also can see that there were very limited maintenance strategy publications before 1991, but after that relatively increases year by year. So, it can be understood that maintenance-related studies have become an interesting issue for researchers around the world.

Although there are so many models, methods and strategies have been proposed, only a few that actually have been applied for real NPP maintenance activities [6]. This is because NPP is a conservative industry that is usually strictly regulated. Operators cannot develop their strategic maintenance just based on engineering judgement and economic motive but must consider several regulations. Regulation becomes a boundary that must be obeyed by the operator in the preparation of maintenance strategy. The differences in regulation will affect the flexibility of operators in applying maintenance strategy. The differences in maintenance strategy finally also affecting the electricity generation cost. Therefore, this study is intended to review several NPP maintenance study publications systematically, mapping and discussing them technically.
Firstly, we classified some publications based on the web of Knowledge result by filtering using some combination of keywords such as “maintenance”, “inspection”, “nuclear power plant”, “NPP” and the combination of several keywords. To get the more specific publications, filtering has been done manually regarding their abstracts, topics and titles. Since many applicable publications not specifically discussing maintenance strategy for NPP but have a strong correlation, so we also use those articles as references.

The remainder of this article is organised as follows. Section 2 will be started by establishing maintenance strategy framework as the basis for next section discussion. Section 3 discussing system modelling that usually used for nuclear industry. Section 4 discussing failure modelling including the type of failure, repairability, data availability, and failure model. Section 5 describing optimisation modelling. Section 6 discussing maintenance strategy. Section 7 general discussion, and finally will be closed by conclusion on Section 8.

2. NPP maintenance framework

Based on IAEA publication, the primary purpose of the NPP maintenance programme is to ensure the equipment and components are ‘fit for purpose’ and provide the required functionality to enable safe and reliable power production [7]. Furthermore, IAEA also described that maintenance of NPP including preventive and remedial measures, both administrative and technical, necessary to identify, prevent and/or mitigate degradation of a functioning structure, system or component (SSC) [7].

The division that has a responsibility for maintenance usually develops maintenance strategy before or at the beginning of commissioning. That maintenance strategy will be used for several years and will be revised periodically depend on the new finding by following management concept through Plant – Do – Check – Act (PDCA) [8]. Generic steps for making maintenance strategy plan is started by clustering and system identification, risk assessment analysis to identify critical components, defining maintenance strategy and the last step is optimisation based on some known constraints as shown in Fig. 2.

Many models, techniques and methods have been developed for optimising maintenance strategy on various engineering fields, especially for NPP. For the purposes of this article, we would like to break down the discussion by proposing maintenance framework as shown in Fig. 3.
3. System modelling

System modelling is one of the most critical steps in the maintenance strategy development. The most important thing on the modelling or how to make a model that is a simplification of the real system by using limited data but on the other side should be able describing the real condition.

To make a model, three kinds of data should be used. These data such as technical data, operation data, and testing & maintenance history data [9]. Those kinds of data probably can be gotten not only directly from the plant itself but also from the other plants that have a similar system configuration. To get an accurate model, the contribution from experts that well understand the system will be very helpful.

![Figure 3. NPP maintenance framework](image)

There are three things that give a big contribution to the NPP maintenance modelling, such as modelling level, the modelling method, and updating data/result. Those things will be varied depending on the purpose of the modelling.

3.1. Modelling level

NPPs are one of the most complex installation plants in the world since they are constructed from thousands of components. For certain purposes, NPP is grouped into several systems. The grouping may vary depending on the point of view [10]. For example, in terms of function, the system in the NPP can be grouped into power generation and safety system. Power generation can be categorised into several systems, such as nuclear reactors, steam generators, steam turbines, cooling systems, etc. Each of these systems then also can be broken down into several components and parts.

Systems modelling depends on the scope and purpose of modelling. At least modelling can be categorised become plant/system level and component level. The purpose of plan/system-level modelling is to identify and categorize the importance of components on the basis of Reliability
Centred Maintenance (RCM) strategy [11]. IAEA recommends the used of RCM as the basis of NPP operation & maintenance [12]. Modelling for RCM strategy probably can be done to overall plant level. But since plant level of NPP is very complex with millions of components, so, it will be very difficult and need a high computational resource. Clustering and break down the plant becoming some systems and analyse it into smaller scope will make critical component identification become more easily [13]. Component level modelling is usually done to get more detail reliability characteristics understanding of a component. By understanding the characteristics of a component in more detail, then specific maintenance activities probably can be done more realistically and precisely. Furthermore, each modelling level needs different appropriate modelling techniques.

3.2. Modelling methods

Nowadays there are many modelling techniques that are usually used in the industry. Some of them such as Failure Mode Effect Criticality Analysis (FMECA), Reliability Block Diagram (RBD), Fault Tree Analysis (FTA), Markov models, Bayesian Network, Petri Net, Cause-Effect Diagram, Root Cause Analysis, HAZOP models, Fuzzy models, etc. From those methods, only some of them become famous for nuclear industry application.

