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ORIGINAL ARTICLE

Maintenance policy optimization—literature review and directions

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Abstract Numerous of maintenance policies were developed due to the change in the manufacturing environment and the growing of technologies in the past few decades. Due to fluctuation (oscillation, instability) phenomena of the manufacturing industry, it is difficult to identify an optimal maintenance policy that actually suit for a manufacturing system. Thus, a lot of efforts have been done in order to assist manufacturing industry in finding an optimal maintenance policy. This paper attempts to review past and current research on optimal maintenance policy selection issues associated with methods used as well as the applications. Published literatures were systematically classified based on certainty theory in operation management classification model in term of certainty, uncertainty, and risk. Furthermore, a sub family had been classified based on the approaches used in determining the optimal maintenance policy. The possible gap occurred between academic research and industrial application in maintenance policy optimization is also discussed in detail, and several possible ideas are put forward to reduce the gap. More importantly, the paper is intended to provide a different view on classifying these models and give useful references for personnel working in industrial as well as researchers.

Keywords Maintenance · Maintenance policy · Optimization techniques · Certainty theory

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1 Introduction

Nowadays, manufacturing industries are aiming higher operation efficiency, effectively, and economically to survive in the fiercely competitive global economy. Proper maintenance has been drawing more and more attention in contributing industries towards prolonging the system's effective operational lifetime and also improves the reliability and availability of the system to ensure the delivery of high-quality product to customers on time. Overall, maintenance can be described as a combination of all technical and administrative actions including supervision, action intended to retain or restore the system into a state in which system can perform a required function [1].

However, it is imperative to highlight that maintenance cost can even achieve 15 to 70% of the expenditure or even could exceed annual net profit in many cases [2, 3]. Nevertheless, no matter how large the amount of expenditure is, it is impossible for manufacturing industries to abandon maintenance. Thus an appropriate and optimized maintenance policy is required for maintenance management in accomplishing all maintenance activities to save a significant of money [4, 5]. In other words, optimal maintenance policy is able to provide a deliberate plan of action that usually containing a set of rules used to provide guidance for maintenance management in conducting an effective maintenance [6, 7].

Earlier, maintenance policy was only optimized based on a sole aim to reduce the maintenance cost without considering other factors which were equally important included reliability [8]. Most of the time, minimizing maintenance cost will limit the reliability level to an unacceptable in practical. So, to obtain the best performance and the balance between these aims, maintenance policies, maintenance costs, reliability measures, as well as other factors should be considered simultaneously. In the literature, maintenance policy optimization models are classified based on certainty theory. On applying, different approaches on optimization has been classified into different types of models which will be further discussed in subsequent section.

The specific objectives of this paper are to:

- To suggest a classification of available literature in policy optimization.
- To identify the available case study or application in the field of maintenance policy optimization.
- To identify the critical observations on each classification.
- To identify emerging trends in maintenance policy optimization.
- To suggest directions for future researches in this field based on above identification.

This paper aims to review the optimization methods used in determining the optimal maintenance policy as well as its' application areas. Following is the organization of the paper. Section 2 presents an overview of maintenance policy overview. Section 3 briefly presents the introduction on maintenance policy optimization model. Section 4 describes the classification of optimization model based on certainty theory. Section 5 presents the findings of the reviews. Finally, Section 6 concludes with the suggestions and future research directions.

2 Maintenance policy overview

Maintenance policies can be grouped into different class according to the way it deals with breakdowns and maintenance. Variety of maintenance policy classification is widely analyzed in scientific literature: Wang [9], Bevilaqua and Braglia [10], Swanson [1], and Khazraei and Deuse [11]. Figure 1 shows the classification of maintenance policy that will be presented.

Typically, there are five types of policy classified under three categories. Corrective maintenance policy which is the first and also the oldest type of maintenance policy applied in manufacturing industry [12]. It only aims to repair or restore the system back to its operational condition which involves simple procedure without scientific study. Maintenance will only be carried out after the failure occurs when CM policy is implemented. Sharma et al. [13] stated that CM policy is considered a feasible policy to be adopted in the cases where profit margins are large. However, this maintenance policy may cause large production losses, serious damage to the system, person, and environment due to the unexpected failure.

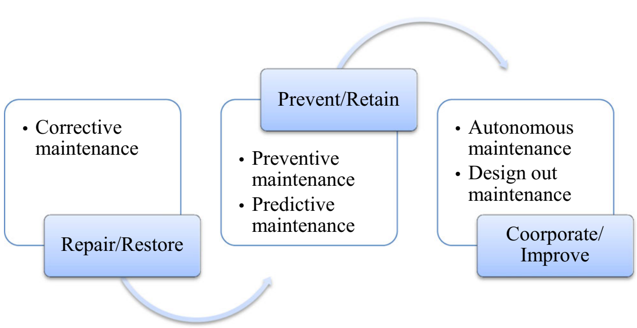

Fig. 1 Classification of maintenance policy

With the increasing size and complexity of manufacturing industries, failure of a small component can cause complete shutdown to the whole system which sometimes may cause a disaster, implying the loss of large amount of money. The idea of maintenance has moved to another level where maintenance is used to prevent the occurrence of failure and to retain the system in proper operation condition. Consequently, a more scientific maintenance policy namely preventive maintenance (PM) policy associated with reliability engineering was introduced to extant the life span by performing fixed interval maintenance to reduce or even to prevent the possibility of failure [14]. Most system is maintained with a significant amount of useful life remaining when PM policy is applied [12]. Nevertheless, it is difficult to identify the optimal maintenance interval when the historical data is lacking, and this will lead to unnecessary maintenance [15].

Manufacturing industries tend to be more flow-oriented and high-capital-intensive after 1970s, but the expectation of a trouble-free operation process is still unachievable. Therefore, predictive maintenance (PdM) policy which also referred to as condition-based maintenance policy was proposed with the growth of technology. Similar with PM policy, PdM policy is also aims to prevent failure and retain the system operational condition but with the utilization of advanced technology. The maintenance under the PdM policy is carried out according to the actual condition of the system. Maintenance management can easily and clearly point out an abnormal situation by monitoring the data collected by the sensors. However, PdM is not always the best policy of maintenance, especially from the cost effectiveness aspect [16]. Sometimes, there will be a number of systems for which condition monitoring is not particularly appropriate and not all systems can be monitored due to the economic constraints [17].

Nowadays, maintenance is no longer considered as necessary evil but can be turned to profit maker [18]. Manufacturing companies try to use maintenance to create more profit. Maintenance is no longer just repairs or restoration (CM policy), prevention or retention (PM policy), or prediction (PdM policy) but corporation and improvement. Maintenance has moved up from the barrier of maintenance and advanced to improve the system reliability from other aspect like engaging operators to conduct maintenance and redesign the system according to the operational environment. Maintenance jobs are not simply under the responsibility of maintenance department alone anymore. The maintenance responsibility is given to every single person in the plant in order to achieve higher and better utilization of the system. Autonomous maintenance (AM) has brought about new maintenance concept where maintenance and production department are cooperating to accomplish the maintenance jobs [19]. It has turned the maintenance function into partnership relationship with every person in the manufacturing industry. Nevertheless, an effective AM policy will require a set of proper education and training for all level persons in manufacturing industry to gain sufficient skill and knowledge in order to gain full benefit from this policy.

Design out maintenance (DOM) policy is a policy aims for improvement rather than just conducting maintenance of the system operation. The focus of DOM is to improve the system design to make the maintenance easier or even eliminate it. Redesigning a more ergonomic system for both operator and maintenance personnel is also another major task of DOM. However, improvement-based maintenance policy requires high level of knowledge and experience as well as training.

As mentioned, each of the maintenance policy has their special attributes, and one must know that determining an optimal maintenance policy is the most crucial in maintenance management especially when the manufacturing industries consists of multiple systems with different maintenance characteristics [20]. Obviously, optimal maintenance policy for different systems is necessary to increase availability and reliability levels, furthermore to reduce the unnecessary investment [21]. With the significant of the optimal maintenance policy in the manufacturing industry, numerous of publications were to develop an effective approach in determining optimal maintenance policy.

3 Maintenance policy optimization model

The key result of optimization is to identify values of the designed variables that either maximize or minimize the objective function [22]. In the maintenance context, optimization can be stated as finding a balanced maintenance solution that closes to the objective under certain criteria by using preferred approach [23]. In short, it covers four aspects included modeling the system function and possible consequences for the system, description of the available information about the system (a set of design variables), objectives function, and an analytical approach as shown in Fig. 2.

