EVALUATION OF ALTERNATIVE MAINTENANCE STRATEGIES ON A COMPLEX SYSTEM IN THERMAL POWER SYSTEMS

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Abstract

In recent years, due to the continuous development of the industry and the rapid increase in the system complexity, maintenance policies have become more important. Unplanned downtimes due to unexpected failures may lead to huge problems in almost all industry branch. However, carrying out maintenance more than the required to prevent unexpected failures increases maintenance cost significantly. Thus, balancing the number of reactive and proactive maintenance is very important.

The aim of this thesis is to develop maintenance methods under the reactive, condition-based and proactive maintenance strategies using dynamic Bayesian networks (DBNs) in thermal power plants. DBNs which are are probabilistic graphical models, are selected to model the system because they are very effective to formulate the stochastic and structural dependencies between the components. In this study, we evaluate alternative maintenance strategies on a complex system based on two factors: total number of maintenance and total maintenance cost in a given planning horizon. The proposed maintenance methods are simulated on a multi-component thermal power plant system which has a very complex structure with hidden components among which there are stochastic and structural dependencies. Scenarios are designed considering the maintenance dependability of parallel systems during proactive activities and different reactive cost structures. As a result, performances of all proposed maintenance strategies and methods are compared and analysed under each scenario and the most promising ones are highlighted.

Keywords: DBN, reactive maintenance, proactive maintenance, complex systems

TERMİK SANTRALLERDE KULLANILAN KARMAŞIK BİR SİSTEM ÜZERİNDE ALTERNATİF BAKIM STRATEJİLERİNİN DEĞERLENDİRİLMESİ

Özet

Son yıllarda, endüstrinin sürekli gelişimi ve sistemlerin karmaşıklığının artması ile bakım politikaları daha önemli hale gelmiştir. Beklenmedik arızalar nedeniyle ortaya çıkan planlanmayan arıza süreleri, hemen hemen tüm endüstri kollarında büyük sorunlara yol açabilir. Ancak, beklenmedik arızaları önlemek için gereğinden fazla bakım yapılması da bakım maliyetlerini önemli ölçüde artırır. Bu nedenle, reaktif ve proaktif bakım sayısının dengelenmesi çok önemlidir.

Bu tezin amacı, termik santrallerde olasılıklı grafik modeller olan dinamik Bayes ağlarını (DBN'ler) kullanarak reaktif, koşul bazlı ve proaktif bakım stratejileri kapsamında bakım yöntemleri geliştirmektir. Sistemi modellemek için bileşenler arasındaki yapısal ve stokastik bağımlılıkları formüle etmek için çok etkili olan DBN'ler seçilmiştir. Bu çalışmada, karmaşık bir sistemde alternatif bakım stratejileri iki faktöre dayanılarak değerlendirilmiştir: belirli bir planlama ufkunda toplam bakım sayısı ve toplam bakım maliyeti. Önerilen bakım yöntemleri, aralarında rassal ve yapısal bağımlılıklar olan gizli bileşenlerin bulunduğu çok karmaşık yapıya sahip çok bileşenli bir termik santral sisteminde simüle edilmiştir. Paralel sistemlerin bakım bağımlılıkları ve farklı reaktif bakım maliyetleri dikkate alınarak senaryolar oluşturulmuştur. Sonuç olarak, önerilen tüm bakım stratejilerinin ve yöntemlerinin performansları her senaryo altında karşılaştırılmış ve analiz edilmiş, en iyi bulunan yöntemler açıklanmıştır.

Anahtar kelimeler: Dinamik Bayesçi ağlar, düzeltici bakım, proaktif bakım, kompleks sistemler

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To My Dear Readers...

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List of Abbreviations

RAH	**R**egenerative **A**ir **H**eater
BB	**B**all **B**earing
RS	**R**otor **S**haft
WI	**W**inding **I**nsulation
HRG	**H**ub **R**eduction **G**ear
RI	**R**AH **I**nsulation
Hc	**H**oneycomb
RR	**R**otor **R**otation
CR	**C**oal **R**ank
Sg	**S**lagging
$\mathbf{FEM_{fp}}$	**F**ault **E**ffect **M**yopic Method with worst state posterior probability
$\mathbf{FEM_{wp}}$	**F**ault **E**ffect **M**yopic Method with best state posterior probability
$\mathbf{FEL_{fp}}$	**F**ault **E**ffect **L**ook-Ahead Method with worst state posterior probability
$\mathbf{FEL_{fp}}$	**F**ault **E**ffect **L**ook-Ahead Method with best state posterior probability
$\mathbf{REM_{fp}}$	**R**eplacement **E**ffect **M**yopic Method with worst state posterior probability
$\mathbf{REM_{fp}}$	**R**eplacement **E**ffect **M**yopic Method with best state posterior probability
$\mathbf{REL_{fp}}$	**R**eplacement **E**ffect **L**ook-Ahead Method with worst state posterior probability

$\mathbf{REL_{wp}}$	**R**eplacement **E**ffect **L**ook-Ahead Method with best state posterior probability
CIPM	**C**onstant **I**nterval **P**roacitve **M**aintenance
DIPM	**D**ynamic **I**nterval **P**roacitve **M**aintenance
ThPM	**Th**reshold Based **P**roacitve **M**aintenance
RM	**R**eactive **M**aintenance
PM	**P**roactive **M**aintenance
SD	**S**tandart **D**eviation
CI	%95 **C**onfidence **I**nterval
GH	**G**ames **H**owell test result
Tk	**T**ukey test result
I	Set of components
I'	Set of eligible replaceable components
T	Set of time periods
i	Index for components
$i*$	The components selected for replacement
t	Index for time periods
$TCost$	Cumulative total maintenance cost
$TCost$	Cumulative total maintenance cost
ψ_i	Total maintenance cost of node i
AC_i	Maintenance action cost of node i
AD_i	Action duration of node i
DC_i	Downtime cost of node i
W	The best state
F	The worst state
ef_{it}	Efficiency measure of component i in period t
C_{it}	State of component i in period t , $i \in I$
O_t	State of observation node in period t
A_{it}	State of the action node belong to component i in period t
ε	Accumulated evidence consisting of the replacement history

pci	Proactive constant interval for CIPM
$CIMT$	Array of constant interval maintenance periods
pdi	Proactive dynamic interval for DIPM
pmt	Next proactive maintenance time for DIPM
thr	Threshold level of ThPM
$TabuDur$	Tabu duration
$TabuDurList$	Array that keeps the tabu duration of each component
$TabuList$	Array that keeps the tabu components

Chapter 1

Introduction

With the rapidly developing technology in recent years, the structure of the systems used in the industry has also started to change rapidly. Simple industrial mechanisms, usually consisting of one or a few components, in the past have been replaced by systems which consist of more components, but are also more structurally complex. Although these developments benefit companies in many ways, they also cause difficulties in understanding the system and making appropriate plans. It is important to figure out the dependencies between the components, especially in risk, safety and maintenance management where system reliability should be prioritized. It should be noted that any misunderstanding and wrong calculation can seriously harm companies, both financially and spiritually. Moreover, many factories and companies with well technological infrastructure have been established, and this has led to the escalation of competition. To survive in this competitive environment, keeping systems available is the most important point. Otherwise, deliveries to the customer are delayed, which could result in loss of trust and thereby loss of customer in the long term. In addition to these, loss costs and, in some cases, penalty costs also cause companies to remain in a difficult situation.

The most effective way to avoid these situations is to maintain the systems regularly. In the most common sense, maintenance is the set of tasks performed to sustain the operation of the established order in a factory [1]. Maintenance can be categorized in two main strategies as proactive and reactive [2]. Reactive maintenance is carried out to correct a malfunction or to remove an emergency situation whereas proactive maintenance is performed to avoid possible downtimes before the system stops because of a failure. It is a known fact that proactive maintenance reduces the unexpected downtime of the system and reduces costs considerably if it is applied effectively. However, although proactive maintenance can prevent possible failures in the system substantially, it does not completely prevent the occurrence of unexpected failures [3]. In such situation, it is necessary to carry out reactive maintenance immediately to ensure that the fault is remedied as soon as possible.

Maintenance has always played an important role since the first industrial revolution when machines came into our lives and mass production began. Initially, a system or machine malfunction would be noticeable only when it was not working, and the component that caused the system to fail was determined by observation and only reactive maintenance was performed on that component. However, with the escalating complexity of the systems, it has become more complicated to understand and make maintenance plans by observing which component has broken the system [4]. Thus, new and smart maintenance methods have begun to emerge. Especially with industry 4.0, as the state of the system and its components and the probability of failure can be understood with the help of sensors, proactive maintenance methods that reduce maintenance costs have become widespread.

1.1 Classification of Maintenance Philosophies

Maintenance is a requirement that has existed since ancient times. From the routine repairs of the oldest hand tools to the maintenance of modern machines, maintenance and repair has an important place in our lives. But for hundreds of years, people thought there was no need for repair unless their tools were damaged. But this is not a viable approach in today's facilities, especially when it comes to industries that have to use multi-component systems and smart factories . At this point, different maintenance strategies have been developed. Kothamasu et al. [5] classified the maintenance philosophies in his study in which current paradigms and practices on system health monitoring and prediction are discussed. Inspired by this study, maintenance philosophies can be classified as in Figure 1.1.

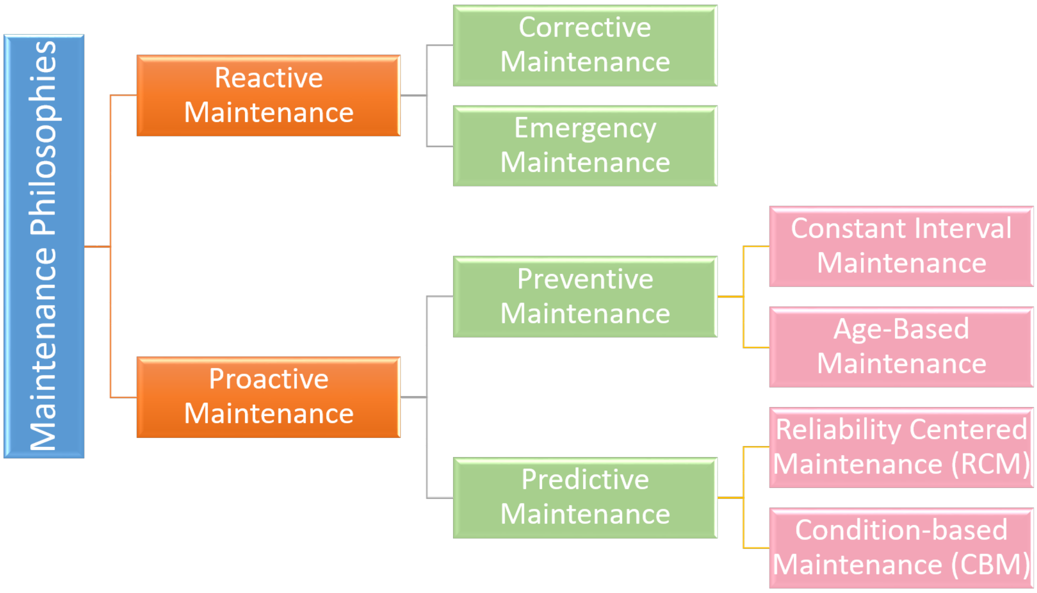


Figure 1.1: Classification of maintenance philosophies.

Maintenance strategies are basically divided into two as reactive and proactive. Reactive maintenance is applied when the system fails. Conversely, proactive maintenance is implemented to avoid from the failure or to decrease the deterioration probability of the components [6]. Reactive and proactive maintenance are also classified within themselves depending on the way they are detected and applied.

1.1.1 Reactive Maintenance Strategies

Reactive maintenance is categorized as corrective and emergency maintenance.

Corrective Maintenance

Corrective maintenance is the maintenance performed to correct the malfunction which is detected during an inspection, preventive maintenance or work. The failures are generally do not threat the health of the system, their quick maintenance will be more beneficial for the continuity of the system. The need for corrective maintenance in a system cannot be prevented.

Emergency Maintenance

Emergency maintenance is applied when a malfunction occurs that threatens the health of the system and workers and the continuity of the operation. Unlike corrective maintenance, the need for emergency maintenance can be greatly reduced with a regular preventive maintenance program.

1.1.2 Proactive Maintenance Strategies

Proactive maintenance can be grouped under two headings as preventive and predictive [7]. In the former, the system is maintained at predetermined intervals, while in the second, a certain criterion which is generally relates to the reliability of the system must be met to maintain the system.

1.1.2.1 Preventive Maintenance Strategies

Preventive maintenance can be further divided into two as constant interval and age-based maintenance[8].

Constant Interval Maintenance

In constant interval maintenance, components are replaced or maintained at predetermined times according to a constant interval, regardless of situation of them or system. Thus, in this maintenance strategy, components can be unnecessarily replaced or maintained even if they are not needed, and this can result in excessive costs [9].

Age-Based Maintenance

Age-based maintenance is done when the component or the system reaches a certain age, and age of the maintained component is reset when maintenance is performed [10]. In the previous one, component maintenance is carried out at predetermined time intervals, regardless of the condition of the components. However, in this strategy the age of the components is considered while taking maintenance decisions.

1.1.2.2 Predictive Maintenance Strategies

In predictive maintenance, a prerequisite for the condition of the system must be met to maintain the system. The aim is to keep the system at the highest level with the least number of maintenance required, thus reducing maintenance costs [11]. Predictive maintenance can be categorized as reliability centered maintenance (RCM) and Condition-based maintenance (CBM).

Reliability Centered Maintenance (RCM)
RCM tries to improve the reliability and usability of the most crucial points in the system and minimize system failures and maintenance costs. The main aim is to find the optimum point where system reliability and profitability intersect with the number of maintenance [12].

Condition-Based Maintenance (CBM)
CBM enables the maintenance decision to be performed in regard to the actual state of the equipment or system. CBM indicates that maintenance should be carried out when specific indications indicate the possibility of poor performance or unexpected failure. For a machine, these symptoms are detected by visual inspection, performance data, vibration data, and analysis of planned test results. A proper CBM plan reduce maintenance costs considerably as a result of avoiding unnecessary maintenance [13].

1.2 Dependencies in Multi-Component Systems

To select the best maintenance strategy for multi-component complex systems, understanding the dynamics of the system is essential and it is only possible by defining the dependencies and cause-effect relations among the components correctly. Complex systems consist of many components which may be interdependent to each other. For maintenance decisions, three types of dependencies are encountered among the components, i.e., structural, economic and stochastic [14]. In addition to these three, another type of dependency, resource, has been recently described by [15].

1.2.1 Structural Dependency

This type of dependency is traditionally explained as two components that are dependent on each other must be maintained together, they cannot be renewed or repaired separately. That is, even if only one of the two components fail, the other must also be disassembled [16]. Keizer et al. [15] divide structural dependency into two as technical dependence and performance dependence. In the first, maintenance of a particular component may require or prohibit the maintenance of other components. In the second, the configurations of the components, i.e., parallel systems, series systems, are considered.

1.2.2 Economic Dependency

The economic dependency between the components implies that if a group of components are maintained collectively, total maintenance cost is either reduced (positive economic dependence) or increased (negative economic dependence) in comparison to the total of singular maintenance costs of the respective components [17, 18]. The best example of economic dependence is group maintenance of components. In this way, loss of profit can be reduced thanks to reducing downtime or higher costs may be generated due to unnecessary repair of parts in the group. Also, there are both positive and negative economic dependencies in k out of n systems. There is a positive economic dependency in the serial systems where n=k. In the systems where n>k (redundant systems), while there is a positive economic dependency when a component fails, negative economic dependency occurs as long as the system operates.

1.2.3 Stochastic Dependency

In stochastic dependency, the deterioration of one component affects the other components. In this type of dependency, when a component fails, the life time distribution of other components that are dependent to it is also affected by this deterioration [19]. If this deterioration cause failure of the other components, it is called Type I failure interaction. On the other hand, if a malfunction of one component influences the failure rate of the other component dependent to it or induces shock damage on it, this is called Type II failure interaction [20, 21].