3.2.1. Failure Mode Effect and Criticality Analysis (FMECA). FMECA or some time simplify only become Failure Mode Effect Analysis (FMEA) was one of the first systematic techniques failure analysis that developed by US Military [9]. FMECA is widely used as reliability analysis technique in the initial stage of system development [14]. There are some basic consent of FMECA, such as; how each part can conceivably fail, what mechanisms might produce those modes of failure, what is the effects of the failures, is the failure in the safe or unsafe condition, how the failure can be detected, and what inherent provisions are provided in the design to compensate for the failure [15].

FMECA analysis is done through weighting and ranking. At the end of the analysis will be obtained which component has the greatest weight that means require greater attention and which components have a low weight which means no need to be prioritised [13]. FMECA is a very famous hazard identification in the nuclear industry and still become an important tool to design an NPP [16]. FMECA analysis provides a good sense of the implementation of the preparation of RCM strategy [7]. However, classical FMECA method has resulted in poor maintenance recommendations [17]. That is because analysis of FMECA methods is not able to provide a more specific impact analysis of the failure of a component or a group of components and their correlation with the failure of the entire system. This method also does not give an idea of the easy way of which components can be repaired online when the system is in operation, and which components should only be fixed during the shutdown condition. Therefore, to solve those problems, some studies have been done by Peeters et al. [18] and Liu et al. [19], by combining between FMECA and Fault Tree Analysis (FTA). Some other efforts also have been done by modifying and/or combining FMECA with Analytic Hierarchy Process (AHP), Fuzzy logic, Waste Priority Number (WPN), etc. such as have done by Zhang et al. [20], Sutrisno et al. [21] and Fattahi & Khalilzadeh [22].

As a mature method and can be used together with the other methods, FMECA still be used widely in nuclear maintenance studies and real applications. Some papers reporting the used of FMECA for NPP maintenance purposes such as by Yoshikawa & Nakagawa [23], Park & Jung [24], Lee et al. [25], Jun et al. [26], and so on. Flanagan et al. [27], Alzbutas & Voronov [28], Rajiv Kumar & Pooja [29], Tapia et al. [30], Tesini & Palmer [31], Pinna et al. [32], Burgazzi [33] also used FMECA to do risk analysis and maintenance purposes for the nuclear fusion reactor technology.

3.2.2. Fault Tree Analysis (FTA). The FTA method was first developed by Bell telephone laboratory in 1962 which was intended to analyse the safety of Minuteman missile launcher control system [13]. This method is further developed by Boeing company for the safety analysis of their aircraft industry [9]. The use of FTA became very intensive for NPP after the publication of Rasmussen report (WASH-1400) in 1975 which became an early foothold in probabilistic safety analysis for the nuclear
industry [13]. Currently, FTA is widely used as a mature technique in NPP safety analysis and is also included in the preparation of RCM strategy as recommended by IAEA [7][34].

FTA analysis for maintenance strategy can be done both qualitatively and quantitatively [13]. Qualitative analysis can be obtained from identification of cut set. While the quantitative analysis of the calculation of failure probability of the system based on the failure probability of each component that compiled it. The qualitative analysis of FTA is based on the cut set that can be easily seen based on the number of components that compose them. Cut set that is only compiled by one component means that if that component failure, then will cause a certain failure on the entire system. While the cut set composed of two or more components implies that there is a redundancy so that the failure of one of them will only increase the failure probability but will not cause a failure of the entire system. Cut set that constructed by many components mean that they have better redundancy. While the quantitative analysis on the FTA is done by calculating the failure probability of the system and/or cut set based on the failure probability of each component by following Boolean algebra rules [35].

There are some methods that can be used to increase the sensitivity of FTA analysis, such as combining with FMECA as discussed above, integrating with component important index concept, Dynamic FTA (DFTA) development, combining with Fuzzy logic, etc.

Important index methods have been used widely in many kinds of literature including ASME [36] and IAEA standards [34]. Some of the most famous important index such as Birnbaum's measure, Risk Achievement Worth (RAW), Risk Reduction Worth (RRW), and Fussell-Vesely's measure. The other important indexes also have been proposed in some literature, such as by Hwang [37], Wang et al. [38], Lin & Li [39], and Dui et al. [40]. Important indexes provide a good sense for various maintenance purposes.

DFTA was proposed because of the limitation of traditional FTA that is not able modelling dependency condition in the complex configuration like the NPP. DFTA provides dynamic gates such as a spare gate, functional dependency gate, priority gate, and sequent gate [41]. Some literatures discussing DFTA that have less or more correlation with NPP reliability/availability and/or maintenance, such as by Verlinden et al. [42], Shin et al. [43], Fourneau [44], Ruijters & Stoelinga [45], Chiacchio et al. [46], Rao et al. [47] and Jankovsky et al. [48]. DFTA gates can be constructed by deploying Markov models, Bayesian Network, etc. into classical FTA.

Analysis using FTA becomes quite difficult for very unlikely events and with limited data. Because of that some researchers like what have done by Purba [49] combining the FTA with a Fuzzy logic concept.

3.2.3. Reliability Block Diagram (RBD). RBD basically has a similar concept to FTA [15]. If the dependency of each component on FTA is represented by the OR gate, then in RBD it is denoted by the series structure. While the independence of the FTA which is described by AND gate, then has the same meaning as the parallel structure in RBD. Just like FTA, RBD analysis can also be done both qualitatively and quantitatively. Qualitative analysis can be seen from the series structure of the system also called cut set as in the FTA. While quantitative analysis is done by calculating the failure probability of an overall system with the calculation based on the failure probability of each component based on the series or parallel relationship. More deeply quantitative analysis can be done by using the important index exactly similar with the important index in FTA.

