

Maintenance optimization models and criteria

Adriaan Van Horenbeek · Liliane Pintelon ·
Peter Muchiri

Received: 13 September 2010/Published online: 19 April 2011

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Abstract Due to widespread automation and the high capital tied up in production equipment, the importance of maintenance is ever increasing. This makes maintenance an investment opportunity to be optimized, not a cost to be minimized. Academics have recognized this and many maintenance optimization models have been published over the years. Most of these models focus on one optimization criterion or objective, making multi-objective optimization models an underexplored area of maintenance optimization. Moreover, there is a big gap between academic models and application in practice. It is very difficult for industrial companies to adapt these models to their specific business context. This article reviews the literature on maintenance optimization models, with special focus on the optimization criteria and objectives used. To overcome flaws in present optimization models, a generic classification framework of maintenance optimization models is presented. All factors that have an influence on the optimization model will be made explicit and their links will be established. The framework is a starting point to develop business specific optimization models and enables decision making in e-maintenance. Moreover, it ensures a fit between the business model of a company and the maintenance optimization model right from the beginning. Future research will be on the development of a

maintenance optimization model taking into account the most relevant optimization influence factors and criteria for a situation at hand.

Keywords Maintenance optimization · Maintenance optimization models · Maintenance optimization criteria · Decision support · eMaintenance

1 Introduction

Asset management, more specifically maintenance management, is a big issue nowadays. The economic downturn and the dynamic business environment drive companies to seek more efficient and effective maintenance. Companies recognize that maintenance can provide value to their business. While in the past maintenance was only seen as a cost factor, having a negative effect on the productivity of the company. Decision models can help companies to determine the value of maintenance. Literature provides quite some decision models to determine optimum maintenance policies. However, these are limited to very specific problems. Dekker (1995b) already came to the conclusion that more application oriented research should be done. Currently, the gap between academic models and application in a business specific context is still the biggest problem encountered in the field of maintenance optimization. In literature, case studies are often only used to demonstrate the applicability of a developed model, rather than finding an optimal solution to a specific problem of interest to a practitioner. Nicolai and Dekker (2007) came to the conclusion that case-studies are not well represented in maintenance optimization literature, although maintenance is something that should be done in practice and not

A. Van Horenbeek (✉) · L. Pintelon · P. Muchiri
Centre for Industrial Management, Catholic University of
Leuven, Celestijnenlaan 300 A, 3001 Heverlee, Belgium
e-mail: adriaan.vanhorenbeek@cib.kuleuven.be

L. Pintelon
e-mail: liliane.pintelon@cib.kuleuven.be

P. Muchiri
e-mail: Peter.muchiri@cib.kuleuven.be

in theory. Furthermore, Dekker (1996) describes the aspects of maintenance optimization models which cause the gap between theory and practice. He describes six aspects, whereof the most important ones are: models are difficult to understand, many articles are written for mathematical purposes only, companies are not interested in publications and the models often focus on the wrong type of maintenance. Scarf (1997) and Garg and Deshmukh (2006) also address this problem by noting that too much attention is paid to the development of new optimization models, with little regard to their applicability. They come to the conclusion that a shift from theoretical research to applied research is required. This illustrates that the aspect of usefulness by solving real problems through model fitting is often forgotten. Maintenance practitioners do not know which of the many available maintenance optimization models fit their specific problems. Moreover, they lack the time and experience to develop, themselves, an optimization model that satisfies their business specific needs (Dekker 1996). Another limitation perceived in literature is that most of the models focus on only one optimization criterion (Wang 2002), making multi-objective optimization models an underexplored area of maintenance optimization. Although single-objective optimization is attractive from the modeling point of view, this approach does not capture all important aspects of a real-life situation.

Many surveys on maintenance optimization already appeared in literature (Cho and Parlar 1991; Dekker 1995b, 1996; Jardine and Tsang 2006; McCall 1965; Nakagawa 2005; Pham and Wang 1996; Pierskalla and Voelker 1976; Scarf 1997; Sherif and Smith 1981; Valdez-Flores and Feldman 1989; Wang 2002). Although they give a nice overview of different available optimization models, they do not assist practitioners in deciding which model to use or in developing a model that fits their needs. Except for Wang (2002), who gives an overview of the influence factors that should be considered in an optimal maintenance policy. But in our view, not all factors are included. Dekker (1995a) also developed a framework that covers several optimization models in a uniform model. Though some research is already done in this field, business specific maintenance optimization and decision making remains a still underexplored area of research. Certainly when looking to the integration of maintenance optimization models into decision making in industry. When looking at multi-objective maintenance optimization some research has already been done (Bucher and Frangopol 2006; Ilgin and Tunali 2007; Martorell et al. 2002). But this is still limited to optimizing certain criteria (cost, availability, reliability) while these are not valid or important in certain industrial cases or do not take into account all business specific objectives. One of the concluding remarks Scarf (1997)

makes is that the understanding of the optimization process is at least as important as the models themselves. Dekker (1996) supports this view by mentioning that it is important to know which models to use for certain problems. Moreover, a general problem structure that fits most of the problems is necessary.