1.2.4 Resource Dependency

This type of dependency exists if limited resources are available for the maintenance activities. For example, if many components require the same set of spare parts and this set is limited, there is resource dependency between these components [15].

1.3 Methods for Modeling the Dependencies

Numerous methods have been used in the literature to identify the dependencies between the components. The most popular ones are fault tree analysis (FTA) [22], event tree analysis (ETA) [23], bow-tie analysis [24].

Fault tree analysis aims to reveal combinations of all event chains that can cause it when an undesirable event occurs [25]. When defining the dependencies between components, this method tries to find out which component or components can cause the failure of the main system. In the event tree method, the results of an event and the probabilities of these results are examined. In these two methods, only two-state decision mechanism can be used while defining the dependencies between events. That is to say, the events are connected to each other by the "AND-OR" gates.

Bow tie analysis combines event tree and fault tree analysis [26]. When considered from this point of view, these methods are limited in defining the dependencies between the variables within the scope of a maintenance problem.

On the other hand, Bayesian networks are another frequently used method to define dependencies between components. The reason for this is the success of Bayesian networks in updating the failure probability estimates of the variables under certain evidence. In addition, Bayesian networks have a wider modeling capacity than other approaches. Apart from that, techniques such as FTA, ETA and bow tie analysis are based only on the stationary structure of the components and the probability update are difficult. Bayesian networks are more successful in determining dependencies between components [27].

Dynamic Bayesian networks (DBNs) are extended versions of BNs by adding the time dimension which makes them more successful in dynamically monitoring the state of the system through the planning horizon under certain evidence.

1.4 Motivation of the Thesis

As a result of a research done on literature, it has been observed that the maintenance problem of complex systems is not studied enough, and component-based maintenance policies are generally recommended. Therefore, the purpose of this thesis is to address the maintenance issues of a complex system that we encounter in real life as a whole. In such systems, different dependencies may be occurred between components. So, these dependencies are modeled with DBNs and maintenance policies under different maintenance strategies are developed.

Özgür-Ünlüakın and Bilgiç [28] proposes four different methods to choose component to be replaced under a policy where the reliability of the system is not allowed to fall below a threshold reliability level in a system that has no possibility to take observations. Because of not being able to observe the system, reactive maintenance is not performed in the system under consideration. The proposed methods can be used only in the selection of the component to be replaced when the system falls below the specified threshold.

Karacaörenli [29] uses the methods in [28] on an experimental system which have four components that have no dependencies between them. However, as distinct from [28], these methods are handled in a reactive maintenance planning under partial observations. Also, two more proactive maintenance strategies are developed with and without opportunistic view. Our study differs from that study basically by the real-life complex system handled where there are more than four components and there are dependencies among its components and some of the components have more than two states.

On the other hand, this study aims to enrich the methods proposed in [28] firstly where they can be used for also both reactive and proactive maintenance in a real partially observable system with multi-state components which have complex dependencies between them. In addition to these methods, four new methods are proposed that can be used under any type of maintenance strategy. This is because, unlike the previous study, some of the components in this study have more than two states, and considering the probability that the component is in the best state is not the same as considering the probability of being in the worst state. Thus, evaluating the probabilities of components being in the best state and being in the worst state generally indicates different actions to be performed at a maintenace time. Exploiting this fact, one more maintenance rule is developed for each maintenance method available in the literature.

Also, proactive maintenance strategies introduced in [29] and [28] is enhanced to be valid in complex multi-state real-life systems. Tabu procedure is proposed in proactive maintenance strategies in order to select the component to be maintained more effectively and more accurately. All maintenance strategies are also compared on a complex multi-component real system. As the real system, thermal power plants have been chosen where maintenance is very important and not doing it correctly can cause both financial losses and environmental damage. The regenerative air heater (RAH) which provides air heating in air-gas system is selected to be studied because of its complexity and importance in thermal power plant systems.

1.5 Organization of the Thesis

This study is structured as follows: Chapter 2 provides a review of the literature. Evolution of DBNs, their applications in the literature, maintenance problems addressed in complex systems, and finally maintenance problems in thermal power plants are presented in Sections 2.1, 2.2, 2.3, 2.4 respectively. The proposed methodology is detailed in Chapter 3. Section 3.1 gives a brief of probabilistic graphical models, Bayesian networks and dynamic Bayesian networks. In Sections 3.2 and 5.2, reactive and proactive maintenance methods are explained in details respectively. Chapter 4 shows the the construction of the DBN model for the application of the proposed methodology to a regenerative air heater system which is used in thermal power plants. Computational analysis based on the case study and its results are presented in Chapter 5. And finally Chapter 6 concludes the study and directs further study alternatives.

Chapter 2

Literature Survey

With the rapidly developing technology in recent years, the complexity of systems and interactive relationships between system components have increased. As a result, in the case of any malfunction in the system, the number of components triggered from it, and therefore maintenance and repair costs, also increased rapidly. Proper and timely maintenance planning is crucial to minimize these costs, and has been worked frequently in the literature, especially recently.

The most important point of proper maintenance planning is a correct definition of the relationships between the components in the system. To do this, various approaches have been proposed and used from past to present. Dynamic Bayesian Networks are very successful in defining the relationships between variables in both maintenance and other fields. Thermal power plants are the systems where maintenance planning is the most critical and a wrong maintenance decision causes huge environmental and financial losses when it does not made correctly. However, this issue has not been studied much in the literature since thermal power plants are complex systems which are difficult to model.

In this chapter, the evaluations of DBNs from past to present, applications of DBNs on maintenance and related fields, maintenance applications in complex systems and thermal power plants are provided.

2.1 Evolution of Dynamic Bayesian Networks

The first thing to be done in the maintenance planning is determining the components of the system to be maintained, the fault conditions and the factors that will reveal these fault conditions. These factors can be caused by the own age of the components or the effect of the condition of other components on this component. For this, first of all, the dependencies between the components should be determined well. The methods frequently used in the literature to identify the dependencies between components are fault tree analysis (FTA), event tree analysis and bow-tie analysis.

Fault tree analysis is a top-down deductive failure analysis, where, when an undesirable situation occurs in a system, the causes of this condition are tried to be found by combining and analyzing all sub events with using Boolean logic[30]. This analysis method is commonly used in safety and reliability engineering to guess failure times of a system, to describe the best ways to minimize risk, and to estimate the probability of a safety accident or a specific functional system failure. FTA was first discovered at Bell Laboratories in 1962 by H.A Watson to evaluate the Minuteman I Intercontinental Ballistic Missile Launch Control System under the US Air Force Ballistic Systems Division contract [31]. Since then, its use has become increasingly widespread and is generally used by reliability experts as a failure analysis tool.

On the other hand, event tree analysis is a graphical representation of the logic model that determines and measures probable outcomes in pursuit of an initiation event, and ensures an inductive approach for reliability assessment because they are created using advanced logic [32]. The event tree name first appeared in the 1970s during the WASH-1400 nuclear power plant security study, when an alternative method was needed due to the wideness of fault trees [33].

The bow tie method is a risk assessment method that can be used to analyze and indicate causal relationships in high-risk scenarios. The method takes its name from the shape of the diagram that looks like a bow tie. A bow tie diagram does two things: first of all, a bow tie gives a visual summary of all possible accident scenarios that may exist around a particular danger; second, by determining control measures, it shows what a company is doing to control these scenarios. With these aspects, it can be said that this analysis is a combination of fault tree and the event tree analysis. The first "real" bow tie diagrams are said to be seen in the HAZAN (Hazard Analysis) lecture notes given at the University of Queensland of Australia (1979), but how and when the method was found is not fully understood [34].

All of these methods are limited in defining dependencies between the variables. On the other side, Bayesian networks (BNs) are a applicable method to define inter-component dependency. Bayesian networks were first introduced by Judea Pearl in 1985. This type of network can be used to represent deep causal information, and if the links are used not only to store real information but also used to direct and activate data flow in calculations, it turns into a computing architecture [35].

Dynamic Bayesian Networks (DBN) is an expanded version of BNs by adding the time horizon. A DBN is a Bayesian network that associates BN variables with each other in consecutive time frames. This is often called Two-Time BN (2TBN) because at any point in T, it says that the value of a variable can be calculated from the internal regressors and the value just before the time (T-1). DBNs were developed by Paul Dagum in the early 1990s at the Stanford University Medical Informatics Department [36]. Dagum aimed to create a general probabilistic representation model to use in nonlinear and time-dependent fields by combining traditional linear state-space models such as Kalman filters, linear and normal prediction models such as ARMA, and simple dependency models such as hidden Markov models [37].

2.2 Applications of DBNs in Maintenance and Related Fields

Dynamic Bayesian networks are a common approach in the literature. They are used mostly in prognosis, fault detection, reliability, risk analysis and safety. Table 2.1 gives a summary of the usage areas of DBNs in the literature.

Muller et al.[38] propose an e-maintenance approach based on probabilistic modeling, which can dynamically monitor systems degradation to adjust the time of proactive maintenance. While developing this prognosis approach, stochastic deterioration models based on prior knowledge and expert evaluation, deterioration indicators based on historical data and causal relationships of the components in the system based on physical laws are considered and used as a whole. The methodology is created in five steps: functional modeling, dynamical modeling, behavioral modeling, event modeling and prognosis modeling of the system. Dynamic Bayesian networks are used to integrate the structure of the system, causal relationships between variables and distortion processes of the components in the behavioral modeling phase which is a combination of functional modeling and dynamic modeling processes. This approach is experienced on a metal coils system.

In [39], a DBN-based prognosis method is proposed with considering the protection layers and its effects on the system to make the failure prognosis analysis more accurate. The prognosis method is used to predict system failures. DBN model of the system consists of the effect of activated barriers which need to activate automatically or manually before the action and human effect such as inspections, emergency plans, as protection layers. A flue-gas energy recovery system is given as a case study.

Hu et al. [40] create an integrated safety prognosis model that includes the DBN and ant colony algorithm to forecast the reliability, performance and safety of a complex system to take a precautions for a system failure. This model uses the DBN and ant colony algorithm together to demonstrate the propagation path of failures. The dependencies of the equipments and randomness of the failures are considered. Gas turbine compressor system, which has a very complex structure, is chosen as a case study.

In [41], a DBN framework is proposed to determine the current state, to predict what will be its future status under current evidence, and to choose the best recovery action for a partially observable, externally exposed system. In the study, this modeling is explained based on a power supply system of a spacecraft and different abnormal situations and fault simulation scenarios are taken into account. Results demonstrate the validity of the proposed model.

Hu et al. [42] introduce a DBN-based approach that can reveal the underlying causes of failures, especially in complex industrial systems where hazards can arise in the event of a possible failure. First, a HAZOP analysis is carried out in order to determine the relationships between the components in the system correctly, to reveal possible causes of a failure and to identify hazard scenarios properly. Based on this analysis, the DBN model is created. This DBN model is used to find the root causes when a potential failure signal is received.

Hu et al. [43] use HAZOP, multi-level flow modeling (MFM) and DBN methods together for a fault diagnostic model. As a preliminary study for HAZOP, MFM is developed firstly and then fault propagation path analysis is made. According to this analysis, different HAZOP scenarios are handled and the DBN model is created based on HAZOP results. The aim is to detect faults before an accident occurs in complex systems.

Liu et al. [44] introduce an approach to find common causes of failures using DBNs in subsea blowout preventer which is a multi-component parallel system. They consider the common cause failures in which multiple components in a system fail for the same reason. Also, sensitivity analysis is made based on imperfect coverage factor, failure and repair rates.

Salazar et al. [45] offers a model predictive control approach that consider the use of actuators to maximize control performance of the systems while maintaining their reliability. In the study, system reliability is handled with a global approach in which Birnbaum's measure of importance is used, and the equivalent effects of individual components on system reliability are handled with a local approach. DBNs are used to measure reliability.

Z. Li et al. [46] provides a reliability analysis approach for multi-state variables by using Markov processes and DBN model together. Transition probabilities in the DBN model are defined pursuant to the information revealed in the Markov process. Repairable components which can be subjected to perfect or imperfect repair and non-repairable variables which have to be replaced when they fail are considered separately. In addition, for observable elements, condition-based maintenance can be taken into consideration. A control unit is taken as case study in which conversion of a fault tree model to BN and later to DBN is also explained.

Chang et al. [47] propose an approach that uses DBN modeling to predict the risk of fatigue failure in subsea wellhead dynamically. The current risk of failure can be forecasted using fatigue accumulated in the well. In addition, the probability of fatigue failure in the wellhead in any future time frame can be estimated based on DBN model.

In [48], a Bayesian network model approach which is also consider the dynamic changes of the components so that the risk calculation can be done correctly, especially in hazardous areas such as the chemical industry. In the study, a dynamic fault tree analysis is created firstly and then it is shown how this fault tree can be transformed into a dynamic Bayesian network.

Wu et al. [49] offer an approach to identify conditional probabilities and consequences of dangerous events using DBN and bow tie analysis. The approach considers both the effect of deterioration and dynamic model parameters. First, a bow tie model was created, then this model was converted to DBN. DBNs have been used to reveal the root causes of risks that occur during the offshore drilling operation.

In [50], a dynamic Bayesian approach which takes into account also the changes that occur as construction progresses, for the safety analysis of road damage in tunnel construction. This approach provides both backward and forward-looking inferences. A metro tunnel construction in China is used as a case study to prove the adaptability of approach to a real life project.

Codetta-Raiteri et al. [51] express how DBNs can be applied to model cascading effects which mean mean that the deterioration of the dependent components in the system affects each other in interdependent dynamic systems. DBNs are preferred because they are good at modeling the effects of cascading events. In the study, a power grid containing multi-state components is considered as case study. Maintenance action probabilities are also taken considered in addition to system failure probabilities.

DBNs are frequently used also in maintenance problem. Two different approaches based on Dynamic bayesian networks for planning inspections and maintenance are presented in [52]. In one of the approaches observable variables are used, and in the other simulations based on Bayesian updates are used. They evaluated the comparisons of these approaches in terms of cost.

Hu et al. [53] use DBNs and HAZOP analysis together to provide an opportunistic predictive maintenance method for a gas turbine compressor system. To analyze and learn the system, HAZOP is applied and then a DBN model is created in the light of this information. This method aims to find optimal maintenance time to decrease the cost and increase the reliability and safety. Using DBN model, optimal maintenance time of each component, when the cost of the maintenance is minimum, can be identified. In addition, if maintenance of a component affects the working of the dependent components, the components can also be maintained at the same time. In this way, the cost of stopping (down time cost, set up cost...) can be reduced.

In addition to these areas, DBNs are also used in different areas that we frequently encounter in our daily lives such as health, economy, supply chain problems, predictions of natural events and use of public transportation services.

Sandri et al. [54] create a DBN model using historical data to predict the order of organ failure in intensive care units. In the study, a learning algorithm is applied to create conditional probability tables. The generated DBN model can be used to predict which organ will fail at the next time based on the failure of an organ at the moment, as well as the occurrence of multiple organ failures on the same day.

Dabrowski et al. [55], the probability of a future banking crisis is calculated dynamically by DBN modeling using the Markov probability structure. Three different DBN models are compared to logit model and signal extraction method using a data set from various European countries. Despite of difficult of application, it is propounded that the proposed methods are more effective. Thanks to this approach, future crises can be estimated more accurately and necessary precautions can be taken.

Kao et al. [56] recommend using Dynamic Bayesian networks to uncover the causes and consequences of problems occurring in the supply chain. In the study, a model previously studied in [57] with cause-effect diagrams is transformed into a DBN model, which is better at modeling causal relationships in supply chain problems.

M. Li and Liu [58] provide an approach for predicting the path and intensity of storms using wavelet analysis and DBNs together. When the data acquired from the actual data and the results of the DBN model are compared, it is deduced that the predictive power of the proposed approach is high.