The similarity between RBD and FTA makes conversion from RBD to FTA and vice versa become very easy. Just like FTA, traditional RBD also has a limitation regarding dependency modelling that make researchers such as what has been done by Ahmed et al. [50] developing Dynamic RBD. But on the other side, maybe because of that similarity make the used of RBD for NPP risk analysis and maintenance strategy is become not as popular as FTA. Some researchers that deploying RBD on their NPP maintenance studies such as Verlinden et al. [42], Nguyen et al. [51], and Radim Briˇs & Petr Byczanski [52].
3.2.4. **Markov models.** Markov models are memoryless modelling and a continuous time stochastic process. There are at least four kinds of Markov models used in different situations depending on sequential state observation and adjustment of the system on the observation, such as Markov chain, Hidden Markov model, Markov decision process, Partially observable Markov decision process. Those Markov models have been used widely for mechanical modelling, especially for reliability modelling.

Markov models also very popular for maintenance purposes especially modelling for the single failure of a component. Markov models are very powerful because it can illustrate the failure of the process in detail to present a good quantitative analysis. Related works regarding component degradation on several engineering fields and of course also can be used for NPP maintenance modelling such as like have been done by Liu & Zio [53], Raza & Ulansky [54], Panagiotidou [55], Curcuru et al. [56], Letot & Dehombreux [57] and many more. But since they need complex calculation, Markov models are very complicated if be used for modelling a large system [42]. Therefore, Markov models are usually combined with the other models for modelling large system but on the other side also has detail processes. Markov models can be used as the basis of DFTA and DRBD algorithms such as have been done by Pirriou et al. [58], Bucci et al. [59], Merle et al. [60], Rao et al. [47] and Bouissou & Bon [61]. Some researchers also combine Markov models with Bayesian networks such as have been done by Guo et al. [62], Bueno et al. [63] and Lin [64].

3.2.5. **Bayesian Network.** In some ways, the point of view between Bayesian and traditional statistical concepts are very different and has led to controversy [65]. Those who tend to use the Bayesian concept are usually referred as Bayesian. While those who use the concept of classic statistics commonly referred as Frequentist. Apart from these points of view, for some purposes, the Bayesian theory is powerful for solving many problems, especially regarding prediction, incomplete data, etc.

The interest in the use of the Bayesian network as maintenance modelling has been increasing from year to year. This is because, in the real world especially in nuclear industry, some data required in modelling are unknown or less precise, such as imprecision in the failure criterion, the problem in record keeping, or interpretation. The limited number of NPPs especially for components with very limited quantities also makes it difficult to obtain precise statistical failure data. Often, modelling is also confronted with how to combine qualitative information that is very difficult to do by using traditional statistical methods [65]. Therefore, Bayesian probably will become the basis of future maintenance modelling for nuclear industry [66]. Some works dedicated for nuclear reliability and maintenance strategy using a Bayesian network such as have done by Belyi et al. [67], Kang & Golay [68], Popova et al. [69], Mancuso et al. [70], Chen et al. [71], etc.

3.2.6. **Petri Net.** Petri net was first presented by Carl Adam Petri in 1962 and has similarity approach with Markov models [15]. The advantage of Petri Net modelling is in its visualisation that makes it easier to understand. Petri Net modelling is a two-way graph that consists of place, transition and arrows. But not like Markov models, Petri Net relatively easier to be applied for a huge system modelling.

According to the data from Web of Knowledge, the use of Petri Net on nuclear study is still limited. There are only 45 publications covering the use of Petri Net in the nuclear area and about 870 publications for the wide area of reliability (based on searching result on March 30th, 2017 by using key words “nuclear power plant AND petri net” and “reliability AND petri net”). Therefore, there are wide opportunity to conduct studies related to use of Petri net. Majority of publications discussing NPP reliability using Petri Net modelling related to human reliability and control systems. Some of these publications such as have been done by Lee & Lu [72], Bai et al. [73], and Kumar et al. [74].

3.2.7. **Other methods.** Several other methods are also developed to determine the maintenance strategy for NPP such as Hazard and Operability Study (HAZOP), Analytic Hierarchy Process (AHP), and Beta-factor model. HAZOP and AHP have been used widely in several engineering fields but not
too famous for NPP maintenance strategy. Only small amount of publications deploying HAZOP and AHP for maintenance strategy on their study such as what has been done by Guimarães & Lapa [75], Carnero [76], Azadeh et al. [77], Pekka [78], and Bertolini & Bevilacqua [79]. Beta-factor model was introduced by Fleming in 1975 [15]. The idea of the beta-factor model is splitting failure rates become two, individual failures for the specific item and failures that affect all the items in a voted group. Beta-factor model becomes famous for NPP maintenance since it can be used for modelling Common Cause Failure (CCF). There are some publications discussing maintenance modelling using Beta-factor, such as by Kančev & Čepin [80] and Duy & Vasseur [81].