Based on the above stated problem environment, the objective of this article is to develop a general classification framework or problem structure of maintenance optimization models, with special focus on the optimization criteria and objectives. The framework involves listing all factors (e.g. maintenance actions, optimization criteria, maintenance effectiveness) that have an influence on how a maintenance optimization model is built, and establishing their links. By doing so, knowledge will be gained on how to build an optimization model and on the important factors in certain business specific cases. This approach turns around the normal reasoning in model building, instead of fitting a certain case study to a developed optimization model, an optimization model will be fit to a practical problem. The classification framework will enable decision making in companies by giving an overview of different approaches to maintenance optimization. By doing so, it will be possible to fit already existing optimization models to specific cases if applicable. And if not, the framework will give insight on how to model this optimization process, which is according to Scarf (1997) the most important. Furthermore, the classification framework can be used as a starting point for the development of a new business specific maintenance optimization model. In this way, the framework will ensure an integration of maintenance optimization models in decision making in industrial settings, by closing the gap between academic research and application in practice.

This will be done by first reviewing, and at the same time classifying, the pertinent literature on maintenance optimization models in Sect. 2. In Sect. 3 all possible maintenance optimization criteria will be determined. The final classification framework together with possible applications and future work will be presented in Sects. 4 and 5. Finally the conclusions will be stated in Sect. 6.

2 Optimization models

A literature review will be given on different maintenance optimization models and the input parameters influencing and steering this optimization process. These, together with our own additions, will be used later on to construct the optimization classification framework. The review will be done by defining different important maintenance optimization classes. These optimization classes are groups of input parameters necessary to construct a maintenance

optimization model. All these maintenance optimization classes will be discussed in the following subsections. Besides these, the possible outputs of a maintenance optimization model will be listed in the last subsection.

2.1 General modeling techniques

By general modeling techniques, we mean choices that have to be made for optimization problems in general. The most important ones are: continuous or discrete optimization, static or dynamic optimization, deterministic or probabilistic optimization, constrained or unconstrained optimization and single-objective or multi-objective optimization (Pintelon and Van Puyvelde 2006). Maintenance specific modeling decisions are; component or system perspective and finite or infinite planning horizon. While in most of the optimization models a component perspective is taken, a framework for a predictive maintenance-based schedule derived from a system-perspective is developed by Ming Tan and Raghavan (2008). Wang (2002) and Nicolai and Dekker (2007) also take the planning horizon into consideration when classifying different optimization methods. Some maintenance optimization models for finite time periods exist, but these models are still an underexplored area of maintenance optimization (Nicolai and Dekker 2007).

2.2 Maintenance concepts, policies and actions

A maintenance concept is a set of maintenance actions and policies and the general decision support structure in which these are planned and supported (Pintelon and Van Puyvelde 2006). Well known maintenance concepts are total productive maintenance (TPM) (Nakajima 1988) and reliability centred maintenance (RCM) (Moubray 1997). The maintenance policies (e.g., failure-based maintenance, time/use-based maintenance, condition-based maintenance) trigger a maintenance action when a certain event happens (e.g., failure, time-limit and condition-limit). Different maintenance actions like corrective maintenance, corrective replacement, preventive maintenance and preventive replacement are possible in different situations. The implementations of these concepts, policies and actions all have an influence on the optimization modeling. All maintenance optimization models, starting from a certain maintenance policy, try to optimize this specific policy. The output of the optimization model will also depend on the maintenance policy and actions used. For example, a time-based maintenance policy will optimize the timing of maintenance, while a condition-based maintenance policy also tries to optimize the time of inspection or the triggering threshold (Jardine and Tsang 2006). Nowadays, maintenance optimization modeling is shifting

to optimization of condition-based and predictive maintenance policies (Barata et al. 2002; Grall et al. 2002a; Grall et al. 2002b; Jardine et al. 2006; Marseguerra et al. 2002; van der Weide et al. 2010; Yang et al. 2008).

In most maintenance optimization models, maintenance action duration (repair and maintenance times) is assumed to be negligible (Pham and Wang 1996). Nevertheless, making this assumption can have a big influence on the determination of the optimal maintenance policy. By making this assumption, availability of the equipment and the value of maintenance are not taken into account. This can result in suboptimal solutions to the maintenance optimization problem, which makes maintenance action duration an important factor to take into account in the maintenance optimization process. Several optimization models already recognize and incorporate this (Boschian et al. 2009).