Roos et al. [59] propose a method of using DBNs to estimate short-term passenger density on the Paris metro line. The model has been provided to work even when there is missing data by applying structural expectation maximization algorithm.

Article	Application Area	Issue
Muller et al. [38]	Prognosis	Mechanical Systems
Hu et al. [39]	Prognosis	Energy Systems
Hu et al. [40]	Prognosis	Gas Turbine
Dabrowski et al. [55]	Prognosis	Banking crisis
Codetta-Raiteri and Portinale [41]	Fault detection	Spacecraft
Hu et al.[42]	Fault detection	Petrochemical Industry
Hu et al. [43]	Fault detection	Petrochemical plant
Sandri et al. [54]	Fault detection	Health
Marini et al. [60]	Fault detection	Health
Liu et al. [44]	Reliability	Subsea systems
Salazar et al. [45]	Reliability	Drinking water network
Z. Li et al. [46]	Reliability	Control Unit
Chang et al. [47]	Risk Analysis	Subsea Systems
Barua et al. [48]	Risk Analysis	Level Control
S. Wu et al. [49]	Risk Analysis	Offshore drilling
X. Wu et al. [50]	Safety	Tunnel Construction
Codetta-Raiteri et al. [51]	Cascading Effects	Power grid
Nielsen and Sorensen [52]	Risk Based Maintenance Planning	Wind turbine
Hu et al. [53]	Predictive Maintenance	Gas turbine system
Kao et al. [56]	Diagnosis	Supply chain
M. Li and Liu [58]	Forecast	Storm
Roos et al. [59]	Forecast	Railway transportation

Table 2.1: Selected DBN applications.

2.3 Maintenance in Complex Systems

Maintenance has always been a very important element since the early days of industrial systems. Especially, with considering that the failure of one component in complex systems can quickly affect other components, proper maintenance planning is required in such systems. Due to the difficulty of modeling, maintenance in complex systems is not very often studied, and they are handled in the literature with different approaches. However, the systems addressed in the studies are generally two-state systems and are not taken from real life. In addition, one of the proactive or reactive aspects is considered in the studies. In this study, both reactive and proactive maintenance using DBNs were studied on a real life system consisting of multi-state components. Also, the system handled in this study has two parallel subsystems which increases the complexity of the modeling due to the increased number of components and at the same time enriches the problem on hand.

Özgür-Ünlüakın and Bilgiç [28] introduce a DBN-based replacement approach for multi-component systems that plans to minimize maintenance cost or number of maintenance without reducing system reliability below a certain level. The reliability of the system is estimated using DBNs, based on the interactions between components. Maintenance time is set as the time before the system reliability drops below the specified level. When this time has come, to select component(s) to be maintained, failure effect and replacement effect methods which consider current or future time posterior probabilities are presented. The computational analysis of the proposed approach is done on a problem which is made dynamic in the study from the very popular static auto diagnosis problem in the literature.

Keizer et al. [61] propose a condition based maintenance methodology for a complex parallel systems with redundant components based on Markov decision processes. Redundant component provides load sharing and reduce the failure rate of each component consequently. However, when one component fails, it increases the load of other components, so the faulty component must be maintained immediately. In addition, redundancy provide less maintenance set-up cost if components are maintained at the same time by group maintenance. So, there are economic dependence between the components in the system discussed. Numerical sensitivity analysis demonstrates that as load sharing increases, the average cost reduces, and maintenance of one faulty component cannot be postponed to wait failure of the other component. As the number of unnecessary components increases, cost savings also increase. Also, it can be said that this policy is more important when set-up costs are higher.

In [62], a maintenance planning methodology which consider maintenance time, maintenance method and group maintenance at the same time for a complex system based on Markov Decision Processes. The reason for considering the maintenance time is that if maintenance is planned too late, it will cause more costs, or if it is done too early, the components that do not deteriorate will also be replaced unnecessarily. Firstly, the optimal or near optimal time and type of maintenance for each component separately tried to be found. Then, system level maintenance program is optimized. MDPs have been used to identify economic and structural dependencies between system components.

Alrabghi and Tiwari [63] presents a new method that can combine all maintenance strategies (corrective, preventive, opportunistic, condition based) for all components in a system to optimize cost function (decrease the cost) with considering spare parts management and production dynamics. The study consider that components in the system may not be identical and each of them may have different maintenance requirements. Discrete event simulation was used to represent the maintenance methods used and their effects on components and the system. It is tried to define finding correct time and correct maintenance policies for each component with the lowest cost.

Martinod et al. [64] propose a maintenance policy optimization that consist of both preventive and corrective maintenance for a multi-component system with dependent components. Stochastic approach under a mathematical framework is used to find optimal maintenance plan to decrease total maintenance cost. As preventive maintenance, block-based and age-based maintenance is used. Also, a clustering method of maintenance actions is proposed. Imperfect maintenance actions are considered. The method is applied to an urban air ropeway transport systems as a case study.

In [65], a condition based maintenance policy based on simulated annealing for a multi-component system which consider the stochastic dependency that means one component affects the rate of deterioration of other components is presented. Stochastic dependence between components is modeled by regression method. The methodology is defined in three stages: first, the degradation model of each component is independently defined, then the interaction of degredation models on a system basis are discussed, and finally the CBM optimization model is created. The numerical experiments are done in an industrial cold box which used in a petrochemical plant.

Dao and Zuo [16] provides a maintenance method for a system with multi-state components that aim to minimize the total maintenance time and cost while maintaining the reliability of the system. There are structural dependencies among the components in the system and the method tries to find optimal maintenance sequence and maintenance actions by considering these dependencies. A directed graphic is used to model the priority relationships of the components in the system, and a backward search algorithm is used to determine the order of maintenance.

2.4 Maintenance in Thermal Power Plants

Thermal power plants are one of the systems where maintenance planning is critical. This is because, any malfunction in such systems may cause serious costs and even problems that may harm human and environmental health. However, due to the complexity of the thermal power plant systems, they have been handled seldom in the literature. In addition, even if they are used in the literature, these studies generally suggest a component-based maintenance methods rather than system-based, components in the systems generally have two states and their relationship are not complex. Thermal power plant system handled in this thesis has multi-state components with complex dependencies between them. Moreover, the system has parallel lines which makes modeling more difficult. To overcome this difficulty, dynamic Bayesian networks are used which are good at modeling complex relationships. Also, the maintenance methodology for a thermal power plant system in this thesis are a system-based maintenance in which situations of all components in the systems are considered at all time periods.

Melani et al. [66] propose a predictive maintenance planning approach of a flue gas desulfurization system in a coal-fired power plant. The main aim of the approach is finding more risky, important component and maintain them firstly and also minimize the maintenance cost. This method consists of three main steps. Firstly, functional tree and internal block diagram are used to determine the working structure of the system. Then, a HAZOP study is presented to learn failure modes, their consequences and maintenance activities in the system. Failure modes is defined with fault tree analysis. Root causes of failure modes are determined and their risk priority number is calculated based on severity, occurrence and detection. Finally, Multi-Criteria Decision is used to decide which component is more critical.

Carazas and Souza [67] presents an approach that aims to balance the failure probability in the system and the cost of this failure in the selection of maintenance policies. In the method, critical elements are determined firstly. Then, maintenance procedures are recommended that can be applied to these critical elements. The purpose of the maintenance procedure is to minimize the risk of failure while not increasing the total maintenance cost. A decision tree is used for this. A lubricating oil system in gas turbines journal bearings is used to analyze the method.

Chapter 3

Methodology and Solution Approach

The purpose of this study is to address the maintenance issues of a multi-component complex system. DBNs were used to express and model the complex relationships between components and the wear and aging of components over time. Eight reactive maintenance methods with two different efficiency measures and three different proactive maintenance strategies are considered. Four of the reactive maintenance methods with one efficiency measures (FEM, FEL, REM, REL) are proposed in [28] initially for an unobservable system. In this study, in addition to these methods, a different variant of efficiency measure is proposed for each method and thus, eight methods are considered totally.

For proactive maintenance, three different strategies are discussed which are constant interval proactive maintenance (CIPM), dynamic interval proactive maintenance (DIPM) and threshold based proactive maintenance (ThPM). CIPM and DIPM are used under a DBN framework in [29]. ThPM is first proposed in [28]. In this thesis, these strategies were implemented on a more complex real-life system which has more components and dependencies among its components. In proactive maintenance strategies, tabu procedure is proposed to make component selection more effective.

Reactive maintenance methods are handled in two ways: number-based and cost-based. In cost-based strategies, a normalization procedure is proposed. DBNs have been used to determine which components in the system need maintenance and to examine the impact of maintenance on the system.

3.1 Probabilistic Graphical Models

Probabilistic graphical models (PGMs) are modeling methods that allow to understand and define common probability distributions in complex structures. Graphical models provide a modeling of a large number of random variables with complex relationships and dependencies with each other eloquently by combining graph theory and probability theory. When using this modeling method, conditional independence between random variables is used. Conditional independence assumption simplifies the learning of the model and inference calculations. Thus, it helps to discuss and model the uncertainty and complexity problems that always pose a problem in the field of engineering. In this study, Dynamic Bayesian Networks which is one of the most well-known probabilistic graphical model are used.

3.1.1 Bayesian Networks and Their Usage in Dependent Systems

Bayesian networks (BNs)are one of the most well-known of probabilistic graphical models. They are the most effective probability networks which are based on the graph theory that can be used when there is uncertainty in a model.

In Bayesian network models, nodes and arrows are used. In the model, nodes illustrate random variables, and arrows between the nodes show the conditional dependencies between those variables. In the structure of BNs, that we will deal with in this study, nodes are lined from cause to effect. That is, the side at the end of the arrow shows the affected variable, and the other shows the variable that affects it. Figure 3.1 shows the Bayesian network structure of a three-component system.

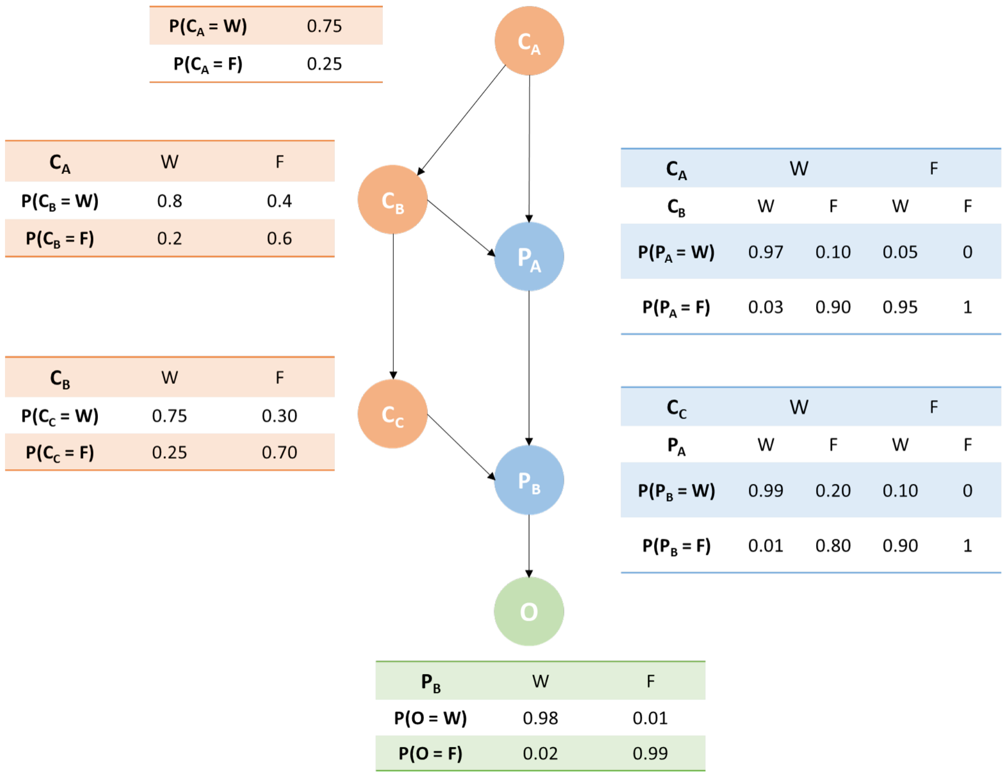


Figure 3.1: A BN model example.

In the model given in Figure 3.1, C_A, C_B and C_C represent the components affecting the operation of the system, P_A and P_B represent the process nodes showing the relationship between the components affecting it, while O represents the observation node that allows the system to be observed from the outside.

As stated in Section 1.2, three types of dependencies are generally handled in models. As an example of stochastic dependency, in this model, component C_B depends on C_A; component C_C depends on component C_B. For instance, when C_A is work, in “W” state, the working probability of C_B is 0.8. However, when C_A fails, the working probability of C_B considerably decreases to 0.4. Other relations can be stated as follows: Process P_A is affected by C_A and C_B; process P_B is dependent on P_A and C_C, and finally the observation node, O, is directly dependent on the P_B process. In the system, components and processes are hidden. However, they can be inferred partially from the observation node.

In any Bayesian network model, together with determining the variables and which variables are dependent, the parameters of these dependencies should also be determined. For this, a conditional probability table (CPT) is prepared which shows the conditional probabilities of each node. As can be seen in Figure 3.1, these tables list the probabilities of the states of the variables according to the combinations of the states of their parent nodes. As seen through the columns of the tables, it should be note that the sum of the probabilities of the states of a variable according to a combination must be 1.

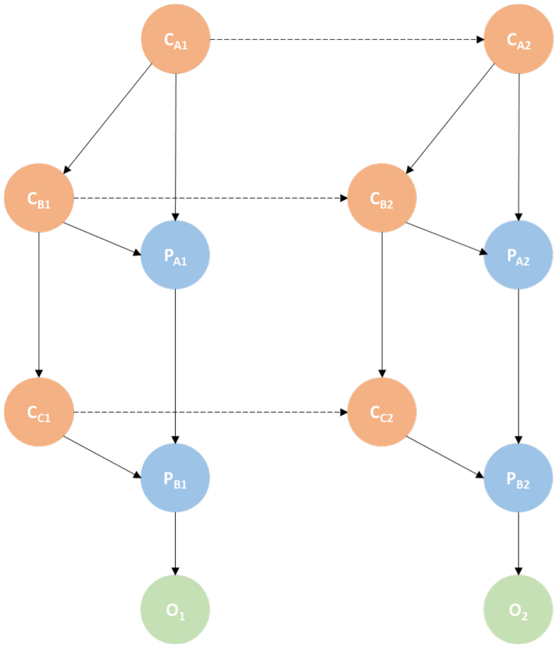
In models created with Bayesian networks, the joint probabilities of the variables are calculated according to (3.1). In the formula, N represents the number of variables in the system, $\mathrm{X_i}$ shows the $\mathrm{i^{th}}$ variable and $\mathrm{Pa(X_i)}$ represents all parents of variable $\mathrm{X_i}$.

$$\prod_{i=1}^{N} P\left(X_i|Pa(X_i)\right) \tag{3.1}$$

3.1.2 Dynamic Bayesian Networks in Dependent Systems

Dynamic Bayesian Networks (DBNs) are constituted by adding time dimension to BNs for evaluating also the effect of time on the system variables and dependencies. A DBN consists of several BNs each of which represents a specific time slice of the DBN. Figure 3.2 shows the conversion of the BN model which is given in Figure 3.1 into a DBN.

In this system, components start at their best states at the beginning of the planning horizon and deteriorate with constant transition probabilities in time. In the figure, transition probabilities of component B at t=2 is shown. When component B is in failure state at t=1, even if component A works at t=2, component B remains in failure state because no maintenance activities is performed. On the other hand, if B works at t=1, its states at t=2 depends on the state of A at t=2. If A fails at t=2, then working probability of B at t=2 decreases.



C_{A2}	W		F	
C_{B1}	W	F	W	F
$P(C_{B2} = W)$	0.98	0	0.60	0
$P(C_{B2} = F)$	0.02	1	0.40	1

Figure 3.2: A representative DBN model.