3.3. Model updating

For this article purposes, modelling can be classified as offline and online modelling based on the updating time. Offline modelling is modelling that update and provide system/component availability/reliability information for a relatively long period. While online modelling is a model that can provide reliability information to a system in real time. Traditionally, Probabilistic Risk Assessment (PRA) for conducting NPP maintenance strategy is based on offline modelling. We can find many publications discussing NPP maintenance strategy using offline updating model. But since the development of the computer technology that enables implementation of rapid calculations has been promoting the growth of online modelling. Living Probabilistic Safety Assessment (PSA) is one of the widest studies that has been becoming a trend.

Online maintenance is one of the most important NPP maintenance strategies. To be able doing maintenance online without breakdown risk probability higher than the requirement, online risk assessment information is required. Online assessment using various methods have been developed by some researchers such as by Zubair et al. [82], Kančev [83], Zubair & Zhijian [84], Jun et al. [26], and He et al. [85].

4. Failure modelling

Understanding of failure modelling in determining maintenance strategy of NPP is very important. For the easier understanding, in this case, we divide failure modelling into several categories based on the type of failure, repairability, the kind of the data and failure mode.

4.1. Type of failure

Understanding the failure characteristics of each component in NPP will greatly determine the accuracy of maintenance modelling. Failure on NPP components can generally be divided into two categories; independent failure and dependent failure [35]. A component is said to be independent if its failure does not cause a failure to the other components. While a component is said to be dependent if the failure of the component also generates another failure. The difference between the two types of failure will very influence the calculation of failure probability of overall plant. The component that has independent failure characteristic can be said to contribute failure probability to all system with the smaller value than components having dependent failure characteristics. A system constructed by independent components can be modelled easily using traditional FTA/RBD and have been used widely in some publications such as what has been done by Baptista et al. [86], Liu, Jie & Zio, Enrico [53], Nguyen et al. [51], etc. But a system with dependent components should be modelled using dynamic modelling such as using DFTA/DRBD, Dynamic Bayesian Network, Petri Net or possibly by combining some models.

Furthermore, dependent failure can be categorised into three; CCF, intersystem dependency failure, inter-component dependency failure [35]. CCF can cause a transient condition and increased unavailability of one or more mitigating system. An example of CCF such as due to damage to one of the main components of an external power supply that causes disconnected from the external power supply. Intersystem dependency failure is the failure of a component that can affect two or more systems, such as the failure of coolant injection pump. While inter-component dependency failure is the failure of a component that can cause the failure of one or more other components in the system.
but will not affect other systems. This different type of failure will ultimately determine how much work to do if a component fails. In addition, this is also associated with overall plant failure probability that will affect the maintenance strategy.

4.2. **Repairability**

Repairability regarding the degree to which a component can be maintained when failure. In general, repairability is only divided become two; unrepairable components and repairable components. Unrepairable components such as the lubricant, filters, etc. cannot be repaired if those components become fail. The solution to unrepairable components is to do the replacement. While the repairable component is a component that able to be repaired by using several improvements, including calibration, minor repair, major repair, or overhauling. The differences in repairability will contribute to maintenance modelling.

Some researchers simplify the modelling by assuming that the system is composed of unrepairable components even actually that system constructed by repairable components. Publications have been done by assuming unrepairable components such as by Compare et al. [87], Bousdekis et al. [88], K. Verbert et al. [89], etc. To get the more realistic results, modelling should be done based on the real repairability of each type of components. But of course, modelling by using repairable components will lead to the more complex calculation. In some publications, the use of the repairable component is limited only to the component level modelling such as have done by Lin et al. [39]. While modelling at the system level is done by breaking the model into two stages, firstly at the system level and then further analysed at the component level like what has been done by Verlinden et al. [42].

4.3. **Data availability**

There are two types of data that can be used in the implementation of maintenance activities, namely probabilistic data and deterministic data. The use of two types of data is highly dependent on the type of the model.

Probabilistic failure data is a data that provides the component failure possibility by using a statistical distribution. Probabilistic data can provide information about the possible lifetime, ageing characteristics of the components, etc. Probabilistic data is used widely in line with the growing of probabilistic modelling which is driven by Rasmussen report [90]. All of maintenance modelling usually using probabilistic failure data.

While deterministic data obtained from several inspection methods and/or sensors can provide some information such as material degradation, temperature, pressure, radiation dose, flow, resistance, etc. That information then can be processed to predict the actual condition of a component. Maintenance that is conducted by using this method is called Condition Based Maintenance (CBM) [34]. Nowadays, CBM has been widely implemented in several industries. The implementation of CBM is supported by the development of the advanced sensors and computer technology. The nuclear industry has also begun implementing CBM even though it is not as fast as in other industries. This is because the nuclear industry tends to implement conservative policies [6].

Furthermore, to improve the accuracy of CBM, several studies have combined failure probabilistic data with deterministic data through data fusion techniques such as by Chen & Jahanshahi [91]. For some cases, this technique can provide a more comprehensive component failure information. But as a relatively new technique, future study to explore data fusion is still needed.

4.4. **Failure model**

There are some kinds of failure model on various reliability and maintenance study. For NPP maintenance purposes we will discuss some of the most used in the literature.