2.3 Maintenance optimization criteria

Optimization is always performed by minimizing or maximizing an objective function. In most of the maintenance optimization models the objective function only takes into account one criterion (e.g., cost, availability, reliability) (Wang 2002). This makes of single-objective optimization a well studied field in maintenance literature, though when looking to real-life cases multi-objective optimization is necessary. Some research has been done in the field of multi-objective maintenance optimization (Bucher and Frangopol 2006; Ilgin and Tunali 2007; Martorell et al. 2002; Okasha and Frangopol 2009), but these always take into account the same optimization criteria. These are cost rate, total cost, availability and reliability. In some optimization models safety (Martorell et al. 2005; Liu 2005) is also considered as one of the objectives. Although this is a nice starting point, not all possible criteria are included in these models. Moreover, no clear-cut method exists on how to determine which criteria are important or should be optimized in a business specific case. It is a strange thing to observe that not a lot of attention is paid to the selection of the right maintenance optimization criteria. Definitely because this is one of the most important input parameters for a maintenance optimization model, because optimizing the wrong maintenance objectives always returns a suboptimal solution. For this reason, all possible optimization criteria, together with prioritizing algorithms that can be used to select the most important optimization criteria, are listed and discussed in Sect. 3.

2.4 Maintenance effectiveness

In an optimization model the effectiveness of maintenance actions should be taken into account, because in real-life

the maintained components are not always restored to an as good as new state (AGAN). Maintenance effectiveness is the degree to which the operating conditions of an item are restored after a maintenance action is performed. Pham and Wang (1996) give an overview of the different possible degrees of restoration:

- Perfect repair or perfect maintenance: the operating condition of the system is restored to an as good as new state, which means that the lifetime distribution, degradation level and failure rate are the same as for a new component.
- Minimal repair or minimal maintenance: the failure rate of the system is restored to the one the system had before the maintenance action was performed, which is referred to as an as bad as old (ABAO) state.
- Imperfect repair or imperfect maintenance: the operating condition of the system is restored to somewhere between as good as new and as bad as old.
- Worse repair or worse maintenance: the system failure rate or actual age of the system increases by performing a maintenance action, but the system does not break down.
- Worst repair or worst maintenance: the system will certainly fail by performing a maintenance action.

Possible causes for imperfect, worse or worst maintenance are repair of the wrong part, partial repair, etc. The Brown–Proschan model (Brown and Proschan 1983) is one of the best known models to account for imperfect repair. Beyond this model, lots of other methods exist to model imperfect maintenance: (p, q) rule, $(p(t), q(t))$ rule, improvement factor, virtual age method, shock model method, (α, β) rule and multiple (p, q) rule. These methods are classified for various maintenance policies by Pham and Wang (1996).

2.5 Modeling deterioration

The modeling of the deterioration process of components and systems is a very important input to a maintenance optimization model. This data provides the basic information on which all decisions about when to perform maintenance or an inspection are made. This deterioration process description should match as close as possible with the real deterioration of the system. This makes that many deterioration models are available in literature. The easiest way to model failure behavior of components is by failure distributions (e.g., Weibull, exponential, normal) or the failure rate distribution (Pintelon and Van Puyvelde 2006). Borgonovo et al. (2000) describes aging of a component by a modified Brown–Proschan model with exponential and Weibull distributions. Linear deterioration and aging models with time are also used in literature (Bucher and

Frangopol 2006; Marseguerra and Zio 2000). Another common way to model deterioration of components is by using Markov chains (Grall et al. 2002b; Marseguerra et al. 2002). Crespo Marquez and Sánchez Heguedas (2002) use a Markov process for repairable systems and finite time periods. A k -state discrete time Markov deteriorating system with time dependent transition probabilities in combination with directed graphs is presented by Marais and Saleh (2009). Although Markov processes are used regularly to model deteriorating components, this approach also has some disadvantages. The analytical resolution is difficult in complex cases (Boschian et al. 2009), the classification of states is arbitrary and the transition probabilities are difficult to estimate and may not be elaborate enough in complex cases (Grall et al. 2002b; Liao et al. 2006). A more realistic approach is to model deterioration by a stochastic continuous state process (Liao et al. 2006), though this has the disadvantage of mathematical complexity when modeling complex systems. Grall et al. (2002b) and Dieulle et al. (2003) model a stochastic continuous state deteriorating system by using a Gamma process. Another well known method to model deterioration of components is the proportional hazard model (PHM). This model was first introduced by Cox (1972) and later on reviewed by Kumar and Klefsjö (1994). In maintenance this model is often used to estimate the influence of different covariates on the time to failure of a system or component (Samrout et al. 2009).