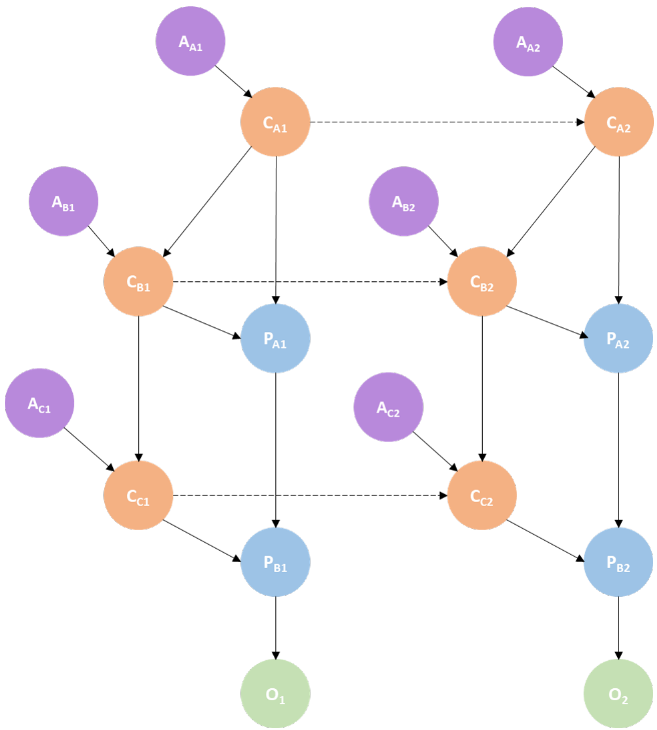


Figure 3.3: A representative DBN model with action nodes.

A_{B2}	Maintain				Do Nothing			
C_{A2}	W		F		W		F	
C_{B1}	W	F	W	F	W	F	W	F
$P(C_{B2} = W)$	1	1	1	1	0.98	0	0.6	0
$P(C_{B2} = F)$	0	0	0	0	0.02	1	0.4	1

Table 3.1: Transition probabilities of $\mathrm{C_{B2}}$ with action node.

Figure 3.3 demonstrates the DBN model with action nodes added. It is needed because in DBNs, it is not possible to model maintenance of components directly. To give the effect of maintenance, an action node is defined for each component. In this way, after deciding whether or not to maintain a component, the state of the respective action node is changed according to the maintenance action decided. The aim of the action nodes is preventing the effect of maintenance or replacement of components on other components' past and therefore current states and failure probabilities. Table 3.1 shows the transition probabilities of component B at t=2 with the effect of action node. The table indicates that if action node of $\mathrm{C_{B2}}$, namely $\mathrm{A_{B2}}$, is in "Maintain" state, the probability of component B's being in working state is 1 at t=2 whatever the state of $\mathrm{C_{A2}}$ and $\mathrm{C_{B1}}$ is. Otherwise, probabilities without action nodes which is given in Figure 3.2 are valid.

The joint probabilities of the variables in a DBN can be calculated as in (3.2).

$$P(X_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(X_t^i | Pa(X_t^i)) \tag{3.2}$$

where T is the number of time slots, N is the number of random variables in a time slice, X_t^i is the i^{th} node in time-slice t, $Pa(X_t^i)$ represents all the parents of X_t^i in the current and also in the previous time slices, X_t represents all variables in time slice t, and finally $X_{1:T}$ represents all variables in the network, i.e, $X_1, X_2, \ldots, X_T$.

3.2 Reactive Maintenance Strategy

Eight reactive maintenance methods with two different efficiency measures are proposed in this study. The first efficiency measure is "fp" which consider the probability of the components or observation node being at the worst state. The second measure, "wp", consider the probability of the components or observation being at their best state. The reason for using two different measure is that the variables in the system can have more than two states, and therefore the consideration of the variable with maximum worst state probability and the variable with minimum worst state probability does not give the same result.

The following sections provide details of the general flow and recommended maintenance methods for number-based reactive maintenance.

3.2.1 General Flow of Reactive Maintenance

The general flow chart of the reactive maintenance policy is given in Figure 3.4. At each time t, under the evidence collected so far, the probabilities of the observation node is calculated and a sample is taken from state space of the observation node. If this sample indicates a system failure, reactive maintenance is carried out using one of the methods (FEM_{fp}, FEM_{wp}, FEL_{fp}, FEL_{wp}, REM_{fp}, REM_{wp}, REL_{fp}, REL_{fp}) which will be explained in detail in Sections 3.2.2 - 3.2.5. These methods are used to decide which component should be maintained. The observation node is rechecked after the maintenance of the relevant component and, if necessary, another component is selected from the remaining components according to the same method for maintenance. The list of evidence is updated as components are maintained. This process continues until the end of the planning horizon.

The general flow algorithm of the reactive maintenance policy is given in Algorithm 1. Algorithm 2, 3, 4, 5, 6, 8, 7, 9 show the algorithm of FEM_{fp}, FEM_{wp}, FEL_{fp}, FEL_{wp}, REM_{fp}, REM_{wp} and REL_{fp} and REL_{wp} methods, respectively. "F" and "W" specified in algorithms and formulas show the worst and best state of the

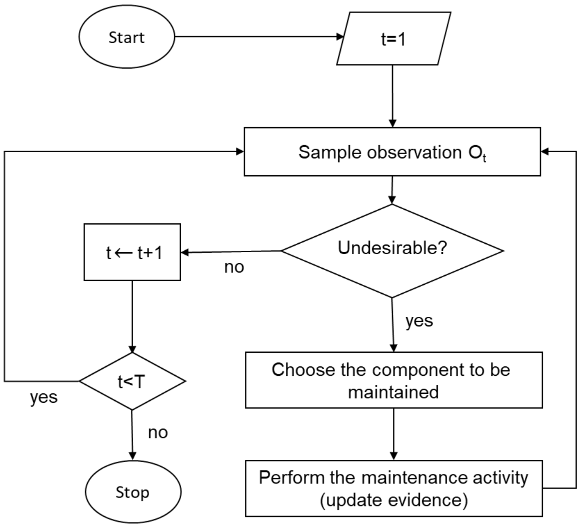


Figure 3.4: General flow of reactive maintenance.

related variable. AC_{i^*}, AD_{i^*}, DC_{i^*}, ψ_{i*} represent the action cost, action duration, duration cost and total maintenance cost of node $i*$ respectively and $TCost$ represents the cumulative total cost until time t. O_t shows the state of the observation node in time t. If number-based reactive maintenance is applied, cost related parts in formulas and algorithms are not used. A_{it} = "1" given in equations and algorithms represents that action node of the component i brings it to the best state which means it is maintained.

Algorithm 1 Pseudocode of the reactive maintenance policy.

Set t=1, TCost=0
for t=1:T **do**
    Set $I' = I$
    Sample observation node O_t
    while O_t = "F" and I' is not empty **do**
        Select component i^* for maintenance (using Algorithms 2, 3, 4, 5, 6, 7, 8, 9)
        Calculate $\psi_{i*} = AC_{i^*} + AD_{i^*} \times DC_{i^*}$
        $TCost = TCost + \psi_{i*}$
        Update $\varepsilon \leftarrow \varepsilon \cup \{A_{it} = \text{“1”}\}$
        Sample observation node O_t
        Update eligible component list $I' \leftarrow I' | \{i^*\}$

3.2.2 Failure Effect Myopic Methods ($\mathbf{FEM_{fp}}$, $\mathbf{FEM_{wp}}$)

This method takes into account the posterior failure probabilities of the components, according to the evidence accumulated so far when the observation node "F" is observed in a period of time t. To calculate these probabilities, two different efficiency measure which is given in (3.3) and (3.4) where C_{it} represents the state of component i in period t are used. When using the first of these measures, the worst state probabilities of the components are calculated, and the component with the highest probability is selected for maintenance if and only if the number of maintenance is considered. The second measure calculates the probability of the components being in the best state and selects the component with the lowest probability. When maintenance costs are considered, the component which have lowest cost with the highest probability of being in the worst state or with the lowest probability of being in the best state is selected to be maintained.

$$ef_{it}^{FEM_{fp}} = P(C_{it} = \text{“}F\text{”}|\varepsilon \cup \{O_t = \text{“}F\text{”}\}) \tag{3.3}$$

$$ef_{it}^{FEM_{wp}} = P(C_{it} = \text{“}W\text{”}|\varepsilon \cup \{O_t = \text{“}F\text{”}\}) \tag{3.4}$$

Pseudo-codes of the methods that consider the maintenance cost are given in Algorithm 2 and Algorithm 3 respectively. The efficiency measure given in (3.3) is converted to the cost-effective one by dividing it by the action cost to be compatible with the argmax operator. On the other hand, the efficiency measure given in (3.4) is converted to the cost-effective one by multiplying it by the action cost to be compatible with the argmin operator.

Algorithm 2 Pseudocode of $\mathrm{FEM_{fp}}$

1: Calculate $ef_{it}^{FEM_{fp}} = P(C_{it} = \text{“}F\text{”}|\varepsilon \cup \{O_t = \text{“}F\text{”}\})\ \ \forall i \in I'$
2: Calculate $e{f_{it}}^{FEM_{fp}} = [ef_{it}^{FEM_{fp}}/\Psi_i]\ \ \forall i \in I'$
3: Select $i^* = argmax\{e{f_{it}}^{FEM_{fp}}\}$
4: **return** i^*

Algorithm 3 Pseudocode of $\mathrm{FEM_{wp}}$

1: Calculate $ef_{it}^{FEM_{wp}} = P(C_{it} = \text{“}W\text{”} | \varepsilon \cup \{O_t = \text{“}F\text{”}\}) \;\; \forall i \in I'$
2: Calculate $ef_{it}{}^{FEM_{wp}} = [ef_{it}^{FEM_{wp}} * \Psi_i] \;\; \forall i \in I'$
3: Select $i^* = argmin\{ef_{it}{}^{FEM_{wp}}\}$
4: **return** i^*

3.2.3 Failure Effect Look-Ahead Methods ($\mathbf{FEL_{fp}}$, $\mathbf{FEL_{wp}}$)

These methods also consider the failure effect posterior probabilities of the components as in FEM methods. However, in this time, the probability of worst or the best states of the component in the next period is used, not in the period in which the observation node is observed as “F”. The efficiency measures which calculate the probabilities of the components are given in (3.5) and (3.6) while the pseudo codes of the cost-effective methods are given in Algorithm 4 and Algorithm 5.

$$ef_{it}^{FEL_{fp}} = P(C_{i,t+1} = \text{“}F\text{”} | \varepsilon \cup \{O_t = \text{“}F\text{”}\}) \tag{3.5}$$

$$it^{FEL_{wp}} = P(C_{i,t+1} = \text{“}W\text{”} | \varepsilon \cup \{O_t = \text{“}F\text{”}\}) \tag{3.6}$$

Algorithm 4 Pseudocode of $\mathrm{FEL_{fp}}$

1: Calculate $ef_{it}^{FEL_{fp}} = P(C_{i,t+1} = \text{“}F\text{”} | \varepsilon \cup \{O_t = \text{“}F\text{”}\}) \;\; \forall i \in I'$
2: Calculate $ef_{it}{}^{FEL_{fp}} = [ef_{it}^{FEL_{fp}} / \Psi_i] \;\; \forall i \in I'$
3: Select $i^* = argmax\{ef_{it}{}^{FEL_{fp}}\}$
4: **return** i^*

Algorithm 5 Pseudocode of $\mathrm{FEL_{wp}}$

1: Calculate $ef_{it}^{FEL_{wp}} = P(C_{i,t+1} = \text{“}W\text{”} | \varepsilon \cup \{O_t = \text{“}F\text{”}\}) \;\; \forall i \in I'$
2: Calculate $ef_{it}{}^{FEL_{wp}} = [ef_{it}^{FEL_{wp}} * \Psi_i] \;\; \forall i \in I'$
3: Select $i^* = argmin\{ef_{it}{}^{FEL_{wp}}\}$
4: **return** i^*

3.2.4 Replacement Effect Myopic Methods ($\mathbf{REM_{fp}}$, $\mathbf{REM_{wp}}$)

In this method, when a reactive maintenance is decided, the component which will improve the condition of the observation node better when it is maintained is selected. If only the number of maintenance is considered, efficiency measure (3.7) and (3.8) select the component that minimizes the probability of seeing the observation node in the worst state and maximizes the probability of seeing the observation node in the best state respectively.

$$ef_{it}^{REM_{fp}} = P(O_t = \text{“}F\text{”} | \varepsilon \cup \{A_{it} = \text{“}1\text{”}\}) \tag{3.7}$$

$$ef_{it}^{REM_{wp}} = P(O_t = \text{“}W\text{”} | \varepsilon \cup \{A_{it} = \text{“}1\text{”}\}) \tag{3.8}$$

If maintenance costs are also taken into account, in addition to these efficiency measures, it is considered that the selected components have the lowest cost and the calculations given in Algorithm 6 and Algorithm 7 are used to balance maintenance costs and efficiency measure. The efficiency measure given in (3.7) is converted to the cost-effective one by multiplying it by the action cost to be compatible with the argmin operator.On the other side, the efficiency measure given in (3.8) is converted to the cost-effective one by dividing it by the action cost to be compatible with the argmax operator.

Algorithm 6 Pseudocode of REM_{fp}

1: Calculate $ef_{it}^{REM_{fp}} = P(O_t = \text{“}F\text{”} | \varepsilon \cup \{A_{it} = \text{“}1\text{”}\})\ \ \forall i \in I'$
2: Calculate ${ef_{it}}^{REM_{fp}} = [ef_{it}^{REM_{fp}} * \Psi_i]\ \ \forall i \in I'$
3: Select $i^* = argmin\{{ef_{it}}^{REM_{fp}}\}$
4: **return** i^*

Algorithm 7 Pseudocode of REM_{wp}

1: Calculate $ef_{it}^{REM_{wp}} = P(O_t = \text{“}W\text{”} | \varepsilon \cup \{A_{it} = \text{“}1\text{”}\})\ \ \forall i \in I'$
2: Calculate ${ef_{it}}^{REM_{wp}} = [ef_{it}^{REM_{wp}} / \Psi_i]\ \ \forall i \in I'$
3: Select $i^* = argmax\{{ef_{it}}^{REM_{wp}}\}$
4: **return** i^*

3.2.5 Replacement Effect Look-Ahead Methods (REL_{fp}, REL_{wp})

This method is very similar to REM methods, but this time, when a component is changed in a time period, its effect on the observation node in the next period is considered. Efficiency measures of the $\mathrm{REL}_{\mathrm{fp}}$ and $\mathrm{REL}_{\mathrm{wp}}$ methods are given in (3.9) and (3.10) respectively, while the pseudo codes used in cost-effective version of the methods are given in Algorithm 8 and Algorithm 9 respectivelt.

$$ef_{it}^{REL_{fp}} = P(O_{t+1} = \text{“}F\text{”}|\varepsilon \cup \{A_{it} = \text{“}1\text{”}\}) \tag{3.9}$$

$$ef_{it}^{REL_{wp}} = P(O_{t+1} = \text{“}W\text{”}|\varepsilon \cup \{A_{it} = \text{“}1\text{”}\}) \tag{3.10}$$

Algorithm 8 Pseudocode of $\mathrm{REL}_{\mathrm{fp}}$

1: Calculate $ef_{it}^{REL_{fp}} = P(O_{t+1} = \text{“}F\text{”}|\varepsilon \cup \{A_{it} = \text{“}1\text{”}\}) \;\; \forall i \in I'$
2: Calculate $ef_{it}{}^{REL_{fp}} = [ef_{it}^{REL_{fp}} * \Psi_i] \;\; \forall i \in I'$
3: Select $i^* = argmin\{ef_{it}{}^{REL_{fp}}\}$
4: **return** i^*

Algorithm 9 Pseudocode of $\mathrm{REL}_{\mathrm{wp}}$

1: Calculate $ef_{it}^{REL_{wp}} = P(O_{t+1} = \text{“}W\text{”}|\varepsilon \cup \{A_{it} = \text{“}1\text{”}\}) \;\; \forall i \in I'$
2: Calculate $ef_{it}{}^{REL_{wp}} = [ef_{it}^{REL_{wp}} / \Psi_i] \;\; \forall i \in I'$
3: Select $i^* = argmax\{ef_{it}{}^{REL_{wp}}\}$
4: **return** i^*

3.2.6 Brief Summary of the Proposed Methods

The criteria evaluated for the calculation and use of the proposed methods are summarized in Table 3.2.