4.4.1. **Delay-time model.** In this modelling, it is assumed that the degradation of a component occurs gradually [15]. At the beginning of the degradation, it is assumed that the event cannot be detected yet or non-detectable state (P). Inspection, test or online monitoring is assumed to be effective to detect a
failure in the Failure Detection Threshold (FDT) area located between the P and the beginning of the actual failure (F). Because of that, FDT is also known as the P-F interval. Delay-time model well known for NPP reliability and maintenance strategy and has been discussed in many publications, such as by Yang et al. [92], Tang [93], and Ma et al. [94].

4.4.2. Multistate model. In the real world, the failure of the component does not only occur in two modes, perfect functionality and complete failure. Most components of the NPP experience multistate failure processes such as that occur in the heat exchanger. Failure of the heat exchanger can be started from leakage or blockage of a small part of the tube, which in turn leads to a decrease in heat transfer capacity. If the damage gets worse, it may also be followed by a fatal blockage and/or an external leakage. Therefore, for certain purposes, multistate model degradation will be more appropriate describing the failure processes nearly real condition. The studies using multistage model have been done such as by Liu & Zio [53], Cannarile [95], and Lin et al. [96].

4.4.3. Degradation model. A study that uses the concept of degradation model especially can be found in the NPP failure probability studies related to the degradation of material and structure, such as what happened in the Reactor Pressure Vessel (RPV). RPV undergoes the very complex degradation processes. RPV degradations which include wears, fatigue, crack generation are caused by many factors such as chemical degradation, high temperature, pressure shock, and atomic displacement by high radiation environment. Degradation behaviour of NPP component is usually modelled by the Stochastic process and can be found on some publications, such as by Weider & Pandey [97], Fan et al. [98], Lin et al. [39] and Martorell [99].

4.4.4. Shock model. Failure of a component is not only caused by internal factors. There are many failure possibilities that are caused by external factors. External factors can come from within the plant itself or even from the external plant. Failures caused by external components but within the plant such as thermal and pressure shock in RPV caused by the failure of the generative heat exchanger [100]. The failure caused by an external event such as vibration caused by an earthquake, flooding by the tsunami, hitting by foreign objects, etc. The failure caused by such events can be modelled by using shock model.

There are four types of shock models that are commonly used, extreme shock models, cumulative shock models, run shock models and δ-shock models [101]. Extreme shock models usually used by define that the failure will occur when the magnitude of a shock exceeds a pre-specified threshold. Cumulative shock models assume that the failure will occur when the cumulative damage from shocks exceeds a critical value. Run shock models in which a failure occurs when there is a run of k shocks exceeding a critical magnitude. And δ-shock models assume that the failure will occur when the time lag between two successive shocks is shorter than a threshold δ.

Shock degradation modelling have been studied intensively such as by Zhu et al. [102] and Weide & Pandey [97]. But study regarding NPP failure because of external factor-related maintenance activities is still limited. One of a good example regarding external shock study has been done by Liu et al. [103].

5. Optimisation modelling

5.1. Optimisation criteria
Although we can find many kinds of criteria that can be used for NPP optimisation strategy, generally that can be categorised become three; minimum cost, maximum availability/reliability and minimum production loss.

As a high-risk installation, the most important parameter in NPP optimisation is reliability/availability that has closed correlation with safety. Safety must be the highest priority for NPP operation [104]. To keep the safety level at the highest level, the reliability/availability system
must also be maintained at the highest level. Therefore, in NPP optimisation modelling, maximum reliability/availability value is mostly used as constraint parameter on the overall publications.

Production loss or electricity production optimisation can be reduced by keeping the NPP operating at the maximum operating conditions. This is directly related to system availability/reliability. Unavailability of some components because of failure or maintenance activities may cause NPP to shut down condition or decreasing of production capacity. Therefore, through good maintenance scheduling activities, plant shutdown or decreasing of production capacity can be reduced.

Since maintenance activities are the largest operation cost [5], minimising maintenance cost becomes one of the most important things to make NPP can compete with various types of other power plants. Failure in the determination of the implementation of the maintenance decision may be able causing failure of other components, other systems or even the entire plant itself. On the other word, the decision in determining the maintenance strategy will greatly affect the cost. For example, in the application of TBM, if there are too short component replacement interval, the cost will increase gradually. Unnecessary inspection interval, testing and installation of sensors also potentially increase the expenditure that should be suppressed.

Several constraint parameters for optimisation also will affect what kinds of optimisation technique that should be used.

5.2. Optimisation techniques
There are many optimisation techniques that can be used depending on the number of parameters. Optimisations that only use two or three parameters may be solved with simple mathematical equations model. But optimisation that using many constraint parameters will need more complicated calculation and very hard to be solved manually. There are many techniques have been developed for optimisation based on a computer algorithm. Some of that technique commonly used for NPP optimisation by using multi constraints will be discussed below.

5.2.1. Genetic algorithm. The Genetic Algorithm (GA) is the most widely used optimisation method in various fields of study for optimisation purposes. GA was first developed by Alan Turing in 1950 that mimics the process of natural selection in the concept of genetics [105]. The use of the GA concept became popular significantly in line with the development of computer technology.