Before going into detail on the classification of maintenance policy optimization model, a brief definition of a model would be appropriate to give better appreciation of the detail discussion on the maintenance policy optimization model. According to Chen and Trung [24], model is a description of a process, system, or concept, in simple and systematic way which usually involves an explicit mathematical formalism of the process being studied. In maintenance policy optimization aspect, a model is a description of a process to model, analyze, and determine the optimal maintenance policy under predetermined maintenance objectives and criteria. According to Geraerds [25] and Marais and Saleh [26], models used to derive optimal maintenance policy generally cover four main aspects:

- A description of the system being maintained;
- A model on how the system deteriorates and the consequences thereof;
- A description of the available information on the system and the available response options;
- An objective function and an analytical framework (or tools) according to which the optimal maintenance policy is to be derived.

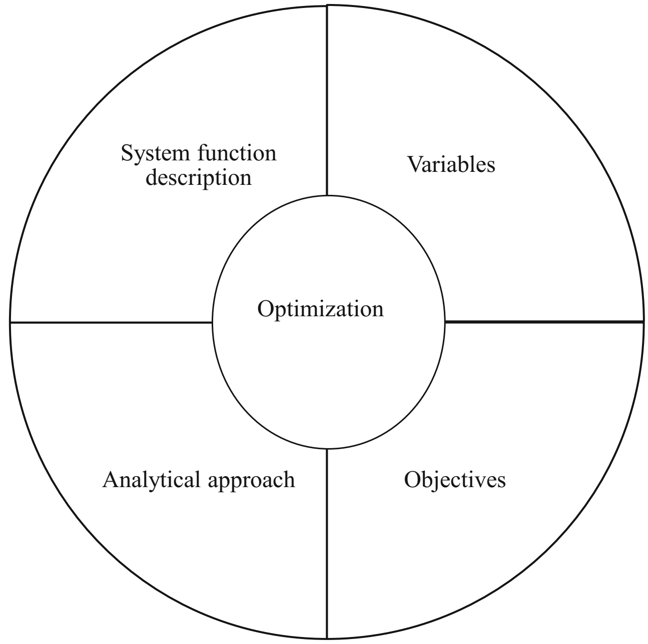

Fig. 2 Regular element in optimization process

4 Classification of maintenance policy optimization model

There are several scientific classifications that have been conducted on maintenance policy classification: Bevilacqua and Braglia [10], Swanson [1], and Khazraei and Deuse [11]. A unique classification based on the certainty theory is adopted to categorize the maintenance policy optimization model. In the context of operation management, there are several types of model classification based on different classification principles. In this study, the model is classified in term of degree of certainty: certainty, risk, and uncertainty according to Tersine [27]. Figure 3 illustrates the certainty theory continuum.

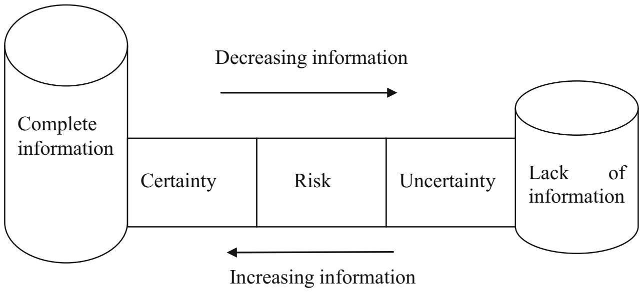

Fig. 3 Certainty theory continuum

Degree of certainty is referred to the information available about the states of nature influencing the system under optimization analysis. In optimization process, it involves different level of information according to the method used. As shown in Fig. 3, the level of knowledge can influence the degree of certainty of the optimization process. Commonly, optimization is a critical yet complex process that involve variable of information. With higher degree of information available, the accuracy of the optimization results will increase. However, due to the different methods used, the information required may be unavailable. Different assumption or vague information is applied in order to achieve the optimization purpose. The degree of assumption or vague information can be classified into risk or uncertainty level accordingly. Figure 4 displays the main classification of maintenance policy optimization model according to the certainty theory.

Referring to Fig. 4, graphical model is the only model under certainty category. Meanwhile, risk category consists of three models included mathematical, simulation, and artificial intelligence. Heuristic, hazard, and multi-criteria decision making (MCDM) are the three models classified under uncertainty category. The detail of each model in terms of method used and case study will be discussed.

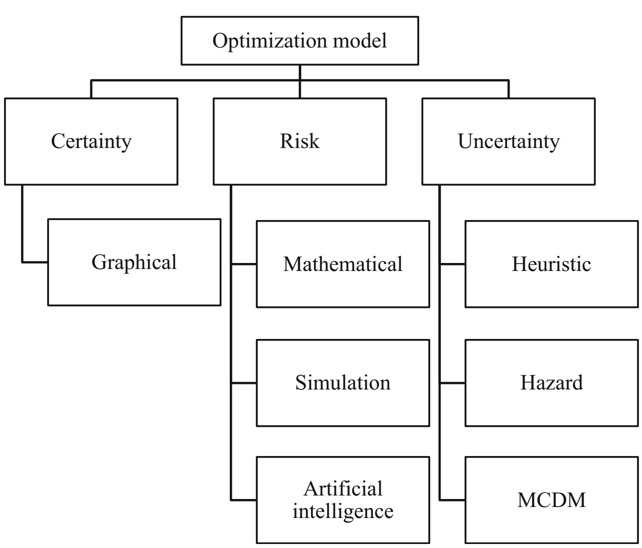

Fig. 4 Classification of maintenance policy optimization model

4.1 Certainty category

In certainty category, there is only one state of nature for each strategy. In essence, the probability of specific state of nature will occur is one (perfect knowledge) [27]. The policy is simply pointed with the most desirable outcome via enumeration of all policy. It is generally simple and does not require complicated optimization procedure. Graphical based model uses either graph or figure to denote the optimal maintenance policy according to the value of predetermined criteria is the only model categorized under certainty category.

Labib [28] came out with a simple graphical model named as decision-making grid (DMG) for optimal maintenance policy selection depending on the downtime and failure frequency of the system. The developed DMG was implemented in an automotive industry producing roof systems. Fernandez et al. [29] had extended the work from Labib [28] used DMG to identify the optimal maintenance policy. In this case, DMG was applied to monitor the performance of the worst system in the disc brake pad manufacturing company. On the other hand, similar research also can be found in Labib [30]. Author adopted DGM to monitor the performance of different systems in automotive industry and suggested optimal maintenance policy accordingly.

By referring to DMG suggested by Labib [28] and Khalil et al. [31] had proposed a modified DMG. The modified DMG used failure cost as decision criteria instead of failure duration. Systems in aero-industry were used to illustrate the application of the modified DMG. The extension work of DMG also can be found in Burhanuddin et al. [32]. Authors put more efforts on enhancing on measuring system's efficiency where authors proposed the modified DMG to a food processing industry rather than automotive industry. In Tahir et al. [33], the researches applied tri-quadrant technique to cluster the DMG in order to increase the effectiveness of the DMG for production plant in small- and medium-sized industries.

In order to improve the effectiveness of DMG, Tahir et al. [33] had conducted a study on integrating the fuzzy logic into DMG and demonstrated with a set of food industry maintenance data collected by Burhanuddin et al. [32]. Fuzzy logic also been integrated to the DMG in order to specify what maintenance policy was suitable to the system based on the criticality and reliability [34]. The application of developed fuzzy logic DMG was presented in a failure-prone manufacturing system. Rather than using DGM, Gupta et al. [6] had put forward another different graphical model using control chart to conduct the analysis on optimal maintenance. A case study on Armoured Flexible Conveyor in underground coal mine was established to demonstrate the developed approach.

Graphical model is simple but may be less accurate because it considered limited criteria. For example, in the study conducted by Labib [28], downtime and failure frequency were the only two criteria involved. More comprehensive policy selection needs to consider several different aspects like safety and environmental problems. Besides, there is very low possibility to have complete information in optimization process due to various factors such as operational environment, data collection, and management system. Table 1 tabulated the summary of method used together with its application under certainty.

4.2 Risk category

With risk category, the states of nature are known and can be described stochastically. The optimization process is conducted by knowing the probability distribution of the state of nature. Based on the current information of the state of nature, it able to predict future possible condition and determine the suitable optimal maintenance policy. Typical model under risk category are mathematical, simulation, and genetic algorithm.

4.2.1 Mathematical based model

Mathematical model can be found as the most frequently used model in optimization research area. It is an abstract model that uses mathematical language to describe the system. It is very useful in estimating the system's state of nature by using limited information. By using the stochastic principle, the possible condition including system itself and variables that influence the system can be predicted. Optimization process can be conducted along with the predicted information. According to Almeida and Bohoris [35], the general mathematical model steps can be divided into four main steps included problem definition, necessary information, preference elicitation, and modelling the state of nature optimization. The review of the mathematical model focuses on the methods that are used to model the state of nature including deterioration process or failure distribution.