Due to the emergence of condition-based and predictive maintenance, deterioration models for these maintenance policies are developed. Jardine et al. (1998) developed a PHM with Weibull baseline function and time-dependent stochastic covariates for condition-based maintenance. This model takes into account both the age of the component as well as the condition of this component. A semi-Markov decision process is used by Chen and Trivedi (2005) to model deterioration of a condition-based maintenance problem. A cumulative stochastic point process is used by van der Weide et al. (2010). Marseguerra et al. (2002) uses Monte Carlo simulation and genetic algorithms to determine the optimal degradation level beyond which a preventive maintenance intervention should be taken by optimizing profit and availability. A multi-component simulation modeling approach is taken by Barata et al. (2002) to find the optimal degradation threshold for performing preventive maintenance actions. Liao et al. (2006) introduces a condition-based availability limit policy which achieves the maximum availability of a system by optimally scheduling maintenance actions. Other papers not only try to find the optimal degradation threshold, but at the same time optimize the inspection schedule or policy (Grall et al. 2002b). Recently many articles address the problem of predictive maintenance decision making. Predictive

maintenance uses current and prognostic information, like the remaining useful lifetime of components, to optimally schedule maintenance actions, while condition-based maintenance only uses current component state information. The benefit of also using information about future degradation over only using currently observed information is illustrated in different publications (Camci 2009; Yang et al. 2008). Finally, Wu et al. (2007) developed a predictive model that uses an artificial neural network to estimate the life percentile and failure times of roller bearings. Proactive maintenance decisions can be made based on the prognostic information which results in a dynamic maintenance schedule.

2.6 System information and configuration

System information can be complete or incomplete; when incomplete some expert judgment will be necessary to determine all essential information about the system. Dekker (1996) states that a maintenance optimization model comprises four aspects whereof the first aspect is a description of the technical system, its function and its importance. This is necessary to understand the working principle, determine the criticality, system configuration, etc. of the equipment at hand. Dekker (1996) states that analyzing data without knowing the underlying mechanisms can lead to wrong decisions, which stresses the importance of having the proper system information. Furthermore, this system information will reveal dependence, when present, between components of a multi-component system. When no dependence between components is present the maintenance decision reduces to an optimal policy for each component. There are three types of dependence between components, namely economic, failure and stochastic dependence. Nicolai and Dekker (2007) give an overview of maintenance models for multi-component systems using a classification scheme based on the dependence between components. Group maintenance policies and opportunistic maintenance policies are summarized by Wang (2002).

The system configuration is, together with the component dependence, important system information necessary for maintenance optimization modeling. Different configurations are possible: single-unit, multi-unit, series, parallel, K-out-of-N, standby, etc. For all of these system configurations different optimization models are available. The review papers all address single-unit and multi-unit systems, while Nicolai and Dekker (2007) review literature on K-out-of-N systems. A maintenance policy for a K-out-of-N system under a condition based maintenance strategy is presented by de Smidt-Destombes et al. (2004) and by Lu and Jiang (2007). Pham (2010) estimates reliability of K-out-of-N systems with exponential lifetimes for n

independent and identically distributed components. Furthermore, series-parallel systems (Barata et al. 2002; Bris et al. 2003; Coit and Smith 1996; Levitin and Lisnianski 1999; Marseguerra et al. 2002) and standby units (Vaurio 1997) are also common system configurations addressed in literature.

2.7 Data sources

Data availability is often seen as the biggest obstacle to overcome to make the implementation of maintenance optimization models possible in real-life case studies (Dekker 1996). Failure data are necessary to model the deterioration of components, operating data to model the working conditions and cost data to evaluate different maintenance policies. Maintenance information systems mainly contain accounting information on events, while these data are not valuable for maintenance optimization modeling (Dekker 1995b). Moreover, problems exist with the acquisition of cost data. Direct maintenance costs (e.g., personnel cost, component cost) are relatively easy to quantify. However, indirect maintenance costs (e.g., accelerated wear, rework) and the value of maintenance (e.g., increase in availability) are very difficult to determine. Because of these problems some publications were made taking into account model and data uncertainty (Bunea and Bedford 2002; Rocco et al. 2000; Sanchez et al. 2009). A general classification framework of maintenance optimization models, like presented in this article, can assist in determining the important data that are necessary in specific cases, reduce uncertainty about some parameters and avoid time loss by gathering irrelevant data. Together with the concept of e-maintenance a framework like this has the potential to solve the data problem (Muller et al. 2008).