GA is used widely in several areas of maintenance strategy, such as inspection and replacement optimisation and maintenance schedule. There are some NPP maintenance strategy publications that use GA such as by Hadavi [106], Lapa et al. [107], Aghaie et al. [108], Wang et al. [109], Jiejuan et al. [110], etc. Some publication like have been done by Silva et al. [111] also discusses the development of the optimisation algorithm that modified from GA concept.

5.2.2. Hill climbing algorithms. This kind of algorithm is based on the concept that deterioration transitions between solutions are probabilistically accepted by comparing a deterministic function to an exponential random variable [112]. Not as popular as GA, there are only a few publications discussing NPP maintenance optimisation using hill climbing algorithm.

5.2.3. Particle swarm optimisation. This optimisation technique was developed by Eberhart and Kennedy in 1995 [113]. This technique is initialized with the random population and searching for the optimal solution by updating generations. But not like GA, this technique uses potential solution that called particle through the problem space by following the current optimum particles. Although relatively new, we can find quite a lot of maintenance optimisation publication especially for NPP that use this technique, such as by Chou et al. [114], Carlos et al. [115], and Pereira et al. [116].

5.2.4. Other optimisation techniques. We also can find some other unpopular optimisation techniques that can be used for NPP maintenance strategy purposes, such as Mesh optimisation [117], Population-Based Incremental Learning [111], Loading Pattern Optimisation [118], etc.
6. Maintenance strategy

6.1. Maintenance policy
IAEA Technical Document 1590 describing the importance of the RCM concept for the optimal operation and maintenance of NPP. RCM determines what maintenance activities need to be performed to support the maintenance strategy [34]. To be able performing RCM effectively, firstly we need to identify critical components by doing a risk assessment like what can be seen on Fig. 2 before what kind of maintenance policy should be followed by a group of components can be determined. Furthermore, IAEA breakdown NPP maintenance policy become several kinds such as what can be seen on the Fig. 4.

![Figure 4. Maintenance structure [34]](image)

6.1.1. Corrective maintenance. Corrective maintenance or breakdown maintenance is the most primitive maintenance activity that was very common in the past. According to Ayo-Imoru & Cilliers [6], corrective maintenance is used widely until the 1950s. But especially in nuclear industry, corrective maintenance strategy was used totally until 1975 by doing daily reactive maintenance [12]. As the name, this kind of maintenance will be done if only the components are already broken. Corrective maintenance can be categorised become two; planned corrective and unplanned corrective. The planned corrective policy will be used for components with relatively short time reliability, so maintenance department usually already has prepared for a spare parts and/or components replacement. The only advantage of corrective maintenance is the assurance of optimal use of components in all lifetime ranges. However, NPP should not follow corrective maintenance mechanism totally. This is because the failure of a component can lead to a system failure that can ultimately lead to greater losses. Such losses may include accidents, environmental damage, partial damage of the installation, termination of production processes, or maybe severe accident cause damage to plant, environment and fatality. Ayo-Imoru & Cilliers have been identified some disadvantage of corrective maintenance, such as downtimes, unplanned outages, the high cost of operation, production and repairs, lots of emergencies, and unsatisfied of the customer [6]. Because of that, to optimise overall plant operation, identification of less important components that can follow corrective maintenance should be done.

6.1.2. Preventive maintenance. Preventive maintenance was introduced in the 1970s as an answer to the deficiency of corrective maintenance [6]. The basic philosophy of preventive maintenance is how to make maintenance can be done just before a component fails so the system downtimes and the emergency will not happen.
According to IAEA, preventive maintenance for nuclear industry was introduced in 1980 [12]. At that time, preventive maintenance successfully reduced the maintenance cost but still cannot improve components reliability significantly. By using the lesson learned from the aircraft industry, in 1992 RCM was introduced to the nuclear industry [12]. Finally, to get better improvement both for cost and reliability, CBM was introduced in 2002 [12].

CBM is not a substitute for RCM and preventive maintenance strategy [12]. RCM address two issues, how to categorise important components and less important components, and what kind of maintenance policy should be followed by those components to minimising cost and improvement system reliability. On this section, we will not discuss RCM separately since it becomes the basis of this article framework.

6.1.2.1 Time-Based Maintenance (TBM). The first kind of preventive maintenance was introduced is Time Based Maintenance (TBM). The concept of TBM is based on the statistical probability of a component lifetime that can be known from the statistical failure probability data. Some useful concepts that have been breaking down from failure probability concept such as Mean Time to Failure (MTTF), Mean Time Before Failure (MTBF), Mean Time to Repair (MTTR), etc. These concepts are used as tools for estimating the maintenance planning interval of a component. Based on the cycle of improvement, TBM then can be categorised become two; Calendar Operational Based and Operational Time Based. Calendar Operational Based Maintenance is generally used for components that are estimated to be degraded irrespective of the duration of operation, such as a lubricant, sealing, filter, etc. While Operational Time-Based Maintenance is intended for components that degradation processes are based on the operational period. So, in this case, the same components that are used on different systems will have a maintenance interval in different time ranges depending on the length of operation of the overall system.