3.2.7 Normalization Procedure

The main purpose of all cost-effective proposed methods is to achieve a balance between effects of the cost and probability and to select the most efficient component for maintenance. However, the dominance of one measure over the another creates a problem in calculating a general measure that includes both. This is usually due to different unit ranges and consequently different max-min ratios. In this study, the posterior probabilities of the variables and the maintenance costs

Horizon	Method	Probability	Operator
	Fault Effect Approaches		
Myopic	$\mathrm{FEM}_{\mathrm{fp}}$	Worst state	argmax
	$\mathrm{FEM}_{\mathrm{wp}}$	Best state	argmin
Look-ahead	$\mathrm{FEL}_{\mathrm{fp}}$	Worst state	argmax
	$\mathrm{FEL}_{\mathrm{wp}}$	Best state	argmin
	Replacement Effect Approaches		
Myopic	$\mathrm{REM}_{\mathrm{fp}}$	Worst state	argmin
	$\mathrm{REM}_{\mathrm{wp}}$	Best state	argmax
Look-ahead	$\mathrm{REL}_{\mathrm{fp}}$	Worst state	argmin
	$\mathrm{REL}_{\mathrm{wp}}$	Best state	argmax

Table 3.2: Details of the proposed methods.

of the components are taken into account to calculate the efficiency measures of each cost-effective method. Maintenance costs of the components are predefined so that the difference between the largest and the smallest cost, and hence the maximum-minimum ratio, becomes a certain value. On the other hand, posterior probabilities of variables can vary in each iteration. Therefore, they are unstable depending on the calculated values and their max-min ratio is at most infinite and at least 1. If the max-min ratio of the probabilities is not high enough, i.e. the max-min ratio of the cost values is not lower, the component with the lowest maintenance costs can be misleadingly selected by maintenance methods as the most efficient component. When the max-min ratio of the probabilities is high, the effect of cost is not sufficiently considered.

A normalization procedure is proposed that allows to adjust the cost values and the posterior probability values to the same range in order to avoid the unfair dominance of less costly components or dominance of probabilities when cost are not adequately considered. The calculation used in the normalization procedure is given in (3.11).

$$\Psi_i \mapsto \frac{P_{max} - P_{min}}{\Psi_{max} - \Psi_{min}} \times (\Psi_i - \Psi_{min}) + P_{min} \tag{3.11}$$

In this equation, P_{max} and P_{min} indicate the maximum and minimum values of the calculated posterior probabilities in efficiency measures, Ψ_{max} and Ψ_{min} are the maximum and minimum values of the maintenance costs of the components respectively, and finally Ψ_i shows the total maintenance cost of component i.

3.3 Proactive Maintenance Strategy

Maintenance is the task performed to bring a system to the desired condition so that production can continue regularly and be done at maximum capacity. If maintenance activities are carried out when the system fails, this is called reactive maintenance. Although reactive maintenance is crucial for the immediate correction of the system at the moment, proactive maintenance is essential to keep the system active at all times, prevent unexpected downtime and reduce costs. Figure 3.5 shows an iterative decision-making flow for a general proactive maintenance strategy.

The observation node is sampled at each time interval from the first day of the simulation. When an undesirable situation is observed, which almost indicates an unexpected failure of the system, maintenance actions should be carried out under the reactive maintenance philosophy. On the other hand, when one of the proactive maintenance conditions occurs, maintenance actions must be proactively implemented. These conditions are:

- Coming of pre-scheduled constant interval maintenance time
- Coming of the time for dynamic interval maintenance which is updated dynamically
- Falling of the system reliability below a specified threshold

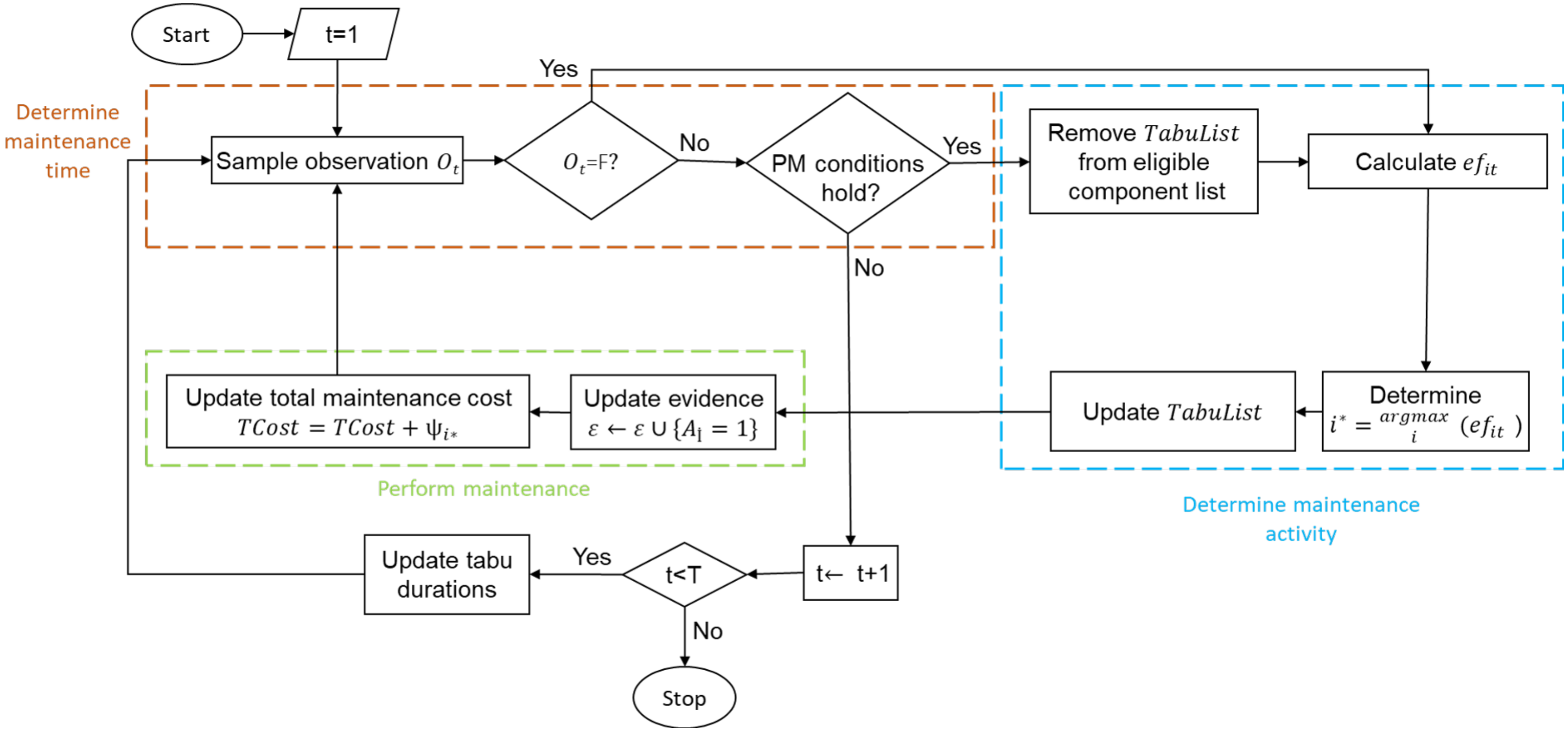


Figure 3.5: General flow of proactive maintenance.

According to the proactive maintenance strategy implemented, only one of these conditions is considered. When the proactive maintenance time comes, if the observation node is also undesirable, “F”, reactive maintenance is applied, because it is assumed that observations in the system are taken in the morning, but proactive maintenance is planned in the evening so that the production flow is not affected much. In addition, it is assumed that proactive maintenance can be performed at most once in each time period due to limited resource allocation. After proactive maintenance is performed, if any other undesired observation is taken in the same time period, reactive maintenance conditions are applied. A tabu procedure which is explained in detail in 3.3.1 to prevent selecting of the same component frequently in proactive maintenance times.

Proactive maintenance strategies are divided into two as preventive and predictive. While preventive maintenance is performed at regular intervals to prevent unexpected downtimes, a predetermined condition must be established for predictive maintenance. In the literature, preventive maintenance is also divided into subclasses: age-based [68] and block-based [69]. In age-based maintenance, preventive maintenance is carried out when the component reaches a predetermined age and the age of the component is set to zero. Also if reactive maintenance is required due to a malfunction or necessity before the preventive maintenance time, the age of the component which is maintained is reset to zero. In the second, preventive maintenance is applied at fixed time intervals and unlike the first one, this interval does not change even if reactive maintenance is needed between two consecutive preventive maintenance. In [29], two preventive maintenance policies are proposed initially, inspired by block-based and age-based strategies for a basic emprical model.In this study, these policies are adapted to a more complex multi-component dependent system. These are constant interval proactive maintenance (CIPM) and dynamic interval proactive maintenance (DIPM) strategies.

Preventive strategies plan proactive maintenance at specific time points using a fixed or dynamic time interval, regardless of the situation of the system. On the other hand, in predictive maintenance, a certain criterion must be met to apply a proactive maintenance, and in general, this criterion relates to the reliability of the system. For this reason, a threshold-based proactive strategy is also used for determining maintenance times adaptively.

3.3.1 Tabu Procedure

If proactive maintenance is done frequently, it is possible to face the case of selecting the same component consecutively. Because in such cases, since all components have a low failure probability and these probabilities are almost not very different from each other, cost values come into prominence in determining the component to be maintained. To prevent this situation, a tabu list is kept inspired by the tabu search algorithm which is a well-known algorithm in meta-heuristic area [70]. Once a component is maintained, it is added to this list and cannot be proactively maintained until the tabu period expires. While the tabu list is only considered at the time points when proactive maintenance is initiated, being at a reactive maintenance time is an aspiration criterion that allows the selection of the components in the tabu list. If more maintenance is needed because an undesirable observation is taken at a proactive maintenance time, component to be maintained is selected among the non-tabu components. In both proactive and reactive maintenance times, components are selected according to the efficiency measure and added to the tabu list.

3.3.2 Constant Interval Proactive Maintenance (CIPM)

The purpose of this strategy is to plan proactive maintenance with constant time intervals, similar to block-based maintenance, throughout the planning horizon. If any malfunction occurs before the system reaches the specified constant time, it is urgently subjected to a reactive maintenance without waiting for proactive maintenance time. In this case, the predetermined maintenance schedule is not updated according to the reactive maintenance time. Unlike block-based maintenance, where the entire system is maintained when preventive maintenance is due, this strategy maintains only one component selected by efficiency measure. Algorithm 10 shows the implementation of the CIPM strategy in a general proactive maintenance framework.

3.3.3 Dynamic Interval Proactive Maintenance (DIPM)

In this strategy, as in the CIPM strategy, preventive maintenance is planned at certain time intervals, but if an emergency-based reactive maintenance is performed between these intervals, the next preventive maintenance time is updated according to the reactive maintenance time, as in age-based maintenance. Thus, preventive maintenance times are dynamically determined according to the reactive maintenance performed between them. In this strategy, preventive maintenance is performed on only one component whereas the entire system is repaired in age-based maintenance. The purpose of developing such strategy with dynamic interval is to reduce unnecessary preventive maintenance that can be programmed shortly after reactive maintenance when the intervals are not updated dynamically, thereby reducing maintenance costs. How to implement the DIPM strategy within a general proactive maintenance framework is shown in Algorithm 10.

3.3.4 Threshold Based Proactive Maintenance (ThPM)

Both CIPM and DIPM are preventive maintenance strategies and plan proactive maintenance at specific time points using a constant or dynamic interval, regardless of the system's condition. In order to determine proactive maintenance times adaptively, a predictive maintenance strategy has been developed that consider the estimation of system reliability.

In the example of the DBN model given in Figure 3.3, $\mathrm{P_B}$ shows the main process node and is the node where the reliability of the system is considered. The reliability of the system is always estimated at the beginning of a time period, t, and if it is below the predetermined threshold, a proactive maintenance is planned at the end of that period. Unlike DIPM and CIPM, this strategy aims to reduce unnecessary proactive maintenance by considering the system condition. Application of ThPM within the general proactive maintenance framework is given in Algorithm 10.

3.3.5 Generic Algorithm of the Proactive Maintenance Strategies

The pseudo code of the generic proactive maintenance strategy is shown in the Algorithm 10, where the strategy and parameters of the applied strategy are given as input. This general pseudo code differs in initiating and updating parameters, depending on the strategy used. In the algorithm, the line 15 identifies the maintenance time. If the observation node results in "F", it always indicates a reactive maintenance. Alternatively, if it is "W", a proactive maintenance can be decided depending on the values of the three boolean operators of the proactive maintenance strategies.

If CIPM is used, constant proactive maintenance times are kept in the CIMT list which is defined previously according to proactive constant interval (pci). When this time comes and proactive maintenance is performed, the first item of the list is deleted. For example, if proactive maintenance is planned at constant intervals of 15 days (pci=15) in a 300-days planning horizon, the CIMT list is created as [15 30 45 .... 300]. After the first proactive maintenance is carried out on the 15th day, "15" is deleted from the list and the new list becomes [30 45 ... 300].

If DIPM is used, the dynamic proactive maintenance interval (pdi) is given as input to the algorithm. Proactive maintenance time is updated by adding this interval to the current period if a maintenance is performed. By this way, proactive maintenance times are determined dynamically depending on the previous maintenance performed, and hence they are different from the predetermined static proactive maintenance periods in CIMT strategy.

When ThPM is applied, a threshold level (thr) is determined as the input parameter. The threshold level is updated to zero after a proactive maintenance is decided. This is because, after performing a proactive maintenance, the reliability of the system may still be below the threshold and in this situation, another proactive maintenance is needed to increase reliability. However, it is assumed that proactive maintenance can be performed at most once in each time period. By setting the threshold level to zero, the boolean operator comparing the reliability of the system with the threshold level never returns a true value. So, multiple proactive maintenance cannot be performed at a period where a proactive maintenance has already been performed.

After sampling from the observation node, if reactive maintenance is required, the set of eligible replaceable components, I' contains all components. Otherwise, I consists of components that are not on the tabu list. If observation node is in "F" state, although proactive maintenance conditions are met, (which are that the first element of the CIMT list is equal to time t), dynamic proactive maintenance time has come or system reliability is below the threshold, reactive maintenance is applied. If it is proactive maintenance time and the observation node is in "W", one of the proactive maintenance strategies is applied. In both cases, the component to be maintained is selected according to the eight methods presented in Section 3.2 and this component is added to the tabu list.

Proactive and reactive maintenance costs differ due to action duration ($\mathrm{AD_i}$) and downtime cost ($\mathrm{DC_i}$) values of components. Iteration cost (ψ_i) is calculated by using reactive maintenance cost values if the observation is in "F" state, and otherwise by using proactive maintenance cost values. Total cost is updated by adding iteration cost. After each maintenance, the component that is maintained is removed from the eligible component list, so if a maintenance is required again on that period, another component is selected from the updated eligible component list.

When a component is maintained, it is added to $TabuList$ in order to prevent selecting the same component in a subsequent proactive maintenance time. $TabuDurList$ keeps tabu duration of all components which are in $TabuList$. After each time period, tabu duration of the components are updated. For example, if the tabu duration is selected as 5 days, when a component first enters the tabu list, its value in the $TabuDurList$ becomes 5 and the next time period, it drops to 4. When the tabu duration value of the component decreases to 0, the component is removed from the $TabuList$.