One of these methods used in mathematical model is proportional hazard method (PHM). PHM had been widely used to model system variables, external factors which included environmental conditions and working conditions and age of system [36]. In the real environment, it is usually difficult to specify the quality of maintenance precisely. The failure times of system always affected by different covariates. Therefore, PHM uses the proportional age reduction factor to the baseline of hazard rate or to operation time [37]. There are several works that has been conducted in maintenance optimization. For example, Martorell et al. [38] adopted PHM to model the system's life distribution by considering parameters related to surveillance, maintenance effectiveness, and working conditions of the system. The practicality of the developed method was demonstrated in the nuclear power plant. Application of PHM also been presented by Lugtigheid et al. [36] to model a repairable system reliability with different indicators included accumulated operating time and state of a system depending on its age and degree of repair. Authors tried to integrate more indicators into PHM by using non-homogeneous Poisson process with intensity function (e.g., power-law form). Samrout et al. [37] used PHM as modelling tool to integrate the effect of maintenance on reliability through its influence on the aging process. A hypothetical case with ten components in the form of parallel–series configuration was set up to evaluate the integration impact of the proposed method.

Besides PHM, application of Markov method had also been found in finding optimal maintenance policy. Markov method is a stochastic process in which changes of state occur according to a Markov chain. The time interval between two successive transitions is a random variable whose distribution depends on the state from which the transition takes place [39]. In the study conducted by Gurler and Kaya [40], Markov method had been used to describe the stochastic nature of the system and classified it into several stages varying from perfect functioning to complete failure. Authors had tried to reduce the complexity of the analysis by using cost as an approximation and illustrated it using a set of numbers that used to express the application of the mathematical formulation named as numerical example. Amari et al. [41] who agreed with Gurler and Kaya [40] where failure propagation

Table 1 Summary of method used under certainty category

Method used	Authors	Application
DMG	Labib (1998)	Automotive industry
	Fernandez et al.(2003)	Disc brake pad manufacturing industry
	Labib (2004)	Automotive company
Modified DMG	Khalil et al. (2005)	Aero industry
	Burhanuddin et al. (2007)	Food processing industry
	Tahir et al. (2008)	Food processing industry
	Tahir et al.(2009)	Small and medium industries
	Labib and Yuniarto (2009)	Failure-prone manufacturing system
Control chart	Gupta et al.(2009)	Armored flexible conveyor

should be stochastic had tried to incorporate semi-Markov method to model the stochastic nature of the deterioration process. An example of locomotive diesel engine was used to illustrate the validity of proposed approach. Nourelfath and Ait-Kadi [42] also conducted a similar research to Gurler and Kaya [40] but more specifically on the series–parallel system. Authors also considered the limitation of the maintenance workforce and illustrated the application in a power station coal transportation system that consists of five basic components. Rather than searching a solution to a problem, Anders and Sugier [43] incorporate Markov method into a software named Asset Risk Manager to examine and compare the effects of system in terms of reliability and economic under different maintenance policies. The methodology was established and demonstrated using numerical example.

Markov method had also been suggested by Ge et al. [44] to model the system deterioration in order to determine the maintenance policy that able to maximize the system availability. An example based on air-blast circuit breaker had been put forward to justify the application of the developed method. Markov method was adopted by Kenne and Nkeungoue [45] to describe the dynamics of the system and determine the maintenance policy which would optimize the system life cycle while minimizing the overall cost. Feasibility and effectiveness of the proposed approach had been shown by using a machine tool on a manufacturing system. At the same time, Muller et al. [46] suggested Markov method to describe the dynamic degradation of a system in a manufacturing platform materializing a physical process dedicated to unwinding metal strip and determined the best policy that was suitable. Besides, Markov method also been adopted by Marais and Saleh [47] to model the deterioration process and determine the optimal maintenance policy according to the net present value of different maintenance policy. Two numerical examples were presented to clarify the application of the developed method. Similar research also conducted by Ponchet et al. [48], but the determination of optimal maintenance policy was based on the average long-run cost per unit time. The change of deterioration rate and the difference between deterioration rates on the maintenance decision was also exemplified by numerical examples.

Besides using those common mathematical approaches, there are also few publications found using infrequent mathematical method such as Chelbi and Ait-Kadi [49]. Authors had presented an application of probability density function in probability theory to generate optimal maintenance policy for randomly failing system that was only suitable for the failure that could be detected through inspection. Application of proposed approach is demonstrated on a cutting tool for machining process. Another mathematical approach named as non-linear programming method had been established by Lofsten [50] to plan the optimal maintenance policy in order to obtain the most economic maintenance. The application method was illustrated by using numerical example. Also, Cassady et al. [51] had suggested a combination of classical logic with probability theory to determine optimal maintenance policy for the industry that had limited time to conduct maintenance like military and aerospace industry. A numerical example was used to demonstrate the applicability of the methodology. Goel et al. [52] presented a mixed-integer linear programming for the integrated design, production, and maintenance planning for a multipurpose-process plant. A production line with two different operations to produce ten products from chemical processing plant was taken up as an example to illustrate the proposed approach. At the mean time, Marquez et al. [53] proposed modified Powell method to determine the optimal maintenance policy by comparing the performance between maintenance policies constrained by production rate and buffer capacity. Numerical example was used out to validate the developed method.

Due to rapid changes in technology with systems getting more costly, leasing becomes preferable solution in industry. Thus, Pongpech et al. [54] had come out with an idea to represent the lease period of system failures and determine the maintenance policy that was minimal in total expected cost using non-homogenous Poisson process. The application of proposed method was examined by using numerical examples. Besides, Nielsen and Sorensen [55] had stated that a failure of single component in a system could affect the production rate and, furthermore, increase the production cost. For this reason, authors had proposed Bayesian pre-posterior decision theory to decide the optimal maintenance policy on a single component. A wind turbine system was chosen as a case study in demonstrating the practicality of the suggested method.

Over the years, optimization model has emerged from the fundamental of mathematical model through combination and integration of simulation method. Thus, simulation optimization model has become another research area that gains high popularity in finding the optimal maintenance policy.

4.2.2 Simulation-based model

Simulation model or a computational model is a computable method for running an abstract model over time, where the model can be implemented using computational techniques such as mathematical formalism that used different algorithms [56]. In maintenance, simulations are useful in gaining the insight of the system's operation or to observe their behavior. The information obtained can be applied to identify a suitable policy for the system. Either way, the simulation model is used to generate and predict the potential results by using current or past data.

Monte Carlo simulation is one of the popular methods being used in the maintenance policy selection process. Monte Carlo simulation is computational algorithms that rely on repeated random sampling to compute their results. It is largely to be used when it is unfeasible or impossible to compute an exact result with mathematical methods. Generally, Monte Carlo simulation is used to solve several problems included; optimization, which is to find an optimal value under certain constraints; integration, which is referred as the process of finding a value under multi-dimensional mathematical functions; and inverse problems, to predict the possible value by referring to certain existed values.

Research adopting Monte Carlo simulation in the maintenance optimization usually focuses on identifying the cost effectiveness maintenance policy. An example is a study done by Borgonovo et al. [57]. Authors adopted Monte Carlo simulation to evaluate the system maintenance policy under economic constraints included profit function, obsolescence, aging, and renovation. The application of the simulation was shown by gas compression system taken from Vatn [58].

Rather than maintenance cost, there are also study on how to provide more cost-effective maintenance service. Chen and Popova [59] also presented an application on Monte Carlo simulation estimating the system failure rate and obtaining the optimal maintenance policy that would minimize the total expected servicing cost. Numerical examples were presented to justify the usefulness of proposed method. Barata et al. [60] used Monte Carlo simulation to determine the optimal maintenance policy that can minimize total service cost. The application was also illustrated by using a hypothetical case which consists of a series system with two components.