However, due to the high uncertainty of probabilistic data, the implementation of TBM is still facing several obstacles. The constraints of the early TBM such as costly maintenance, replacement of components that are still functioning well, require more maintenance resources if compared with corrective maintenance.

6.1.2.2 Condition Based Maintenance (CBM). Although TBM can provide better solutions for reducing downtime and reducing emergency situations, there are some serious problems that cannot be solved, i.e. it is impossible to accurately detect when a component will fail simply by using the failure probability data. Failure probability data of NPP is also very limited so that it has a high uncertainty, some NPP components are also produced limitedly, that make it impossible to get statistical data if only rely on operational history. These weaknesses open the possibility of a new maintenance concept called CBM. The concept of CBM is how to make the actual condition of a component can be known more accurately. By knowing the actual condition, then the decision in maintenance activities can be done more precision.

Failure probability data is not enough to perform CBM. Basically, CBM needs deterministic data that can describe the actual condition of the component. There are two ways to get deterministic data; by performing periodic inspection and/or using the appropriate sensors. At the beginning of CBM, periodic inspection is the most famous method that has been done by performing several techniques, such as by doing walk down visual inspection, performing non-destructive testing (NDT), etc. Currently, CBM is growing rapidly in line with the advance development of the computer, electronic and sensor technology. There are many studies that have been conducted to develop the CBM method for the optimisation of various plants including NPP such as what have been done by Liu, Jie & Zio, Enrico [53], Lin et al. [96], Agarwal et al. [119], etc.

6.1.3 Group maintenance and opportunistic replacement. Besides all kinds of maintenance categories described based on Fig. 4, some researchers also proposed group maintenance and opportunistic replacement policy. The idea of group maintenance policy is how to identify and grouping
components with a similar operation condition, so maintenance activities can be performed together. Group maintenance possibly can provide simpler scheduling and able to minimise the complexity of spare part inventory. In opportunistic maintenance policy, an unplanned failure of a critical component/system is considered as an opportunity to perform PM on other component/systems. So, the basic idea of opportunistic maintenance is performing block replacement policy to the whole system/sub-system even if only one component is failed. Zhang & Zeng [120] and Cavalcante [121] have proposed this kind of modelling that can be applied to NPP maintenance strategy.

6.2. Maintenance effectiveness
Generally, maintenance effectiveness can be categorised become three, namely minimal maintenance or As Bad As Old (ABAO), perfect maintenance or As Good As New (AGAN) and the condition between them that is called imperfect maintenance [122]. If the effectiveness of a maintenance action can be denoted as $\delta$, so ABAO repair effectiveness model will assume $\delta = 0$. That means each repair action restores the system to the level it was just before the failure. AGAN will assume each repair action restores the system become a new state and denote $\delta = 1$. In the other side, imperfect maintenance model will denote $0 < \delta < 1$. Based on the available literature, most of NPP maintenance optimisation study used perfect and imperfect maintenance effectiveness concepts. Some publications using perfect maintenance effectiveness such as by Nguyen et al. [51], Kančev, Duško & Čepin, Marko [123], Shin et al. [124], Bousdeksis et al. [88], Van Der Weide, J. A M & Pandey, M. D. [97], and K. Verbert et al. [89]. Some publications using imperfect maintenance such as by Ahmed Raza & Vladimir Ulansky [54], Compare et al. [87] and P. Martorell et al. [99]. Although there are many modelling examples using perfect and imperfect maintenance effectiveness. But it’s a little bit hard to find a publication that uses ABAO concept.

7. Discussion
Maintenance optimisation, especially for NPP, has grown rapidly and produced many well-proposed models, methods and strategies. On the other side, according to the study of Ayo-Imoru & Cilliers [6], most of the NPP maintenance activities around the world are still using conservative approaches and traditional techniques. That study result indicates a wide gap between nuclear industry and academic studies. To bridge that gap, Ayo-Imoru & Cilliers proposed that new maintenance optimisation concepts should be applied starting from components and systems that are the lesser safety concern. If a concept can be applied successfully in less safety concern system/component, it means that concept is proven and ready to be applied to another system/component. In addition, it is not easy to get real data directly from nuclear industries that make realistic NPP maintenance studies also become very difficult. That condition makes most studies are conducted with various assumptions and data limitation. As the implication, most of study results become not ready to be applied directly to the real plant. To fill this gap, special effort to make a better mutual relationship between academia and the nuclear industry is also needed.

RCM has become a mandatory standard that has been implemented by the entire NPP in the world. At the design stage, the nuclear industry has almost always using FMECA method. While FTA has become a very common tool used when determining risk assessment which is the basis for determining the components priority scale in RCM concept. Since an NPP has thousands of components that are used together, and their failure maybe can be affecting the other component or system, the use of conventional FTA become less precision. DFTA as an advanced FTA has fulfilled that problem and have been implemented successfully. In addition, the need for online plant reliability that is become very valuable information for operation & maintenance decision has also been successfully implemented by some NPP. However, the limitations of data that occurring high uncertainty on probabilistic calculations are becoming a big challenge that is difficult to solve by using conventional methods. Bayesian network is a method that theoretically can provide solutions for this limitation. So, the use of the Bayesian network concept as a separate risk assessment method or
combined with the DFTA concept likely will become the next nuclear industry standard. Therefore, the intensive study on the Bayesian network to support RCM is essential.