2.8 Optimization algorithms

When the objectives are set and all necessary information is available an optimization algorithm is used to find the optimal solution to the optimization problem. Analytical and numerical optimization solving are the most common used optimization methods in general (Jardine and Tsang 2006). Weise (2008) gives a general overview of global optimization algorithms and Ehrgott and Gandibleux (2000) review different multi-objective combinatorial optimization methods (e.g., tabu search, simulated annealing, neural networks). An overview of metaheuristics used for optimization is presented by Glover and Kochenberger (2003).

In maintenance optimization many algorithms (e.g., linear programming, dynamic programming) are used, which all have their advantages on solving specific

problems. In most of the real-life maintenance optimization cases, multi-objective optimization is required to ensure a good fit between the model and the industrial problem. In the last few years academics have recognized this, which makes a combination of simulation (e.g., Monte Carlo simulation) and evolutionary algorithms (Coello 2000; Marseguerra et al. 2002; Villanueva et al. 2008) a promising multi-objective optimization algorithm used in maintenance optimization. Optimization algorithms used in maintenance optimization applications are listed in the classification framework described in Sect. 4 of this article.

2.9 Output

Dekker (1995b) describes the results or output of a maintenance optimization model. First, maintenance policies can be evaluated and compared with respect to the optimization objectives and criteria. Only cost and reliability characteristics are mentioned as criteria by Dekker. Secondly, models can determine how often and when to inspect or maintain. In other words, they assist in taking a timing decision. And finally, optimization models can help to determine effective and efficient maintenance schedules and plans (e.g., execution moments, planning shutdowns, work preparation, required maintenance capacity). Furthermore, an optimal control-limit policy (maintenance threshold) for condition-based maintenance can be determined. Jardine and Tsang (2006) introduce a framework consisting of four key decision areas for optimizing equipment maintenance and replacement decisions. Each of these four areas returns specific outputs; these are component replacement time, inspection time and frequency, capital equipment replacement (economic life, repair vs. replace) and resource requirements (workshop machines, crew sizes and composition, right sizing equipment, lease or buy, outsourcing).

3 Maintenance optimization criteria

As can be concluded from the literature study performed, all maintenance optimization input parameters to develop a maintenance optimization model are well studied, except for the maintenance optimization criteria used. The maintenance criteria or objectives used in literature for optimization are limited to the well-known criteria like cost and availability. Moreover, no attention is paid to which criteria are important in specific business cases. For this reason we establish all maintenance optimization criteria that could be used in maintenance optimization and some prioritization methods to determine whether these criteria are important or not in business specific cases are presented.

3.1 Listing all optimization criteria

Coetzee (1998) states that: “The objective of the maintenance function is to support the production process with adequate levels of availability, reliability, operability and safety at an acceptable cost.” Taking this into account there are five important maintenance optimization criteria. Dekker (1996) from his side categorizes the prime maintenance objectives under four headings: ensuring system function (availability, efficiency and product quality), ensuring system life (asset management), ensuring safety and ensuring human well-being. Capital replacement modeling, deciding when to replace a machine with a new one, is another optimization criterion (Jardine and Tsang 2006; Scarf 1997). Other objectives taken into account in literature are safety (Bucher and Frangopol 2006; Martorell et al. 2002; Martorell et al. 2005; Liu 2005), maintenance personnel management (Quan et al. 2007) and spare parts inventory (Ilgin and Tunali 2007). Most of the important maintenance optimization criteria are mentioned in literature, but not all of them are used in maintenance optimization models. In most of the developed models a cost rate or total cost optimization is done. However, the major benefits of maintenance improvement are usually noticed at other working areas like production, inventory, quality, etc. and not at maintenance itself as it usually shows a higher cost. Marais and Saleh (2009) and Al-Najjar (2007) take a better approach by optimizing the value of maintenance. Moreover, all optimization models used in case studies try to optimize a limited number of maintenance criteria (e.g., cost rate, availability), without clear prove that these criteria are the most important ones in this specific case. This can lead to suboptimal solutions. Maintenance has to provide the right value to the right optimization objectives, not always the maximum or minimum to only one of the objectives. In this way the solution to the maintenance optimization problem will evolve to a global optimum which maximizes the added-value of maintenance by considering multiple decision criteria. To overcome these problems a generic list of all possible maintenance optimization criteria is developed (Table 1), taking into account the criteria found in literature and adding the ones we think are also important and are still missing.

When setting objectives in maintenance optimization, one should start from this generic list of maintenance optimization criteria. Based on the experience and expert knowledge available in a company with respect to a specific case, a prioritization among those criteria should be made. Based on this prioritization, the real objectives are derived and an optimal optimization model and solution, with business specific objectives, to the real maintenance problem is found.