Incorporating of reliability issues in simulation also obtained significant contribution on maintenance optimization process. For instance, Monte Carlo simulation had been applied by Silva et al. [61] to measure the impact of maintenance policies on the system reliability and associated costs. Generation and transmission system were presented to show usefulness of the proposed method. Hilber et al. [62] also established a Monte Carlo simulation to search the most cost-effective maintenance policy for electrical networks. Application of Monte Carlo simulation also could be found in Nguyen et al. [63] to determine the most economical and reliable maintenance for variable estimators used in chemical plant in order to improve the accuracy of the estimators. Similar approach also adopted by Clavareau and Labeau [64] to determine the most cost-effectiveness maintenance policy of a system under technology obsolescence. Analytical test case referring to Mercier and Laeau [65] was used to accredit the application of the proposed simulation. Besides, Huynh et al. [66] had put on an idea to consider the system degradation level with maintenance costs during maintenance policy optimization analysis by using Monte Carlo simulation. However, the proposed approach had only been verified through a numerical example. Hu and Zhang [67] had proposed using Monte Carlo simulation to determine the maintenance policy that could minimize the risk of failure. However, the application of proposed approach was illustrated through a numerical example.

There are also several papers found using a simulation method other than Monte Carlo simulation, choosing an effective yet cost-efficient maintenance policy. Houten et al. [68] suggested using simulation to model the function, behavior, and state of a system in order to describe the faults and deterioration of its mechanisms. By comparing the actual behavior with the modelled behavior, suitable maintenance policy could be decided easily. Gear pump in a nuclear power plant had been chosen as simulation subject to illustrate the developed approach. On a similar situation, Li and Liao [69] investigated the performance of deteriorating systems maintained under different maintenance policy by using area simulation. In the simulation process, the best maintenance policy was chosen with the highest steady-state availability. The application of proposed method was justified by numerical example.

Boschian et al. [70] had conducted study on simulating and comparing the performance of different maintenance policy on the system. By the comparison, the maintenance policy which had the best cost-availability compromise was chosen. Authors considered a system with two machines that produce one product to illustrate the application of the method. At the same time, Kaegi et al. [71] had proposed an idea where agent-based simulation was used to simulate the system's interplay and then derived and analyzed the overall system behavior. The maintenance policy was determined according to the capability of optimizing availability of the system under limited workforce. A sample production line configuration with 32 unit systems and five workforces was established to exemplify the usefulness of the proposed methodology. Lu and Sy [5] had implemented agent-based simulation approach for a real-time decision making concerning the maintenance policy optimization problem in a motor engine company.

Other than using the simulation method to evaluate the system performance, it is also been used to simulate the relationship between the maintenance optimization with spare part provision. Spare part provision is referred to the supplying of spare part from the supplier. The spare parts provision can influence the selection of the optimal maintenance since spares are ordered, carried in limited quantity, and depended on procurement lead time. Due to the significant of the spare parts provision, Sarker and Haque [72] joined the spare parts provisioning in the optimal maintenance with minimum costs using simulation package SIMSCRIPT II.5. The input and statistical parameter obtained from Kabir and Olayan [73] were put forward to justify the effectiveness of the proposed approach.

Mattila et al. [74] developed a discrete-event simulation approach to gain insight on the effect of maintenance policies to the operating condition on the overall performance of the aircraft fleet of the Finnish Air Force. The proposed method provided a way to evaluate maintenance effects and determined the optimal maintenance policy for the Hornet and Hawk aircraft. Besides, Takata et al. [75] also presented discrete event simulation work to identify potential deterioration and failures of the products and determine the optimal maintenance policy accordingly. A joint gear of industrial robots was selected as a validation subject for the simulation method. Also, Krishnansamy et al. [76] had put forward an idea using discrete event simulation to solve the maintenance policy problem for a power-generating plant in order to reduce the probability of failure. Discrete event simulation had also been put to use by Dingzhou et al. [77] to simulate and estimate the system availability with overall cost in order to determine the most cost-effective maintenance policy. The application of the proposed method was illustrated by using chemical process plant information taken from Marseguerra and Zio [78].

Meanwhile, application of simulation on finding optimal maintenance policy can also be found in flexible manufacturing system (FMS). For example, Vineryard et al. [79] had established discrete event simulation approach to evaluate a number of potential maintenance policies for a FMS. Besides, Savsar [80] had developed a simulation based on SIMAN language to determine the effects of various maintenance policies on the production rate and operational capability of flexible manufacturing system under different failure time distribution. An example of FMS was adopted to test the usefulness of the methodology. Subsequently, SIMAN language-based simulation approach also been proposed by Savsar [81] to analyze the effect of different maintenance policy on production rate in a FMS.

In the work done by Malamura and Murata [82], the manufacturing process dependability was integrated with maintenance policy optimization using Software SIMUL8 to investigate the maintenance effect on manufacturing system performance and to determine the optimal maintenance policy, respectively. LNG train used for liquefaction and purification from a liquefied natural gas plant was presented to justify the usefulness of the proposed simulation approach. Besides, Azadeh et al. [83] had proposed an integration of data envelopment analysis with Taguchi orthogonal array design (TAOD) to determine the maintenance policy by taking criteria such as production, operator availability, reliability, and efficiency into consideration. A series production with six systems was occupied to justify the feasibility of the proposed approach. Azadeh et al. [84] had presented an integrated fuzzy discrete event simulation with fuzzy data envelop analysis to identify the preferred maintenance policy from production and maintenance perspectives. Series production line with three systems was used to demonstrate the feasibility of proposed method.

Simulation methods are useful in maintenance policy optimization process by imitating the condition while showing the eventual real effects of the maintenance conditions. As the technology grows, new computerized methods based on artificial intelligent have been developed and potentially to carry out the optimization process into another level that may lead to better accuracy and faster result.

4.2.3 Artificial intelligence-based model

Over the years, artificial intelligence (AI) has gain more attention in maintenance area. There are many definitions of AI offered, and the most relevant one is: AI is a field in science and engineering concerned with the computational understanding of what is commonly called intelligent behavior and with the creation of artifacts that exhibit such behavior [85]. Among the AI methods, genetic algorithm (GA) is the most popular optimization method adopted in maintenance policy optimization area. GA is well-known due to their robust search capabilities that help reduce the computational complexity of large optimization problems [86]. GA, which was invented by John Holland in 1960s, is a method used to compute and find the exact or approximate solutions to optimization and search problems [87]. The development of GA is inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. Recently, GA has received considerable attention with regard to its potential as an optimization method for complex problems and has been successfully applied in the area of industrial engineering included maintenance optimization.

GA was implemented by Martorell et al. [88] to determine the optimal maintenance policy to the Emergency Diesel Generator in nuclear power plants. Authors aimed to increase plant safety level by considering more criteria included costs, task force, etc., besides reliability criteria. Moreover, Morcous and Lounis [89] also proposed GA to find the optimal maintenance policy but focused on infrastructure networks facilities. The data from the transport department were used to illustrate the feasibility and capability of the proposed method in programming the maintenance of concrete bridge decks. On the other hand, Ilgin and Tunali [90] had also proposed an implementation of GA to determine the optimal maintenance policy by considering the spare parts provision. Besides, application of GA also can be found in Okasha and Frangopol [91]. Authors have tried to obtain optimal maintenance policy considering system reliability, redundancy, and life-cycle cost by using GA. The application of GA to a bridge superstructure and five-bar steel truss were presented. GA was also established by Chung et al. [92] to determine the optimal maintenance policy for multi-factory production networks in order to maintain the system's reliability in a defined acceptable stage. A hypothesis case with two factories consisting three machines each was created to demonstrate the usefulness of the proposed algorithm.

Other than using GA in the search of optimal maintenance policy from reliability aspect, GA also been utilized by Heo et al. [93] to identify the most cost-effective maintenance policy for power transmission system. Martorell et al. [94] proposed GA for maintenance policy optimization by taking human resources and material resources into consideration. A motor-driven pump was used to illustrate the practicality of the methodology. Moreover, implementation of GA also had been found in Charongrattanasakul and Pongpullponsak [95] in determining the maintenance with minimum hourly cost. Numerical example was used to point up the application.

In addition, there are also several studies found integrating simulation with GA in optimization process with the aims to gain better optimization results. Marseguerra and Zio [96] had presented integration on Monte Carlo simulation and GA to identify the optimal maintenance policy in terms of cost and revenues of operation for chemical process plant logistic management. Integration of Monte Carlo simulation and GA also had been studied by Villanueva et al. [97] but to determine the optimal maintenance policy for safety-related with uncertain criteria. A case study on simplified high-pressure injection system of a pressurized water reactor was established to demonstrate the feasibility of the methodology. Also, Mahadevan et al. [98] had put forward a combination of Monte Carlo simulation and GA to decide the most cost-effective maintenance policy for the raw mill system in cement industry during the planning period.

Table 2 tabulated the summary of the optimization method under risk category, authors, as well as application of the method.