CBM theoretically is better than TBM for reliability and availability optimisation. CBM can ensure the optimal use of a component and reduce unnecessary replacement or repair. As a probability event, failure of a component can occur at any time. Unlike TBM that can be done by calendar-based or time interval base, fluctuations in failure detection by using CBM are very likely. Unexpected fluctuations of failure in various components will be very difficult in terms of spare part inventory and availability of specialized technicians who are able to handle those problems. Jonge et al. [125] have reviewed the application of CBM to TBM in general industry. Their study concludes that under certain conditions, there is a possibility that the application of CBM becomes costlier compared with TBM. Therefore, there is an opportunity to conduct a more detailed NPP maintenance study of which components should follow CBM, TBM, breakdown maintenance, grouping and opportunistic maintenance strategies to achieve overall maintenance optimization without ignoring the supply chain & spare part inventory issues and availability of human resources.

There are two kinds of initial failure that can induce nuclear accident, internally and externally. An internal failure such as failure because of the problem in design and component ageing. Failure because of external factors such as induced by the natural disaster such as an earthquake, tsunami and volcano, also because of the human such as sabotage, missile attract and terrorism. In the fact, all nuclear severe accident that has been happened was not caused by internal factors. The latest NPP severe accident, Fukushima Daiichi accident caused by beyond design basis event tsunami [126]. An event like what happened in Fukushima accident actually very rare and with very low probabilities but in the fact has very high consequence. Estimating rare event like that is not easy and need a special technique to be able to make a good prediction. Some publications have discussed how to calculate and make the prediction for the rare event using some techniques, such as Fuzzy logic and Bayesian Network. Publications discussing failure model caused by external events also have been discussed. But the understanding regarding external accident including the rare event with their correlation with maintenance optimisation is still limited.

Three Mile Island and Chernobyl accident have been happened especially because of human error [127] [128]. By analysing events related to NPP maintenance, Ballesteros et al. [129] also found that around 47% maintenance problems caused by human-related activities. From Ballesteros study, we can understand that there are some considerable problems in the human reliability that must be solved to improve maintenance performance. Actually, there are several studies have been done regarding human reliability such as have been done by Kim et al. [130] [131], Rollenhagen et al. [132], Asadzadeh & Azadeh [133], and Zou et al. [134]. Those studies propose some maintenance concepts by combining technical optimisation issues with human reliability concepts. Although this article is not intended to discuss maintenance strategies related to human reliability, by looking at existing data, human reliability cannot be ruled out. Therefore, this article also emphasizes the importance of study to understanding how to integration between human reliability with maintenance optimisation strategy.

Unfortunately, NPP maintenance optimisation strategy is not only related to engineering problems but beyond of that. NPP maintenance is closely related to the regulation as well as the management policy. Although the regulation is generally based on scientific evidence, the regulation is not always free from political will. However, NPP operators are required to follow regulation in performing maintenance. In addition, in carrying out maintenance, operators also need to pay attention to economic factors. So, in this case, there are at least three important factors that affect the maintenance decision; regulation from government, scientific evidence and economic considerations from the plant management itself. Furthermore, this correlation is illustrated as can be shown in Fig. 5.
Although IAEA published several standards series that can be adopted by each country as their regulation and built knowledge management system that can be used widely by member counties, the differences in the relationship condition of those factors as illustrated in Fig. 5 will still exist since there is another influential factor, such as culture, political conditions, innovation, industrial environment etc. Because of that, it is important to identify this correlation to make an optimum maintenance from the whole side approach. On the government side, good regulation will encourage the achievement of safety aspects but on the other hand, also facilitate the implementation of new technologies to optimise the installation function. And in the NPP operator side, the organisational aspect is also very crucial. Both of those issues are not engineering issues that make the future study to determine optimum maintenance strategy based on a multidisciplinary approach become necessary.

Furthermore, Ballesteros et al. [129] study also indicated that about 35% of maintenance problems are closely related to the management system. It indicates that in addition to the overall strengthening of soft infrastructure related to the relationship between regulation, scientific evidence and business entities, the improvement on the management aspect of NPP operator organisation is also indispensable. Exploration of the maintenance optimisation strategy in the correlation with management that requires a multidisciplinary approach is also needed.

8. Conclusion

Although many models, methods and strategies for optimum maintenance have been proposed like what has been described above, almost all NPP maintenance activities around the world are based on the breakdown and time-based maintenance. One of the biggest problems on the maintenance optimisation implementation activities is correlating with the regulation system applied in each country. Conservative and rigid regulation system became the strong barrier for the operator to adopt new technology. In the other side, most of the studies have been done only based on generic data that make the results become not ready to be implemented directly into the plant. High uncertainty data also become the strongest barrier when doing maintenance optimisation analysis. To get better data quality, such kind of data including deterministic and probabilistic is needed to be combined using data fusion techniques such as by deploying Bayesian network method. The problem of NPP maintenance optimisation is not only focusing on the component and system failure inside the plant but also has a strong correlation with spare part inventory, human resources, social and political condition, etc. Because of that, there is huge opportunity to do more deeply study regarding maintenance optimisation.
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