Table 1 Generic list of optimization criteria

Maintenance costs (discounted)	Availability
Maintenance quality	Reliability
Personnel management	Maintainability
Inventory of spare parts	Environmental impact
Overall equipment effectiveness	Safety/risk
Number of maintenance interventions	Logistics
Capital replacement decisions	Output quantity
Life-cycle optimization	Output quality

3.2 Business specific criteria

To determine business specific maintenance optimization criteria, several prioritization methods can be used. Ahl (2005) compares five prioritization methods: analytic hierarchy process (AHP), binary search tree (BST), planning game (PG), 100 points method and planning game combined with AHP. A fuzzy multiple criteria decision making method is used by Al-Najjar and Alsyof (2003) to evaluate different maintenance policies. Different methods for prioritizing are also compared by Karlsson et al. (1998). AHP, hierarchy AHP, spanning tree matrix, bubble sort, binary search tree and priority groups are considered in the comparison. The conclusion from this comparison is that AHP is the most promising approach for prioritization, because it yields the highest reliability of the results, it is fault tolerant and the consistency of the decision maker is checked. Moreover, AHP uses relative judgments between the different elements, which is faster and yields more reliable results than making absolute judgments (Karlsson et al. 1998). The analytic hierarchy process (Saaty 1990) is a well-known prioritization method that is also used in maintenance decision making (Bevilacqua and Braglia 2000; Triantaphyllou et al. 1997; Wang et al. 2007; Labib et al. 1998; Bertolini and Bevilacqua 2006; Emblemståg and Tønning 2003; Ho 2008). When using AHP, a decision maker first gives linguistic pairwise comparisons, they are numerically quantified by selecting a certain numerical scale, and finally a priority vector is derived from the numerical pairwise comparisons. To determine a priority among the maintenance optimization criteria, an AHP prioritization approach can be used. Although the AHP method has some disadvantages (e.g., large amount of pairwise comparisons, scalability, rank reversal), these do not outweigh the advantages (e.g. quantitative and qualitative criteria, structure complex problems, consistency of decision maker is checked) of applying this method to a decision process. Furthermore, AHP can be extended to fuzzy AHP, which takes into account the uncertainty of the decision maker (Wang et al. 2007). When the assumption of independent criteria is not valid, the analytic network

process (ANP) should be used (Saaty 1996). The analytic network process is in fact an extension of the analytic hierarchy process. Applying these methods (AHP or ANP) to the selection of maintenance optimization criteria is a starting point to business specific maintenance optimization by deriving a ranking or weights for all criteria which can be used in the objective function(s) of a maintenance optimization model.

It is however also possible to incorporate these maintenance criteria immediately in a multi-criteria decision model (e.g., outranking methods, multi-attribute utility and value theories) for selection of the best maintenance strategy or policy, rather than using them in a weighted objective function for maintenance parameter optimization. Although, these multi-criteria decision methods are mostly used for strategic rather than operational decision making. The most effective maintenance alternative taking into account various factors can be determined by comparing the different alternatives regarding the maintenance criteria. Using these decision models enables the decision maker to take into account all important maintenance criteria and factors that determine the positive and negative effects of a maintenance task or action. One valuable method found in literature apart from the ones described above is the VIKOR method, which is compared to different other outranking models by Opricovic and Tzeng (2007). The VIKOR method is especially useful in MCDM problems with conflicting and incommensurable criteria by finding a compromise between alternatives that is acceptable for conflict resolution. An extension of the VIKOR method based on interval-valued fuzzy sets to incorporate the uncertainty of the decision maker about the weights and ratings of the different attributes is presented by Vahdani et al. (2010). An AHP-enhanced TOPSIS, VIKOR and benefit-cost ratio is developed by Ahmadi et al. (2010) to determine the most effective maintenance strategy for aircraft systems. A state of the art survey on multiple criteria decision analysis is given by Figueira et al. (2005).

4 Classification framework of maintenance optimization models

Maintenance optimization models are already categorized by different authors (Brown and Proschan 1983; Cho and Parlar 1991; Nicolai and Dekker 2007; Pham and Wang 1996; Wang 2002), but there is always a limited focus on certain subjects (e.g., imperfect maintenance and component dependence) of maintenance and a general overview of maintenance optimization models was never given. By doing this it becomes clear to practitioners what is possible with maintenance optimization and which factors should be taken into account in the modeling process. This approach

initiates the closing of the gap between academic research and practical application of maintenance optimization models.