4.3 Uncertainty category

Under uncertainty category, future conditions and their corresponding probabilities are not known [27]. Therefore, in order to accomplish the optimization, the relevant information usually needs to be ascertained based on judgment and utilization via subjective probabilities. A large amount of papers have been categorized under this category and can be separated into three sub-families including heuristic, criticality, and multi-criteria.

4.3.1 Heuristically based model

Heuristic is a “rule-of-thumb”-based problem solving approach that uses logic and experience and knowledge derived from observation [27]. Heuristically based model can speed up the process of finding a satisfactory solution, where an exhaustive search is impractical. For example, Waeyenbergh and Pintelon [99] carried out a study on selecting the optimal maintenance policy with the aid of a decision tree. In the selection process using the decision tree, two types of questions—technical and economic—would be sequentially asked for each proposed maintenance policy. The justification was done according to the knowledge and experience.

In the Waeyenbergh and Pintelon [100], authors had conducted a case study in cigar production industry to validate the method proposed on Waeyenbergh and Pintelon [99]. Different policies had been assigned to six most important systems including supply system of unfinished cigars, supply system of mouth pieces, positioning system of mouth pieces, transport system of cigars cellophane wrapping system, and packing system according to the method proposed in Waeyenbergh and Pintelon [99]. The results showed that the production of cigar had been successfully increased a hundred percent after the implementation. Waeyenbergh and Pintolen [101] discussed the results obtained from the case study by using the developed method on paper Waeyenbergh and Pintelon [99–101].

Meanwhile Carazas and Souza [102] also presented an application of decision tree in determining the optimal maintenance policy with the objective of reducing the likelihood of failure besides reducing the maintenance costs. The case of application to the heavy-duty gas turbine in an open cycle thermal power plant demonstrated the viability and significance of the proposed method. The application of decision tree in determining optimal maintenance policy is also found in Ding et al. [103]. The developed decision tree aimed to select the maintenance policy that could reduce the failure of the drilling system based on feasibility of maintenance policy.

4.3.2 Hazard-based model

Hazard usually means the potential to cause harm either tangible or intangible. As defined, the papers classified under this model have emphasized more on solving the failures effectively rather than just focusing on economic aspect. Improving maintenance quality in terms of safety, as well as reliability without drastic increasing the cost by assigning maintenance policy is a main point of papers. Moreover, most of the authors also put emphasis on implementation of improper maintenance policy without conducting appropriate root-cause analysis can cause out-of-control fire-fighting situation.

Due to growing awareness on hazard and safety issues either human or environmental has bring about the rising of development on hazard-based model in determining the optimal maintenance policy especially in heavy industry or high-risk industry, including oil processing and nuclear plants. For example, Bevilacqua et al. [104] had conducted failure mode, effect, and criticality analysis (FMECA) study on integrated gasification and combined cycle plant in oil refinery industry. Authors tried to determine the most effective maintenance policy that could effectively prevent those failures obtained through FMECA analysis. Tu et al. [105] had established a failure analysis approach to pinpoint the optimal maintenance policy for an advanced electronic manufacturing company. Meanwhile, Leon Hijes and Cartagena [106] implemented

Table 2 Summary of method used with application under risk category

Model	Method	Authors and year of publication	Application
Mathematically based model	PHM	Martorell et al. (1999)	Nuclear power plant
		Lugtigheid (2004)	Theory
		Samrout et al. (2009)	Hypothetical case
		Lawson and Marnotey (2009)	Projector
	Markov method	Gurler and Kaya (2002)	Numerical example
		Amari et al. (2006)	Locomotive diesel engine
		Nourelfath and Ait-Kadi (2007)	Coal transportation system
		Anders and Sugier (2006)	Numerical example
		Ivy and Nembhard (2005)	Numerical example
		Ge et la. (2007)	Air-blast circuit breaker
		Muller et al. (2008)	Materializing platform
		Kenne and Nkeungoue (2008)	Machine tool
		Muller et al. (2008)	Platform used to produce unwinding metal strip
		Marais and Saleh (2009)	Numerical examples
		Ponchet et al. (2010)	Numerical examples
	Probability density function	Chelbi and Ait-Kadi (1999)	Cutting tool
	Non-linear programming	Losten (1999)	Numerical example
	Classic logic with probability theory	Cassady (2001)	Numerical example
	Mixed-integer linear programming	Goel et al. (2003)	Chemical process plant
	Modified Powell method	Marquez et al. (2003)	Numerical example
	Non-homogenous Poisson process	Pongpech et al. (2006)	Numerical example
	Bayesian pre-posterior decision theory	Nielsen and Sorensen (2011)	Wind turbine system
Simulation-based model	Monte Carlo simulation	Borgonovo et al. (2000)	Gas compression system
		Chen and Popova (2002)	Numerical example
		Barata et al. (2002)	Numerical example
		Silva et al. (2004)	Transmission system
		Hilber et al. (2007)	Electrical network
		Nguyen et al. (2009)	Chemical plant
		Clavareau and Labeau (2009)	Hypothetical case
		Huynh et al. (2012)	Numerical example
		Hu and Zhang (2014)	Numerical example
	Agent-based simulation	Houten et al. (1998)	Gear pump
		Li and Liao (2008)	Numerical example
		Boschian et al. (2009)	Hypothetical case
		Kaegi et al. (2009)	Hypothetical case
		Lu and Sy (2009)	Motor engine company
Simulation-based model	SIMSCRIPT simulation	Sarker and Haque (2000)	Numerical example
	Discrete-event simulation	Greasley (2000)	Train maintenance depot
		Mattila et al. (2003)	Aircraft fleet
		Takata et al. (2004)	Joint gear of industrial robot
		Krishnansamy et al. (2005)	Power-generating plant
		Dingzhou et al. (2013)	Using data from Marseguerra and Zio (2000)
		Vineryard et al. (2000)	FMS
	SIMAN simulation	Savsar (2005)	FMS
		Savsar (2006)	FMS
	SIMUL8	Malamura and Murata (2012)	LNG train
	Data envelopment analysis with TAOD	Azadeh et al. (2013)	Series production line

Table 2 (continued)

Model	Method	Authors and year of publication	Application
	Fuzzy discrete event simulation	Azadeh et al. (2014)	Series production line
Artificial intelligence-based model	GA	Martorell et al. (2005)	Emergency diesel generator
		Morcous and Lounis (2005)	Concrete bridge decks
		Ilgin and Tunali (2007)	Numerical example
		Okasha and Frangopol (2009)	Bridge superstructure and five-bar steel truss
		Chung et al. (2009)	Hypothetical case
		Heo et al. (2010)	Power transmission
		Martorell et al. (2010)	Motor-driven pump
		Charongrattanasakul and Pongpullponsak (2011)	Numerical example
	Monte Carlo simulation with GA	Marseguerra and Zio (2000)	Chemical process plant
		Villanueva et al. (2008)	High-pressure injection system
		Mahadevan et al. (2010)	Raw mill system in cement industry

an approach named as multicriterion classification of critical equipment (MCCE) to allow systematic quantification of the criticality of all system and analyzed the consequence of failure and finally determined the suitable maintenance to solve the failure. A case study in urban water treatment plant was used to justify the practicality of the method. Another method using risk matrix had been proposed by Rosqvist et al. [107] as key indicator to determine the optimal maintenance policy. The application of the developed method was shown in gasification plant. Qingfeng et al. [108] had conduct a study using risk analysis to find effective maintenance that is able to increase the reliability, availability, and utilization. A typical rotating system in a petrochemical industry was exploited to test the significance of the developed approach. With the aims to provide better maintenance quality, Li and Gao [109] had came out an idea of integrating FMEA and fault tree analysis to determine the optimal maintenance policy for systems in the petrochemical plant. With similar opinion, Popovic et al. [110] had applied a risk decision factor in determining the optimal maintenance policy for the institute for manufacturing banknotes and coins. Besides, Lv et al. [111] had also suggested a maintenance policy optimization based on risk loss and probability of occurrence. The type of maintenance policy was assigned according to the risk level. A system with eight subsystems was created as a hypothetical case to demonstrate the application of the proposed method.