Algorithm 10 Proactive Maintenance Algorithm

Input Strategy, $pci, pdi, Threshold, TabuDur$
if Strategy = "CIPM" **then**
  Input $CIMT = [pci * 1, pci * 2, ..., pci * \lfloor T/pci \rfloor]$
if Strategy = "DIPM" **then**
  Set $pmt = pdi$
Set $t = 1$
while $t \leq T$ **do**
  if Strategy="ThPM" **then**
    Set $thr = Threshold$
  Sample O_t
  if $O_t \neq$ "F" **then**
    $I' \leftarrow I | TabuList$
  else
    $I' \leftarrow I$
  while $\big((O_t =$ "F"$)$ or $(t = CIMT(1))$ or $(t = pmt)$ or $(P(S_t =$ "W"$|\varepsilon) < thr)\big)$ and (I' is not empty) **do**
    if (Strategy = "CIPM") and $(CIMT(1) = t)$ **then**
      Update $CIMT(1) = [\,]$
    else if Strategy = "DIPM" **then**
      Update $pmt = t + pdi$
    else if Strategy = "ThPM" **then**
      Update $thr = 0$
    Select component i^* for maintenance (using Algorithms 2, 3, 4, 5, 6, 7, 8, 9)
    $TabuDurList(i^*) = TabuDur$
    Update $\varepsilon \leftarrow \varepsilon \cup \{A_{i^*t} \leftarrow 1\}$
    if O_t is "F" **then**
      Calculate $\psi_{i^*} = AC_{i^*} + AD_{i^*} * DC_{i^*}$ (in reactive conditions)
    else
      Calculate $\psi_{i^*} = AC_{i^*} + AD_{i^*} * DC_{i^*}$ (in proactive conditions)
    Calculate $TCost = TCost + \psi_{i^*}$
    Update $I' \leftarrow I' | \{i^*\}$,
    Sample O_t
  $t \leftarrow t + 1$
  Update $TabuDurList$
  $TabuList \leftarrow \{j : TabuDurList(j) > 0\}$

Chapter 4

A Case Study: The Regenerative Air Heater System in Thermal Power Plants

Thermal power plants, especially coal fired ones, which meet 38% of world electricity production [71], are typical examples of complex systems with several interacting components. Maintenance optimization is very critical for these systems as an unexpected failure in these systems can cause serious costs and even harm human and environmental health. However, there are only a few number of studies on the maintenance of thermal power plants. These studies mainly apply integer programming and heuristic methods [72, 73] to small sized problems, thus they do not bring to successful conclusions for complex systems. Therefore, in this study, the results of the reactive and proactive maintenance strategies explained in the previous sections are compared on a multi-component system used in thermal power plants.

4.1 A Thermal Power Plant

The operation of a typical coal-fired thermal power plant is illustrated in Figure 4.1. In thermal power plants, chemical energy in solid, liquid and gas fuels is converted into heat and mechanical energy by the boiler and turbine, and then into electrical energy with the help of a generator. Lignite coal is used as fuel in the power plant discussed in this study. The power plant consists of eight main systems. These systems and their general characteristics are given in Figure 4.2. This study focused on the air-gas system which is one of the most important systems in thermal power plants.

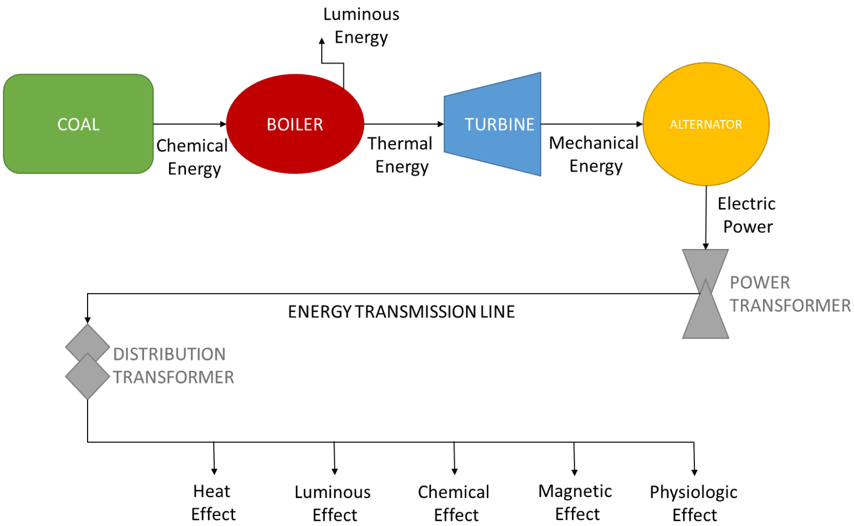


Figure 4.1: General flow of operations in a typical power plant.

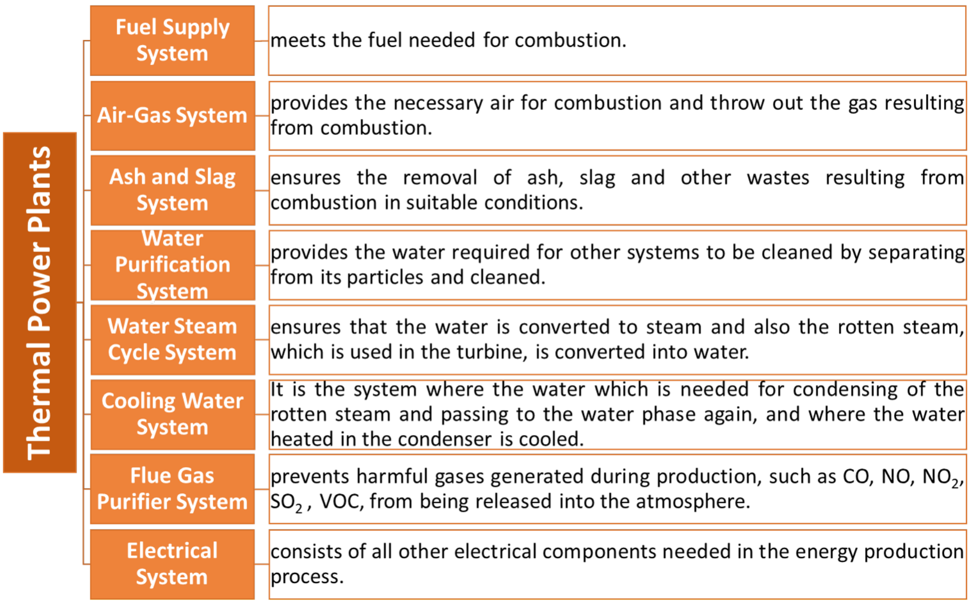


Figure 4.2: Systems of a thermal power plant.

4.2 Air-Gas System in a Thermal Power Plant

The air-gas system is the system that provides the required air for combustion and warms this air in two stages in order to send it to the boiler and the pulverizer and throws out the gas resulting from combustion. Sub-systems in the air-gas system were determined together with the thermal power plant employees. Here, the task descriptions of the sub-systems and their internal integrity are considered. Sub-systems of the air-gas system are fresh air fan, steam preheater, regenerative air heater, induced draft fan and chimney. The scheme of the operation of the air gas system is given in Figure 4.3 where green lines and black lines illustrates the movement of fresh air and flue gas respectively.

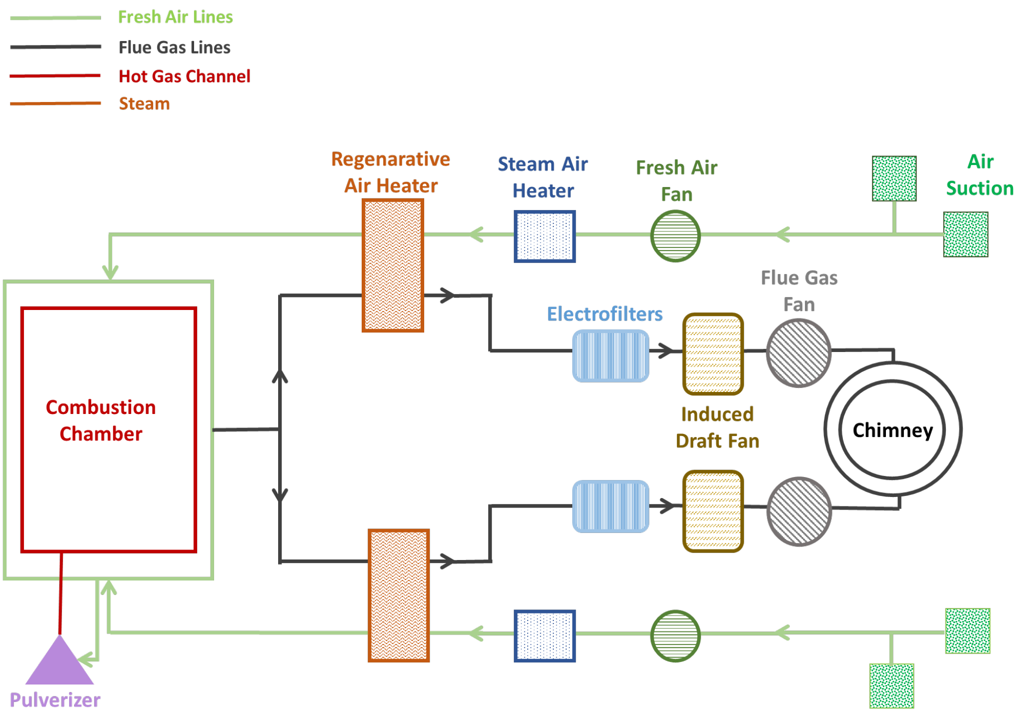


Figure 4.3: Operation flow of air-gas system.

The following events occur in the air-gas system, respectively:

- Fresh air fans let the air needed for drying coal and to carry out the combustion in from outside.

- The air taken with the fresh air fan moves through the steam air heaters and their temperature is raised in the regenerative air heaters.
- The air that comes to the regenerative air heaters with 30-40 °C comes out of them at two different temperatures as 400 °C and 200 °C. Air, which is 400°C, is sent to the pulverizer for drying the, whereas air with 200 °C is sent to the combustion chamber as combustion air.
- The gas resulting from the combustion in the boiler is drawn from the boiler with forced draft fans and sent to the regenerative air heater to heat the regenerative air heater inlet air.
- The gas, which loses heat in the regenerative air heater, is sent to electrofilters to remove ash.
- The cleaned gas is sent to the flue gas purifier system through the forced draft fans and released into the atmosphere.

The air gas system consists of two parallel lines. When any subsystem in these lines fails, the system can continue to operate as a single line, but the capacity is reduced to fifty percent. Subsystems of the air gas system were discussed one by one with the power plant employees. While determining the sub-systems, their tasks and their own internal integrity are considered. Among these, the steam preheater is used only if it is necessary, generally when the air is cold. Among other remaining systems, the regenerative air heater subsystem has been determined to work in this study in terms of its criticality for the thermal power plant's operation (since it provides air to the boiler and pulverizer at two different temperatures), the number of components it covers, and the complexity (random and structural dependencies) between the components.

4.3 The Regenerative Air Heater System

The Regenerative Air Heater (RAH) which is also called a rotary air heater, is used to heat the air. The RAH system which is shown schematically in Figure 4.4 consists of two parallel motor groups (ball bearing, winding-insulation, rotor-shaft), two regenerative air heater, honeycombs and RAH insulation. In the figure, the blue arrow indicates clean air, and the red arrow represents the rotten steam from the boiler. In the RAH system, which moves on a rotating assembly, the air and gas passing through the honeycombs, which is made of hair plates, exchange heat. While the gas losing its heat goes to the electrofilter, the warmed air is sent to the pulverizer and the combustion chamber of the boiler to get the moisture of the coal.

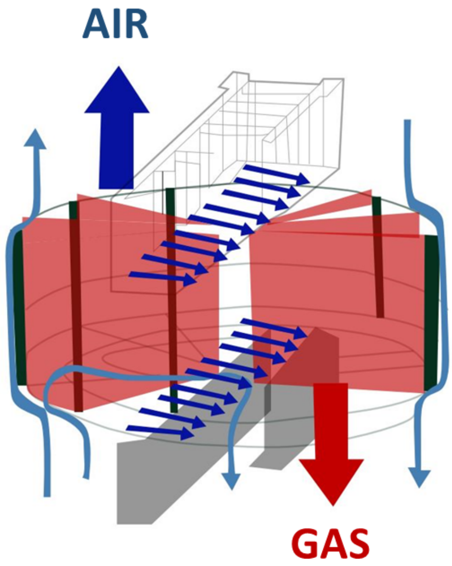


Figure 4.4: 3-D view of the RAH [74].

4.4 DBN Modeling of the RAH System

When creating the DBN model of a system, every information about the system needs to be known exactly. For this, detailed meetings were held with the thermal power plant employees, and a method similar to the Hazard and Operability (HAZOP) analysis which is generally used in the chemical industry was followed during these meetings. The information obtained in these meetings includes all the components in the RAH system, the details of the dependencies between the components, how a component's deterioration affects other components that depend on it, the repair and replacement costs of each component, repair frequency of the components, the cost of downtime due to the failure of the thermal power plant during these repairs, and the mean time to failures of the components. In the light of this information, the model was coded using Matlab - BNT toolbox [75], and the accuracy of coding was checked with the Genie Modeler program [76].

4.4.1 Variables and Their States

While determining the components in the DBN model, the fundamental equipments forming the system and their operations are taken as a basis [77]. The RAH system comprises of ten components: two parallel engine groups (which include ball bearing, rotor-shaft, winding-insulation, hub reduction gear), RAH insulation and honeycombs. Closed and open forms of the DBN model of the RAH system are given in Figures 4.5 and 4.6, respectively. Open form of the DBN model show two consecutive time slices of the RAH system.

There are five types of nodes in the model: dynamic nodes which are shown by orange color, process nodes which are represented by blue color, action nodes which are indicated by purple color, exogeneous nodes which are shown by pink color and an observation node which is indicated by green color in the figures. Dynamic nodes represent changing of the components dynamically as a result of aging. Process nodes show the interaction between components and their parents in a time period. Exogenous nodes represent external factors that cannot be controlled by power plant employees. Finally, the observation node is the node which indicates the state of the system. Table 4.1 depicts the details of the variables.