4.1 Maintenance optimization classification framework

Dekker (1995b) states how he sees an optimization model. It is a description of a technical system, its function and its importance, deterioration of the system, available system information, an objective function and an optimization technique. Wang (2002) developed a general framework for maintenance policy optimization. The inputs used for this framework are: maintenance policies, system configuration, maintenance effectiveness, maintenance cost, optimization criteria, modeling tools, planning horizon, dependence and system information. By changing the system configuration, maintenance effectiveness, planning horizon, analytical tools and dependencies between components, different optimization models are obtained according to Marais and Saleh (2009). Although this gives a good idea about how a maintenance optimization model is built, not all optimization classes discussed in the literature study of Sect. 2 are present. Taking these optimization classes into account, together with the optimization criteria, a general maintenance optimization classification framework is built (Fig. 1). This framework gives an overview of all possibilities for maintenance optimization modeling. The optimization classes (Sect. 2) are the input parameters necessary to construct a maintenance optimization model, and this model will generate the wanted output.

4.2 Application of the classification framework

Dekker (1996) states the need for a set of standard maintenance models that fit different optimization problems. This can be difficult to achieve in reality, but a methodology on how to reach an optimization model that fits a business specific case can be developed. The developed maintenance optimization classification framework gives an overview of all variations that can be considered for maintenance optimization modeling. This makes it easier for industrial companies, as well as for academics, to see what is possible with the current maintenance optimization techniques and which areas still need some further research. The general framework of optimization models presented in this article can be a starting point to fit a maintenance optimization model to a specific problem. In this way a business specific model can be built, starting from the general classification framework and determining the important business specific input parameters for the model. An optimal solution to the real maintenance problem will be found by using the framework as a first step in a

decision support system, which will be subject of future research. Moreover, the framework not only assists in developing a maintenance optimization model, it also helps practitioners to find existing maintenance optimization models that fit their specific needs. Another problem addressed by the classification framework is the data problem mentioned earlier in this article. The maintenance optimization classification framework helps to determine which data are important to incorporate in the optimization model in specific cases. Moreover it helps to decide whether more or less time should be spent to obtain the right data. The framework enables a closer cooperation between academics and industry by showing to practitioners what is possible with maintenance optimization models and ensuring a fit between the model and the real-life case, making companies also more willing to collect and supply data to academics. In other words, the classification framework helps to close the gap between academic research and industrial applications.

4.3 Link with e-maintenance

Besides the selection of the right maintenance optimization criteria, like described earlier in this article, data collection is also very important when optimizing maintenance. The classification framework of maintenance optimization models supports practitioners in building a model, moreover it enables decision making in maintenance optimization. However, without the right data, maintenance decisions are based on wrong or incomplete data, which leads to suboptimal or even completely wrong solutions to the maintenance problem. The introduction of IT applications in maintenance, like in e-maintenance, could provide a solution to this problem (Holmberg et al. 2010). E-maintenance has the capability to provide the decision maker with the right information (e.g., equipment health) at the right time to make the right decision. Moreover the classification framework on maintenance optimization models guides which data should be collected. However, one of the problems e-maintenance is still facing is making the right decision based on all the gathered data, which means the decision models that make the right decision based on the gathered data are still missing (Muller et al. 2008). Liyanage et al. (2009) mentions the development of advanced maintenance simulation software and optimization techniques as one of the most important challenges of e-maintenance applications. The classification framework of maintenance optimization models is a starting point to business specific maintenance decision making, consequently there is a clear link between the framework on maintenance optimization models and the concept of e-maintenance. Maintenance optimization models need accurate data, which can be provided by the concept of