Since analysis involved in hazard-based model is generally subjective and may subject to inaccuracy, thus, Braglia et al. [112] had carried out a study on application of fuzzy logic to allow analysts formulating efficiently the assessment of failure analysis and identify possible optimal maintenance policy accordingly. A process plant in milling field for human consumption flour was presented to justify the importance of the method. Fuzzy logic also been suggested by Sharma et al. [13] for searching the most informative and efficient maintenance policy that able to detect failure causes in the gears of centrifugal pumps in chemical industry whereas Dong et al. [113] had established a selection approach based on combination of fuzzy criticality evaluation and failure mode and effect analysis (FMEA). Case study on steam turbine in a fossil-fired power plant was conducted to demonstrate the applicability of the methodology. Guo et al. [114] put forward newly fuzzy propagation neural network integrated with FMEA to determine the optimal maintenance policy for the petrochemical system. Azedah et al. [115] had also adopted a similar concept where fuzzy logic was integrated with FMEA to capture correct information on the centrifugal pump failure mechanism in petrochemical industry. As stated by authors, with this method, the maintenance policy that improves reliability and safety could be determined. Meanwhile, Sharma and Sharma [116] had combined the root cause analysis, FMEA, and fuzzy logic that permitted the manager to model, analyze, and predict the behavior of the system in a more realistic and consistent manner and plan appropriate maintenance policy accordingly. Practicality of the proposed methodology was fully demonstrated by a case study conducted in paper mill. Braglia and Frosolini [117] had suggested an integration of FMEA with the integer linear programming approach in finding the most economical maintenance policy that could possibly reduce the failure risk of corresponding failures based on allocated budget. The paper manufacturing plant had been adopted as an example in demonstrating the application of the proposed approach.

4.3.3 Multi-criteria-based model

Multi-criteria decision making (MCDM) is also one of the popular methods adopted in the maintenance policy optimization models. The advantage of the MCDM is that it can include the multiple, usually conflicting, objectives into the decision-making process [118]. Conflicting objective is an opposition aim resulting from perceived differences. It is commonly found in the company objectives like maximizing the customer value and minimizing costs. Thus, it is useful in maintenance policy optimizations that usually involve conflicting maintenance objectives such as maximizing system's availability in the lowest cost. In addition, by adopting MCDM, wider aspects such as safety (personnel, system, and environment), added value (spare parts inventories, production loss, and fault identification), and feasibility (acceptance by labors, method reliability) can be focused in order to obtain more accurate and precise results.

There are three main steps in adopting any kind of MCDM. The initial step of implementation is to determine the relevant criteria and alternatives, followed by attaching numerical measures to the relative importance (i.e., weight) of the criteria and to the impacts (i.e., relative performance) of the alternatives on these criteria. Finally, process the numerical values to determine the ranking of each alternative, in this case, the optimal maintenance policy. Different multi-criteria decision making (MCDM) method, like analytic hierarchy process (AHP), weighted sum method (WSM), elimination and choice translating reality (ELECTRE), technique for order preference by similarity to ideal solution (TOPSIS) has been adopted in the multi-criteria model.

Among the developed MCDM methods, AHP is the most widely used in the maintenance selection. AHP was developed by Thomas L. Satty in 1980 [119]. It is a popular and effective method for multi-decision-making by structuring a complicated decision problem into a hierarchy with goal at the highest of the hierarchy, criterions, and sub-criterions at the sub-levels and the decision alternatives at the bottom of the hierarchy. Elements at given hierarchy level are compared in pairs to assess their preference with respect to each of the elements at the next higher level. The alternative with the highest overall score is selected as preferred alternative [120]. There exists quite a number of AHP implementation on determining optimal maintenance policy. For instance, Bevilacqua and Braglia [10] had shown an application of the AHP in an Italian oil refinery processing plant. Authors had brought about a new idea where the selected maintenance policy was not just referring to a single system, but also for a group of systems which had similar failure criticality. Dey [121] has carried out an AHP implementation in determining the inspection and maintenance of oil pipelines that can maximize the availability with minimum cost. Meanwhile, Fazlollahtabar and Yousefpoor [122] had applied AHP to evaluate different maintenance policy for system that is used for a virtual learning. Authors aimed to increase the reliability and availability levels without huge increase in investment. AHP was also put to use by Gassner [123] to determine the optimal maintenance policy for wind turbine industry. Author took different criterion into consideration which was the implications of cooperative alliances. At the mean time, implementation of AHP also been suggested by Ratnayake and Markeset [124] to measure the health, safety, environment awareness, as well as costs issues in selecting a maintenance policy. Case study on oil and gas industry was presented to demonstrate the validity of the methodology. Tan et al. [125] applied AHP to determine most practicable maintenance policy for systems with different operational function in the oil refinery industry.

However, the development and application of AHP in maintenance selection issues have reached the state of maturity. Other efforts such as implementing different MCDM method, the technique for order of preference by similarity to the ideal solution (TOPSIS), and analytic network process (ANP) have given new development in term of maintenance policy optimization. Shyjith et al. [126] adopted TOPSIS in selecting the optimal maintenance policy for ring frame of the spinning mill system in the textile industry. Ding et al. [127] had proposed TOPSIS to determine the maintenance policy that could reduce the failure risk for stripping system in palm oil industry. While the application of TOPSIS has also been found in Ding et al. [128] where a decision making approach based on TOPSIS algorithm has been presented to select the optimal maintenance policy that could reduce the failure of a system. A press system has been adopted to demonstrate the feasibility of the proposed method. Besides, a more general form of the AHP named as analytic network process (ANP) was suggested by Cheng and Tsao [129] in determining the optimal maintenance policy of rolling stock.

Moreover, Zaim et al. [130] had also conducted a study to identify a maintenance policy that enabled to maximize the availability of newspaper printing system with four criteria including cost, safety, added value, and policy feasibility by using AHP and ANP. Authors had reached the conclusion that both methods produced almost similar result. Moreover, the application of ANP has been integrated with the Decision Making Trial and Evaluation Laboratory (DEMATEL) in order to convert the relations between cause and effect of criteria into a visual structural model and handle the inner dependencies within a set of criteria [131]. Feasibility of the proposed methodology had been tested in an automotive manufacturing plant to determine the optimal maintenance policy from security, technical, and economic perspectives.

In the work conducted by Kumar and Maiti [132], ANP had been integrated with a fuzzy approach to determine the maintenance policy that could minimize the system failure and maintenance cost. The robustness of the proposed method had been validated in a chemical plant. Fuzzy ANP had been presented by Rahimi et al. [133] to identify the most appropriate maintenance policy in terms of feasibility, safety, cost, and added value. A setter system in automotive manufacturing industry was adopted to demonstrate the proposed methodology.

Since the multi-criteria decision-making-based model is well known in facing uncertainty and inaccuracy of information problem, new methods have emerged through combination and integration to solve the uncertainty and subjective information faced. Fuzzy logic presented by Lotfi Zadeh is useful in coping with imprecise, uncertain, and subjective information in a more consistent and logical manner [13]. Recently, integration of fuzzy logic with MCDM method has been widely applied in maintenance policy optimization due to its flexibility in measuring uncertainty in the data. Integration of fuzzy logic with AHP can be found in Labib [118] and Wang et al. [15]. Labib [134] established a combination of fuzzy logic AHP with the aim to determine the optimal maintenance policy that able to reduce downtime and failure frequency of system with better accuracy. The application of the methodology was shown in an automotive company with 113 machines while, with similar methodology but more criteria, Wang et al. [15] tried to identify the optimal maintenance policy that is able to increase the availability and reliability levels of systems in power plant.

Recently, the papers found presented integration of AHP with methods other than fuzzy logic has increased. There are four papers found presented work related with integration of AHP and goal programming. Bertolini and Bevilacqua [135] incorporated AHP and goal programming to select an optimal maintenance policy in an oil refinery but taking maintenance burden in terms of the manpower into consideration. Arunraj and Maiti [16] also developed a similar integration to identify an optimal maintenance policy in a benzene extraction unit of a chemical plant in terms of cost and risk. At the same time, a combination of AHP, goal programming, and fuzzy logic was presented by Ghosh and Roy [136] to determine optimal maintenance policy. The application of proposed combination was performed by using data obtained from Wang et al. [15].

Although AHP is a popular method used in solving maintenance policy selection problem, it faces several criticisms including unbalanced scale judgments, uncertainty, and imprecision in pair-wise comparison process. Thus, there are several efforts found to overcome these difficulties. For example, Pariazar et al. [137] suggested an adoption of a rough set theory into AHP to eliminate the inconsistency frequently existing in AHP when performing maintenance policy selection process. An industry which is active in producing standard parts like screw basic, spring nuts, and gasket had been chosen to implement the developed method. Besides, Ilangkumaran and Kumanan [138] introduced the integration of fuzzy AHP and TOPSIS to select the optimal maintenance policy in a more efficient way. Textile industry was used to illustrate the viability and significance of the integrated methodology. Another combination that is AHP-enhanced TOPSIS and VIKOR has been applied by Ahmadi et al. [139] to ensure the consistency and effectiveness of maintenance policy decision making in the air craft system. In order to achieve more effective and accurate decision making, Chen and Chen [140] combined AHP, TOPSIS, and gray relational analysis to evaluate the performance and decide the optimal maintenance policies that suits a semiconductor company. Fouladgar et al. [141] had suggested an integration of fuzzy AHP with fuzzy Complex Proportional Assessment (COPRAS) to overcome the uncertainty in determining and defining the scoring and significance of maintenance policy and criteria, respectively. The potential application of the proposed methodology was demonstrated through justifying suitable maintenance policy for a dump truck used in a copper mine from cost, risk, added value, and policy accessibility aspects. Chan and Prakash [142] had presented an application of fuzzy TOPSIS in determining the optimal maintenance policy from an economic figure of merit associated with measurement criteria from cost, policy feasibility, as well as added value perspectives. Nevertheless, the feasibility of the proposed methodology had only been justified through a numerical example.