The arrows indicated by red dashed lines on dynamic nodes in the closed form and between dynamic nodes in the open form represent the wear and aging of those components over time. The arrows indicated by dark blue dotted lines between the dynamic nodes represent the temporal relationships between those

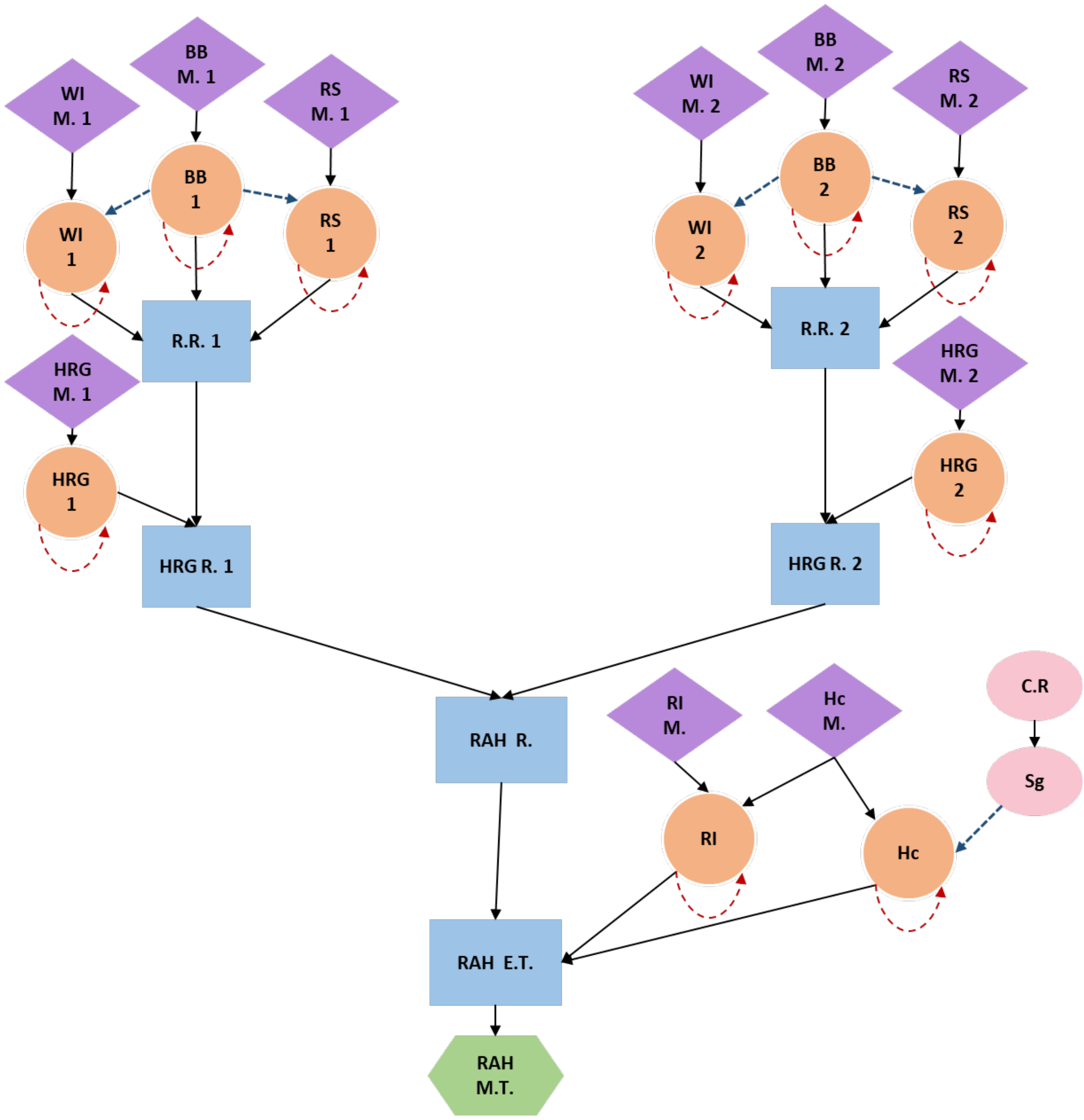


Figure 4.5: Closed form of the RAH DBN model.

components. Other arrows, represented by black straight lines, represent causal relationships between the nodes.

There is no regular inspection at the thermal power plant under consideration. Although power plant employees can control some components manually or by listening during field visits, these are non-systematic inspections and their reliability depends on the experience of the controller. Only the exit temperature of the RAH system can be observed and measured by sensors partly. For this reason, only the “RAH Measured Temperature” is considered in the model as an observation node. As with all sensors, it should not be ignored that this sensor has a margin

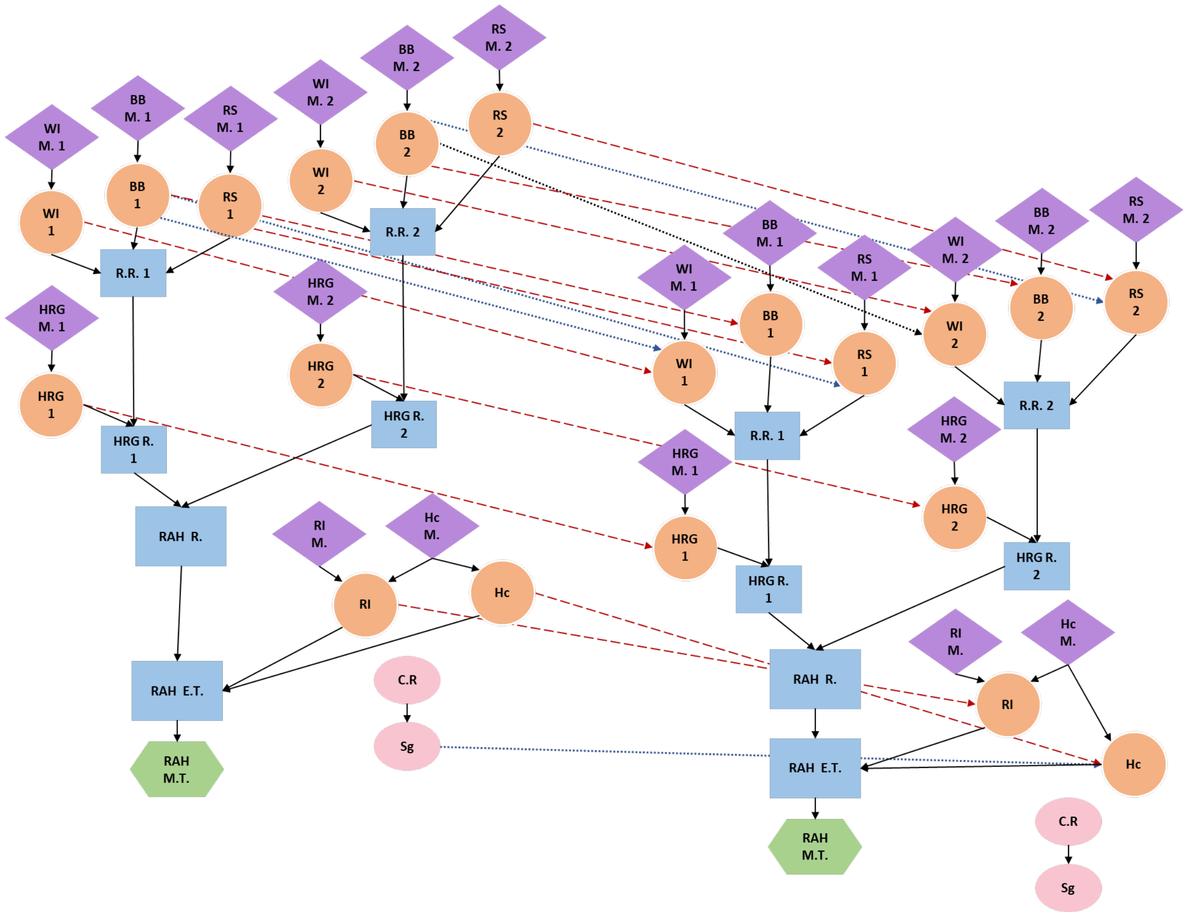


Figure 4.6: Open form of the RAH DBN model.

Symbol	Variables	Quantity	Type	State Space
BB	Ball Bearing	2	Dynamic	"Normal, Loose, Locked"
RS	Rotor-Shaft	2	Dynamic	"Normal, Unaligned"
WI	Winding-Insulation	2	Dynamic	"Original, Burned"
HRG	Hub Reduction Gear	2	Dynamic	"Normal, Broken"
RI	RAH Insulation	1	Dynamic	"Full Integrity, Medium Integrity, Low Integrity"
Hc	Honeycomb	1	Dynamic	"New, Cleaned, Dirty"
R.R.	Rotor Rotation	2	Process	"Rotate, Not Rotate"
HRG R.	HRG Rotation	2	Process	"Rotate, Not Rotate"
RAH R.	RAH Rotation	1	Process	"Rotate, Not Rotate"
RAH E.T.	RAH Exit Temperature	1	Process	"Normal, Low, Super Low"
BB M.	Ball Bearing Maintenance	2	Action	"Replace, Do Nothing"
RS M.	Rotor-Shaft Maintenance	2	Action	"Grind, Do Nothing"
WI M.	Winding-Insulation Maintenance	2	Action	"Replace, Do Nothing"
HRG M.	Hub Reduction Gear Maintenance	2	Action	"Replace, Do Nothing"
RI M.	RAH Insulation Maintenance	1	Action	"Replace, Do Nothing"
Hc M.	Honeycomb Maintenance	1	Action	"Clean, Do Nothing"
C.R.	Coal Rank	1	Exogenous	"Good, Bad"
Sg	Slagging	1	Exogenous	"Yes, No"
RAH M.T.	RAH Measured Temperature	1	Observation	"Normal, Low, Super Low"

Table 4.1: Details of the DBN variables.

of error. Therefore, the RAH measured temperature measured and the RAH exit temperature are represented by different nodes.

The states of the all variables in the model were determined together with the power plant employees. These states of all variables are given in Table 4.1. As an example for the RAH measured temperature, which is the observation node, if the RAH exit temperature is lower than 200°C, it indicates as "Super Low'; if it is between 200°C and 400°C, it indicates a measure of "Low" and finally if it is higher than 400°Ci, it is accepted as "Normal".

The model has a total of 10 action nodes. It is presumed that the changes of the rotor-shaft and honeycombs are made in revisions that occur once a year, if needed. So replacement of them are not defined within the state spaces. The action of "Do Nothing", given in the state spaces of action nodes, allows that component to be left in its own state, without any changes. "Replace" action represents replacement of the component with a new one. "Grind" action in the rotor-shaft maintenance represents the grinding of the rotor-shaft in the case of axial dislocation. Finally, "Clean" action in the honeycomb maintenance represents cleaning of the honeycombs using special chemicals.

4.4.2 System Relationships

The relationships between the variables considered when creating the DBN model of the RAH system are as follows.

- The RAH system comprises two parallel engine groups. When one of these two groups fails, the RAH continues to work with one engine group. Only when the boiler is started initially, both engine groups must operate. In this study, it was assumed that such a situation does not occur. If both engine groups fail, the RAH becomes unable.
- The ball bearing affects the winding and rotor-shaft alignment. Ball bearing interlocks can cause overcurrent, and consequently heating up motor winding, and short circuit.
- In the event of ball bearing interlock and loss of insulation, the motor winding can burn by heating more than the nominal conditions.

- The integrated rotor-shaft are components that provide rotation. When the ball bearing is locked or misaligned, the rotor-shaft may lose their ability to rotate or may be axially misaligned.
- The hub reduction gear is the power train which is used to achieve rotational motion at different speeds. Therefore, the rotation of the hub reduction gear is directly dependent on the rotation of the rotor and the state of the mechanical structure of the hub reduction gear. For rotation of the RAH, at least one of the two hub reduction gear must rotate.
- RAH honeycombs provide heating of the air by rotating. They can be worn away by being affected by the slag formed if the quality of the coal is low. This causes the Luvo outlet temperature to drop, meaning loss of performance.
- RAH insulation is on honeycombs. In the event of leakage in the RAH insulation, the RAH temperature does not reach a adequate level and its performance declines. If the amount of leakage is critical, this may trigger major problems in terms of RAH performance.

Stochastic and structural dependencies are seen among the components in the RAH system. There is a stochastic dependency between the ball bearing and the winding-isolation since interlocking of the ball bearing causes burning of the motor winding. In addition, since loosing of the ball bearing causes the axial dislocation in rotor-shaft and decreasing of rotation ability of the rotor-shaft, the ball bearing and the rotor-shaft have also stochastic dependency. There is structural dependency between the RAH insulation and honeycombs. This is because the RAH insulation needs to be replaced when the honeycombs are cleaned. Thus, when these dependencies and the total number of components in the RAH system are considered, it can be said that the RAH has a complex multi-component structure.

4.4.3 Probability Structure

While determining the causal and transitional probabilities depending on the aging of the components and their relations with each other in the DBN model, historical data (failure data, revision reports and maintenance orders) and the information taken from the thermal power plant employees were used. The probability of the components remaining in the best state is calculated according to the average passing time from the best state to the another state and given in Table 4.2. Transition probabilities for other states are estimated by proportioning according to the information received from the plant employees. The thermal power plant undergoes a major revision that lasts 2 months at the end of each year, and during this revision, all components are renewed or repaired for returning to their best condition. When it is considered that a year is a short period for such a major maintenance, it makes sense to use a constant transition rate in calculations.

Component	**Residence time in the best state (day)**	**Residence time in the best state (year)**	**The probability of staying in the best state**
Ball Bearing	1200	4	0.99916
Winding-Insulation	1500	5	0.99933
Rotor-Shaft	4500	15	0.99978
Hub Reduction Gear	900	3	0.99889
Honeycomb	3000	10	0.99967
RAH Insulation	900	3	0.99889

Table 4.2: The probabilities of staying in the best state of the RAH system components.

In compliance with average transition rates and expert opinions, the conditional probabilities of all components based on time are determined. It is assumed that all components are in the best state initially since the period after the annual revisions are taken as a basis. In later periods, if the action node is in the "Replace" state, the component is brought to the best state again. Table 4.3 shows the conditional probabilities of the RAH insulation which is a dynamic node, as an example. The probability of transition from "Full Integrity" to "Full Integrity " is calculated based on the average number of days spent until the exit of RAH insulation from the "Full Integrity " state, which is found as 0.99889, that corresponds to about 900 days. The transition probabilities from "Full

Integrity" to "Medium Integrity" and "Full Integrity" to "Low Integrity" are obtained by sharing the remaining probabilities based on expert opinions and transition rates, and calculated as 0.00078 and 0.00033 respectively. Likewise, the transition probability from "Medium Integrity" to "Low Integrity" state is calculated according to the elapsed time (500 days) from the intermediate state to the worst state and is found to be 0.002.

RI M.	**Replace**		
Hc M.	**Clean**		
Self (t-1)	Full Integrity	Medium Integrity	Low Integrity
Full Integrity	1	1	1
Medium Integrity	0	0	0
Low Integrity	0	0	0
RI M.	**Replace**		
Hc M.	**Do Nothing**		
Self (t-1)	Full Integrity	Medium Integrity	Low Integrity
Full Integrity	1	1	1
Medium Integrity	0	0	0
Low Integrity	0	0	0
RI M.	**Do Nothing**		
Hc M.	**Clean**		
Self(t-1)	Full Integrity	Medium Integrity	Low Integrity
Full Integrity	1	1	1
Medium Integrity	0	0	0
Low Integrity	0	0	0
RI M.	**Do Nothing**		
Hc M.	**Do Nothing**		
Self (t-1)	Full Integrity	Medium Integrity	Low Integrity
Full Integrity	0.99889	0	0
Medium Integrity	0.00078	0.998	0
Low Integrity	0.00033	0.002	1

Table 4.3: Conditional probabilities of the RAH Insulation.

4.4.4 Cost Structure

Total maintenance cost is calculated using Equation (4.1). It consists of action cost and downtime cost. Action cost includes just maintenance-related costs. Action duration covers the duration from the start of the maintenance until the time it ends. During the reactive maintenance of components, production is not possible. Because of this, until maintenance is completed and the plant restarts production, a downtime cost incurs. However, since the RAH system comprises of two parallel motor groups, the system is not required to stop for the proactive maintenance of a component in these motor groups, then no downtime cost incurs for the components other than the honeycomb and the RAH insulation.

$$\psi_i = AC_i + AD_i * DC_i \tag{4.1}$$

Proactive and reactive maintenance costs are determined according to the information given by the thermal power plant considered. 181 kw of electricity is generated per hour in the plant. 35% of the production is supplied to the domestic market where electricity prices and demands are determined on a daily basis whereas 65% is supplied to firms on bilateral contracts where electricity price is determined by agreements. While calculating the downtime cost per each hour of the proactive maintenance, the overhead expenses of the power plant and the lost income based on the current price for the domestic market and the contract price for bilateral agreements are considered.

If a reactive maintenance is required, the power plant is stopped unexpectedly, and the domestic market and the firms agreed before are stuck in a difficult situation. Because of this, if the committed electricity cannot be supplied to the customer (domestic market or the firms), a penalty payment must be made based on the current electricity price. Then, this penalty cost is added to the proactive downtime cost. When the current electricity prices is taken as 0.40 TL/kw and the price agreed with the firm is taken as 0.30 TL/kw, the downtime costs for proactive maintenance and reactive maintenance are calculated approximately 40,000 TL/hour and 50,000 TL/hour respectively. It is important to note that these costs are incurred because the plant does not produce electricity when the air-gas line does not work depending on a fail or a maintenance task in the RAH system. However, since the thermal power plant has two parallel air-gas lines, when a line fails, the parallel one continues to work with 50% capacity. So, the unit downtime costs are taken as 20,000 TL/hr and 25,000 TL/hr.