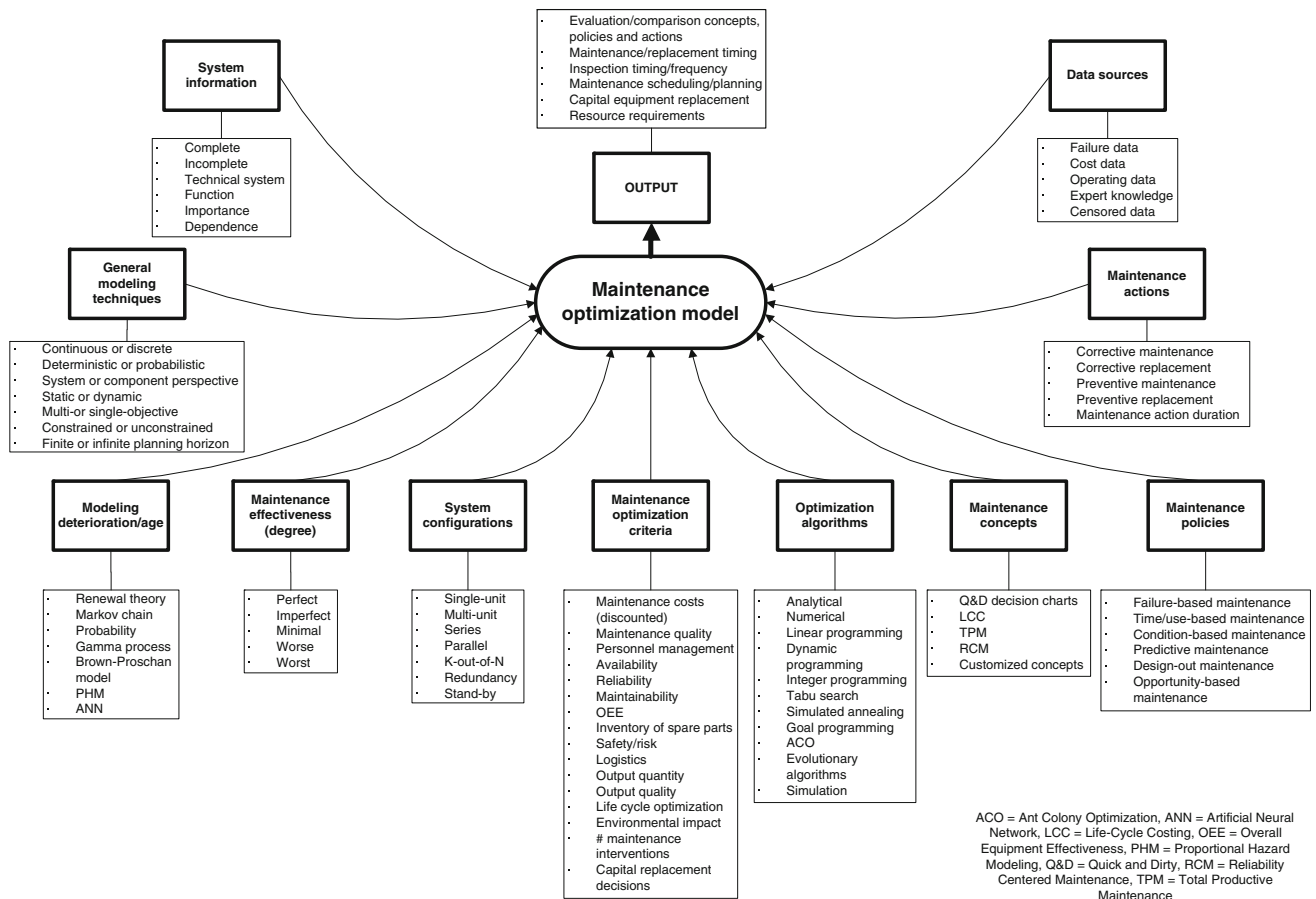


Fig. 1 Maintenance optimization classification framework

e-maintenance, while on the other side e-maintenance needs decision models which can be provided by a decision support tool taking into account the classification framework of maintenance optimization models.

5 Future work

Future work will be on establishing the links between the different maintenance optimization criteria and on determining which parameters have an influence on these maintenance optimization criteria (e.g., the maintenance cost is determined by the direct costs, the indirect costs and the criticality of the system or components). In this way a hierarchical or network structure will be developed and a more thorough AHP or ANP method can be used to determine the relative importance of the different criteria in a business specific context. In a next step, when all criteria are weighted, these weights can be used to construct a weighted single-objective function optimization model or the important criteria can be used in a multi-objective optimization model. Moreover the possibility of developing a maintenance decision support tool based on the

optimization framework will be investigated. The target is to construct a decision structure on how to implement a maintenance optimization model with the available data for a given industrial environment. Furthermore, the applicability of the classification framework in the context of a decision support tool will be validated by performing industrial case studies and by the development of business specific maintenance optimization models.

6 Conclusions

Literature urges for a need for more application based maintenance optimization. Maintenance optimization should not start with developing a maintenance model and trying to fit an application to it, but it should start with an application and try to fit a maintenance optimization model to it.

The literature review on maintenance optimization models shows that already a lot of research has been done in this field. However a flaw in literature is discovered when looking at maintenance optimization criteria. Not all optimization criteria are included in those maintenance optimization models and what is even more important is

the fact that no business specific criteria are taken into account. However, this is very important to fit an optimization model to a real-life case. To overcome these issues a generic list of maintenance optimization criteria is presented.

Taking the literature review and generic list of maintenance optimization criteria into account a general maintenance optimization classification framework is developed. The framework links all possible maintenance optimization techniques and parameters. By doing so, the classification framework assists maintenance practitioners in selecting or developing a business specific maintenance optimization model.

The developed list of generic maintenance optimization criteria together with the general maintenance optimization classification framework helps to close the gap between academic research and application in practice, by enabling business specific maintenance optimization.

Acknowledgments This work has been carried out within the framework of the Prognostics for Optimal Maintenance (POM) project (grant nr. 090045) which is financially supported by the Institute for the Promotion of Innovation through Science and Technology in Flanders (IWT-Vlaanderen). The authors also wish to thank the reviewers for their valuable comments which certainly improved the quality of this paper.

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