Beside the combination of various methods with AHP, there were other integration works presented by Al-Najjar and Alsyouf [143], Jafari et al. [144], and Li et al. [145]. Al-Najjar and Alsyouf [143] had proposed fuzzy logic SAW to evaluate the most informative maintenance policy. Two case studies using rolling element bearing and pump in paper mill industry had been conducted to prove the usefulness of the developed method. Jafari et al. [144] also presented a similar integration with another method named as Delphi method to solve maintenance policy selection problem. Authors had demonstrated the application of the developed approach by using numerical example. Fuzzy logic also had been incorporated with ELECTRE III to determine the optimal maintenance policy for the compressor in the system producing facrylonitrile [145] whereas a combination of fuzzy logic TOPSIS with factor analysis had been established by Mousavi et al. [146] for selecting maintenance policy. A numerical example was presented to accredit the proposed method to identify the maintenance policy by considering the feasibility of each policy. There is also a study related with the application of interactive fuzzy linear assignment method for selecting the optimal maintenance policy conducted by Bashiri et al. [147]. Authors aimed to suggest a better interaction between experts and analytic methodology in order to produce more reasonable result. However, the practicality of the approach only been justified by using numerical example.

Table 3 shows the summary of the uncertainty type maintenance policy optimization model from method used, authors, publication year, as well as related application.

Table 3 Summary of uncertainty type optimization model

Model	Method	Authors and year of publication	Application
Heuristic-based model	Decision tree	Wayenbergh and Pintolen (2002)	Cigar industry
		Wayenbergh and Pintolen (2004)	Cigar industry
		Wayenbergh and Pintolen (2007)	Cigar industry
		Carazas and Souza (2010)	Thermal power plant
		Ding et al. (2012)	Drilling system
Critical-based model	FMECA	Bevilacqua et al. (2000)	Oil refinery industry
	Failure analysis	Tu et al. (2001)	Power plant
	Multicriterion classification of critical equipment	Leon Hijes and Cartagena (2006)	Water treatment plant
	Risk matrix	Rosqvist et al. (2009)	Gasification plant
	Risk analysis	Qingfeng et al. (2011)	Petrochemical industry
	FMEA with fault tree analysis	Li and Gao (2010)	Petrochemical industry
	Risk decision factor	Popovic et al. (2011)	Institute for manufacturing banknotes and coins
		Lv et al. (2013)	Hypothetical case
	Integration of fuzzy logic and FMEA	Braglia et al. (2003)	Process plant
		Sharma et al. (2005)	Flour process plant
		Dong et al. (2008)	Power plant
		Guo et al. (2009)	Petrochemical industry
		Azedah et al. (2010)	Petrochemical industry
	Integration of fuzzy FMEA and root cause analysis	Sharma and Sharma (2010)	Paper mill
	Integration of FMEA with integer linear programming	Braglia and Frosolini (2013)	Paper manufacturing plant
Multi-criteria-based model	AHP	Bevilacqua and Braglia (2000)	Oil refinery
		Dey (2004)	Oil pipelines
		Fazlollahtabar and Yousefpoor (2008)	Virtual learning environment
		Gassner (2010)	Wind turbine industry
		Ratnayake and Markeset (2010)	Oil and gas industry
		Tan et al. (2011)	Oil refinery
	TOPSIS	Shyjith et al. (2008)	Textile industry
	AHP and ANP	Zaim et al. (2012)	Newspaper printing system
	DEMANTEL	Aghaee and Fazli (2012)	Automotive manufacturing plant
	Fuzzy ANP	Kumar and Maiti (2012)	Chemical plant
		Rahimi et al. (2014)	Automotive manufacturing plant
	Integration of fuzzy logic with AHP	Wang et al. (2007)	Power plant
Multi-criteria-based model	Integration of AHP with goal programming	Bertolini and Bevilacqua (2006)	Oil refinery
		Arunraj and Maiti (2010)	Benzene extraction industry
	Integration of AHP, goal programming, and fuzzy logic	Ghosh and Roy (2010)	Using data from Wang et al. (2007)
	Integration of AHP with rough set theory	Pariazar et al. (2008)	Standard production industry
	Integration of AHP, TOPSIS with fuzzy logic	Ilangkumaran and Kumanan (2009)	Textile industry
	Integration of AHP-enhanced TOPSIS and VIKOR	Ahmadi et al. (2010)	Air craft system
	Integration of AHP, TOPSIS, and gray relational analysis	Chen and Chen (2010)	Semiconductor industry
	Fuzzy AHP with fuzzy COPRAS	Fouladgar et al. (2012)	Copper mining industry
	Integration of fuzzy logic and SAW	Al-Najjar and Alsyouf (2003)	Paper industry
	Integration of fuzzy logic, SAW, and Delphi method	Jafari et al. (2008)	Hypothetical example
		Li et al. (2007)	System producing facrylonitrile

Table 3 (continued)

Model	Method	Authors and year of publication	Application
	Integration of fuzzy logic and ELECTREE III		
	Integration of fuzzy logic, TOPSIS with factor analysis	Mousavi et al. (2009)	Numerical example
	Linear assignment with fuzzy programming	Bashiri et al. (2011)	Numerical example
	Fuzzy TOPSIS	Chan and Prakash (2012)	Numerical example
	TOPSIS	Ding et al. (2014a)	Stripping system
		Ding et al. (2014b)	Press system

5 Literature findings

Manufacturing industries have shifted from being mechanism-based to highly technology-based in order to meet the market requirement. Due to the chain effect, areas related to manufacturing also subjected to change especially maintenance function. Maintenance function becomes integrated part of business. It is no longer a supportive role but has become proactive function in business strategy planning [130]. However, turning maintenance into profit maker is a challenging task where the effective planning is essential. Ineffective planning will either lead to over maintenance that cause unnecessary waste, or less maintenance that cause unproductive in manufacturing industry. Of foremost importance in maintenance management is to choose an effective maintenance policy [57]. An optimal policy should able to improve the level of performance of the system by preventing failures while reducing the maintenance expenditures [148–150].

Researches on optimal maintenance policy selection as well as the connection between maintenance and its application areas are explored. Although graphical model categorized under certainty type reveals a simple way of determining optimal maintenance policy, the requirement of a complete set of data occurs as its major disadvantage. Besides, consideration of a limited number of criteria in the optimization process may lead to sub-optimization.

At the same time, papers discussed under risk category are mostly involved fairly complex algebraic calculation written for theoretical research purposes and neglect the application from industry point of view. Validation using numerical example discovered from review becomes a strong evident to prove this point. In addition, maintenance management who does not have strong mathematical theoretical background will find difficulties in understanding the algebraic terms and less confident with model due to numerous of assumption. Application of assumption will limit the possible condition that may actually happen; in addition, not every condition can be translated into algebraic form and replicated accurately. Consequently, it may lead to wrong maintenance policy decision making.

Another limitation perceived is that risk category models focus only on one optimization criterion or limited criteria, mostly focused on variable costs and reliability. It may result in some other important aspects in a real life condition being neglected. There are several papers including those of Bevilacqua and Braglia [10], Syjith et al. [126], and Ilangkumaran and Kumanan [138] that showed the efforts on using more criterions in the optimization process. However, as more criteria are considered, the complexity degree will increase and may require development of special technology for implementation. Bear in mind, development of special technology carries the meaning of extra investment and being time-consuming. It is difficult to persuade industry management to proceed without a strong evidence of the applicability and reliability of the method.

Large amounts of uncertainty category models are explored in the review process, and the trend seems growing in recent years. Models classified under uncertainty show a higher degree of flexibility and practicability compared with the risk type. A number of papers that used the industrial for validation process have proven the practicability and applicability of the developed model from industrial aspect.

Moreover, uncertainty category model also shows the capability of considering different aspects rather than costs such as environmental issues, feasibility of the available policies, and capability of the company to implement selected policy. With this ability, the possibility of sub-optimization can be reduced; furthermore, it provides better vision and consideration in making more effective decisions on optimal maintenance policy optimization process.

Compared with the risk type, uncertainty-type models obviously involved less complex algebraic formulation. It tends to adopt logic thinking-based approaches rather than using complicated algebraic formulation to perform probability analysis. This becomes a major advantage in terms of industrial where actual condition can be reflected with less assumptions and lead to more reliable analysis. Despite this kind of models being capable of providing more reliable analysis, it is still facing difficulties in collecting quality data because these models tend to utilize experience and knowledge which is not well documented. The literature in the early years considered the single method; an increased use of the integration concept is seen in later papers. The growth in amount of papers published recently shows the seriousness in discussing variety of integration to improve the quality of the optimization results. The integration process is able to provide improvement by making up each method's deficiencies especially from data collection process.

Through the review, there is still a big gap occurs between academic and industrial application; it is very difficult for industrial companies to adapt these models to their specific business context. As stated by Utne [151], there exist many which theoretically advanced in determining optimal maintenance policies, but these are limited to very specific problems, and few are applied to solve real-life problems. It has been overstressed on the development of new optimization models, with little regard to their applicability in industry. Therefore, a shift from theoretically based research to applied-based research is required.

An applied-based research must emphasize based on three points: effectiveness, flexible, and easy implementation. In any problem solving issues, the problems must be correctly identified in order to find an effective solution. Of course, it also should be applied in maintenance policy optimization. As mentioned, maintenance policy is to maintain the system functioning. However, the system does not limit to single type of failure with fix trend of failure probability only caused by deterioration time. Sometimes, occurrences of failure is also might be due to other factors included operating load, operating condition, environment humidity, and temperature. All these conditions are different between companies and difficult to be completely represented in algebraic way. Therefore, by only throwing out certain formulas and performing analysis straight away without considering other possible factors that may also affect the failures of the system, it is nearly impossible to identify an effective solution that suits the company the most. And this is the problem frequently found in majority of reviewed papers. As supported by Sharma and Sharma [107], analyzing the data sets without knowing the failure mechanisms can lead to wrong results. Thus, root cause analysis is an essential step in achieving an effective maintenance policy for the manufacturing plant.

Moreover, some optimization methods use the predetermined criteria for optimizations without clear proof of the significance of these criteria in optimization issues. In view of the fact that each company has different objectives and operating conditions, the significance of those criteria to the related company can also be different. Generally, in the ideal condition, it should take all of these criteria into consideration when optimization. However, it is impractical either from academic or industrial point of view. From academic aspect, the method with the possibility to include large amount of criteria will be very complicated and consume a lot of time for analysis. Time is something the industrial aspect does not have. Hence, a procedure is necessary to simplify and prioritize the significant criteria that are most important for optimization.

Flexibility is the most crucial point that will decide whether the proposed method is able to fit into industrial environment or not. Nowadays, highly complex systems and enormous differences of system characteristics have caused difficulties in capturing accurate data. Despite the variety of the methods available for maintenance policy optimization presented, input data are essential, while lack of adequate data can lead to difficulties in analysis. The difficulties in gaining complete data are well known in industry due to limitation of resources and unsystematic management of data, human error, and economic constraints. Data are the most important input element in analysis. This problem has also been exposed in risk-type and uncertainty-type maintenance policy optimization models. Risk-type optimization also needs large amount of data, which may not be available. Even if the data are available, these are frequently inaccurate and thus subjected to uncertainty and cause difficulties in industrial implementation. This is a major problem faced in the past, today, and, most probably, also in the future. This is proven and supported by a similar statement made by Knezevic and Odom [152], Sergaki and Lalaitzakis [153], Louit et al. [154], and Sharma and Sharma [116]. It may be difficult or even impossible to establish rational database to accommodate all operating and environmental conditions. However, as mentioned by Waeyenbergh and Pinteon [99], a lot of data is available but in the implicit form—man's brain. Knowledge and experience can directly reflect the actual situation which is useful but in subjective form. Nevertheless, the estimates provided by experts are inherently subjective and subject to certain inconsistent due to different personnel knowledge and experience. Therefore, an effective approach is required to capture these most valuable data systematically and turn it into reliable quantitative form and use it for analysis.

In order to gain better collaboration between the academic and industry, a look from industrial point of view to consider the limitations and difficulties faced by them is essential, since industry management has time, resources, and knowledge (specific knowledge from academic) limitations. They will not prefer to spend a lot of time just for understanding and justifying whether the method is applicable or not. In the mean time, they do have limited human and material resources available. Therefore, the developed methodology must be simple, easy to set up, and provide fast and accurate results. For instance, if software is required for analysis, it is preferred to use the existing software the company has in order to save time and avoid extra investment. As industrial has time limitation, the duration of optimization analysis process should also been reduced to minimum without affecting the quality of the results.

Despite the application of the optimization models, one can notice that most of the models focused on a sole system or a single sub-system. In view of the fact that the industry is moving to adopt advanced and complicated technologies that may consists of a hundred systems with thousands of pieces of components. Cost and time become great challenges, considering that manufacturing plants usually consists of a hundred or even thousands of systems. It has further discouraged the industrial management in conducting the maintenance optimization process. Thus, a clustering idea to group systems with certain similar characteristics is put forward with the aim to reduce the analysis frequency and duration, yet produce effective results. In other words, systems with similar failure characteristics will be grouped together to perform a single overall analysis, rather than focusing on a single system under the proposed model. Moreover, the duration of optimization process can be reduced drastically, since multiple systems that are grouped together will only require one optimal maintenance policy.

Since the focus of optimization usually involves estimating the potential maintenance policy's performance that has not yet been implemented, associated experienced personnel therefore turn out to be the most preferable option for information collection. As supported by Spurgin [155], it must rely on the experts in related fields and feedback based on their experience to acquire high-quality results. Thus, it has a given advantage for the optimization process in gaining a reliable final result that is suitable for respective manufacturing plants. Besides, integration of expert judgment also enhances the feasibility of optimization model in view of the fact that experts are always available in the related field. However, human judgment is often vague and subject to a high degree of uncertainty. Besides, maintenance optimization is a sea of ambiguities where it is always complex and full of constraints where the existent of no clear boundary which can be described numerically. Thus, it is better to use fuzzy linguistic assessment instead of numerical values. A linguistic variable is a variable which applies words or sentences in a natural or artificial language to describe the degree of value. It allows non-precise in linguistic terms as it is useful in dealing with subjective judgment during the decision making and is relatively easy to capture variables that accurately reflect the actual operating condition.

Referring to the reviewed publications, it shows that MCDM is giving better measurement efficiency with less unrealistic assumption. Meanwhile, MCDM which is capable of taking a large amount of evaluation perspectives into the optimization process will further improve the overall reliability of the final outcome. In addition, the MCDM approach gives a better view for maintenance management without limitation on using only the financial as maintenance policy performance measurement standard. Sometimes, using only the financial measure might obscure the performance on an activity that is unable to be justified through monetary value such as safety issues. This has also been supported by Loften [156] where the author noticed that the manager felt it was inappropriate or unnecessary to convert maintenance measures to financial measures because the capability of improvement signal should not be limited to the economic perspective. Thus, providing a set of comprehensive measurements will be better and easier for maintenance policy performance indicator instead of converting all measures to financial measurement.

6 Conclusions

The maintenance policy optimization models from the certainty perspective are explored in the current paper. In this study, the major reviews focused on the method used and application areas in order to investigate the current standing of maintenance policy optimization issues and further explore possible improvement on related topic. The large number of papers published and reviewed proves the significance that finding an optimal maintenance policy has received high attention either from academic or industrial aspect. Although huge efforts have been forwarded, there are several inadequacies which have been uncovered in recent review. In other words, developed optimization models are still unable to fully cover the gap between academic research and the industrial, since the industrial environment is highly complicated and fluctuates with different factors and variables that are not fully documented and analyzed. Hence, a balance point between academic and industrial needs to be identified in order for both sides to gain maximum advantage from the study.

It is impossible to completely eliminate the gap, but it can be minimized. In this review, it found that systematic methodology structures with three main characteristics, including effectiveness, flexible, and easy implementation, could be a stepping stone to reduce the existing gap. This structured methodology should be able to identify the root cause of the problem, rank the significant criteria, collect effective information, and perform accurate optimization analysis in short duration and, finally, introduce a computerized processing system to facilitate a user-friendly and effective maintenance policy optimization analysis.

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