On the other hand, proactive action cost and action duration are taken half of those in reactive maintenance. The reason for this is that due to the lack of sufficient employees when reactive maintenance is needed, the maintenance takes longer. In addition, the prices of spare parts are high due to being purchased at the last time. The reactive and proactive maintenance costs of all components are shown in Table 4.4.

Component	**Reactive Maintenance**			**Proactive Maintenance**		
	$AC_i(TL)$	$AD_i(hr)$	$DC_i(TL/hr)$	$AC_i(TL)$	$AD_i(hr)$	$DC_i(TL/hr)$
BB	2,000	1	25,000	1,000	0.5	0
WI	15,000	4	25,000	7,500	2	0
RS	1,500	4	25,000	750	2	0
HRG	2,000	2	25,000	1,000	1	0
Hc	1,600	6	25,000	800	3	20,000
RI	100	2	25,000	50	1	20,000

Table 4.4: Maintenance costs and durations.

Chapter 5

Computational Results and Evaluations

All the methods presented in Chapter 3 are used under both reactive and proactive maintenance strategy and are simulated on the RAH system. In addition, the Random Maintenance Method (RND), which does not consider any efficiency measures and selects the components to be maintained randomly, was used to compare with the proposed methods. Each method was run and analyzed using the BNT toolbox in Matlab environment, according to the total number of maintenance and total maintenance costs in a specific planning horizon. The planning horizon has been determined as 300 days by subtracting the revision times that are done annually and lasting 2 months.

In this chapter, ANOVA model is used to compare the performance of the strategies. Model adequacy is checked and all models are found to meet the assumption of normality. However, some ANOVA models violate the constant variance assumption. In these cases, Games-Howell (GH) was used. Otherwise, the Tukey (Tk) test was used for pairwise comparisons.

5.1 Results of Reactive Maintenance Modeling

All the methods proposed under the reactive maintenance strategy are simulated on the RAH system based on both the maintenance number and maintenance costs. The reason for considering both maintenance number and maintenance cost separately is that both have great importance in maintenance planning, and to show that the high number of maintenance does not mean high maintenance costs. ANOVA and post-ANOVA tests were used for comparisons with a 95% confidence interval.

All computational tests were executed on an Intel(R) Xeon processor PC with 2.40 GHz and 12 GB RAM and its equivalent. The average simulation time for a planning horizon of 300 days is approximately 20 minutes for the fault effect methods (FEM_{fp}, FEM_{wp}, FEL_{fp} and FEL_{wp}) and 1.5 hours for the replacement effect methods (REM_{fp}, REM_{wp}, REL_{fp} and REL_{wp}). The reason for the difference is that when fault effect methods is applied, only one inference calculation is made in each maintenance period. However, when one of the replacement effect methods is used, separate inference calculations are made for each component at each maintenance time. In the RND method, since no extra extractions are made because the components to be maintained are randomly selected, the simulation of this method takes approximately 10 minutes. These durations are acceptable for a 300-day time horizon, when it is considered that observation sampling is taken in each time frame and inference calculations made for selecting components when a reactive maintenance decision is taken.

5.1.1 Replication Results Regarding to Total Maintenance Number

The eight methods explained in Section 3.2 were run on the RAH DBN model for 50 replications on a 300-day planning horizon. The model adequacy of ANOVA's normality and constant variance assumptions has been checked and no violation has been encountered. The residual plots that proves this are given in Figure 5.1.

5.1.1.1 Comparison Results of the Proposed Methods

One-factor ANOVA analysis was performed on the proposed number-based methods and it gives 0.000 p-value. This indicates that the performance of at least

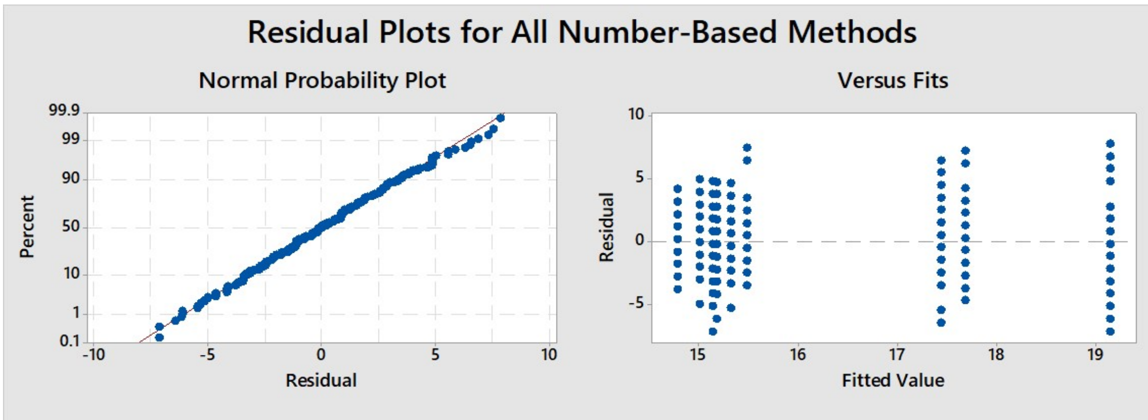


Figure 5.1: Residual plots for number-based maintenance methods.

one of the methods is statistically different from the others. In order to find out which method(s) are different, post-ANOVA analyzes were performed. The results obtained using the Tukey pairwise comparison test at 0.05 significance level are depicted in Table 5.1 and Figure 5.2. In Table 5.1, SD represents standard deviation and Tk represents Tukey test results.

Method	**Avg. M. Number**	**SD**	**95% CI**	**Tk**
RND	19.14	3.12	(18.25; 20.02)	A
FEL_{fp}	17.68	2.85	(16.87; 18.49)	A,B
FEM_{fp}	17.44	3.07	(16.57; 18.31)	B
REL_{wp}	15.48	2.58	(14.75; 16.21)	C
REM_{wp}	15.32	2.40	(14.64; 16.00)	C
REM_{fp}	15.18	2.54	(14.46; 15.90)	C
REL_{fp}	15.14	2.66	(14.39; 15.90)	C
FEM_{wp}	15.00	2.06	(14.41; 15.59)	C
FEL_{wp}	14.78	2.04	(14.20; 15.36)	C

Table 5.1: Results of methods according to the maintenance number under reactive maintenance strategy.

In Table 5.1, the methods that share the same letter in the Tukey test result are not statistically different from each other. ANOVA results show that the worst method is the Random Method (RND) as expected. Performance of all methods, except FEL_{fp}, is statistically better than RND. Since the pairwise confidence intervals of FEL_{fp} and RND contain zero, it cannot be said that these two methods differ from each other statistically. However, it is obvious that if replication number is

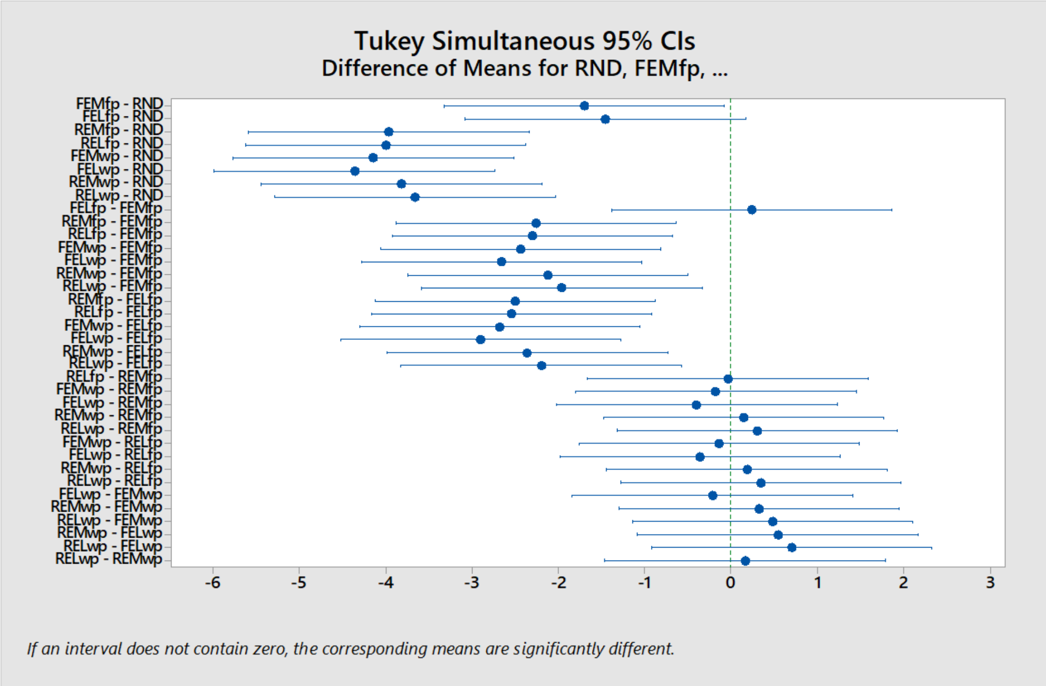


Figure 5.2: Confidence intervals for the average differences of methods for maintenance number.

increased from 50, it is expected that the two methods will be able to differentiate and that FEL_{fp} will also be superior than the RND method since the standard error of the test will decrease. Statistical analysis demonstrates that the methods that give the best results are FEM_{wp} and FEL_{wp}, which are fault effective methods that consider the best state probability of the components. On the other hand, the worst methods after RND is FEL_{fp} and FEM_{fp}, which consider the worst state probability of the components. Thus, it can be said that different posterior probability efficiency measures give different results for fault effect methods.

In replacement effect methods, different subsequent probability criteria give statistically similar results. This is because the probability that the observation node is in an intermediate state ("Very Low") is very low, so the "wp" criterion that consider the intermediate state in maintenance decision cannot differ from the "fp" criterion that does not consider it. However, because replacement effect methods take into consideration the improvement of the state of the observation node and reactive maintenance is applied when the observation node implies a malfunction, applying of REM_{fp} or REL_{fp} is more logical if the REM method is to be implemented. Consequently, FEM_{wp} and FEL_{wp} methods can be expressed as best methods, with regard to the total number of maintenance and also shorter simulation time in the planning horizon.

5.1.1.2 Maintenance Supply Planning of Components

When the observation node implies a malfunction, maintenance should be carried out as immediate as possible. To be able to perform such an urgent reactive maintenance, some resources (spare parts, personnel, test equipment, etc.) must be promptly provided. Therefore, the supply planning of spare parts has a great significance. Therefore, according to simulation results, the average number of annual supply requirements for each component was extracted. The results are given in Table 5.2. Also, the distribution of the components according to the methods are shown in Figure 5.3 in which the requirements of the same components in the two engine groups are summed up.

Methods	BB1	WI1	RS1	HRG1	BB2	WI2	RS2	HRG2	Hc	RI	**Average M. Number**
RND	1.76	2.12	2.18	1.86	2.16	1.76	1.96	2.00	1.74	1.60	19.14
FEM_{fp}	0.00	3.78	2.74	1.78	0.00	3.70	2.34	1.82	0.00	1.28	17.44
FEL_{fp}	0.00	3.90	3.00	1.86	0.00	3.64	2.26	1.74	0.00	1.28	17.68
REM_{fp}	0.14	1.98	1.58	3.00	0.04	1.90	1.46	2.90	2.18	0.00	15.18
REL_{fp}	0.14	2.18	0.46	3.28	0.26	2.34	0.58	3.40	2.50	0.00	15.14
FEM_{wp}	1.54	2.40	0.80	1.88	1.58	2.36	0.90	1.92	0.00	1.62	15.00
FEL_{wp}	1.42	2.38	0.88	1.82	1.46	2.42	0.86	1.82	0.00	1.72	14.78
REM_{wp}	0.02	1.60	1.02	2.60	0.08	1.82	1.30	2.50	4.38	0.00	15.32
REL_{wp}	0.10	1.96	0.26	2.94	0.14	2.14	0.28	2.88	4.78	0.00	15.48

Table 5.2: Maintenance requirements of the components.

According to the results, when the RND method was used, the requirements were homogeneously distributed as expected, since the components were randomly selected during a reactive maintenance time. In fault effect methods, FEM and FEL, "fp" and "wp" measures have different component distributions. While in FEM_{fp} and FEL_{fp} methods, ball bearing is almost never maintained, this component is maintained in FEM_{wp} and FEL_{wp} methods. This result confirms the suggestion of the two different efficiency measures. The ball bearing has 3

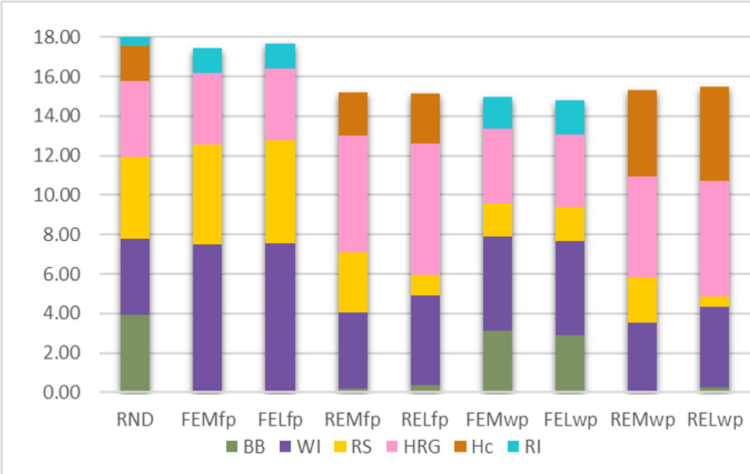


Figure 5.3: Distribution of maintenance requirements of components under reactive maintenance strategy.

states as "Normal, Loose, Locked" and in fact, it does not work effectively in the "Loose" state. The use of the "fp" measure in the fault effect methods overlooks the "Loose" state of the ball bearing when calculating probabilities, and as a result, ball bearing maintenance is not recognized while selecting components. However, in "wp" efficiency measure, calculations are made according to the posterior best working state probability of the components and the "Loose' state of the ball bearing is also taken into consideration. Also, in the FEM and FEL methods, honeycombs have never been maintained throughout the planning horizon. The reason for this is the regular use of a soot blowing system in the thermal power plant to keep the honeycombs clean, as a result of which the aging of the honeycombs slows down and the probability of their deterioration decreases.

On the other hand, it is seen that the honeycombs are maintained in replacement effect methods, where the components are selected according to their improvement effects on the state of the observation node. It should also be noted that these methods has never considered to replace RAH insulation. Although this is thought to be due to the fact that observation node, RAH measured temperature, is very little effected by the RAH insulation, it is actually a result of the structural dependence between the RAH insulation and honeycombs, which is clearly considered in the replacement effect methods. Since the RAH insulation needs to be replaced during honeycomb cleaning, it does not need to be changed separately. Another result to be taken into consideration is that the ball bearing is not maintained at all or maintained too little in replacement effect methods. Since these methods evaluate the effect of the components on the observation node and there are many other components between the ball bearing and the RAH measured temperature in the DBN model, the effect of the ball bearing maintenance is smaller compared to other components.

5.1.2 Replication Results Regarding to Total Maintenance Cost

In this section, the methods compared with respect to the maintenance number in Section 5.1.1 are simulated and compared with regard to the total maintenance cost incurred in a 300-day planning horizon. The reason for comparing maintenance methods in terms of cost also is to show that the results based on maintenance number and maintenance cost will not be the same.

In the cost-based efficiency measure of the reactive maintenance methods given in Section 3.2, it is necessary to balance the posterior probabilities and costs of the components very well in order not to select a component to be maintained in a reactive maintenance time. For this purpose, a normalization procedure has been used. The effects of this normalization procedure on the reactive maintenance methods are described in detail in Section 5.1.2.1.

5.1.2.1 Justification of the Normalization Procedure

In Section 3.2.7, a normalization procedure is proposed, which allows adjusting cost values and posterior probability values to the same range, to avoid unfair control of less costly components or posterior probabilities when cost is not considered sufficiently. To demonstrate the details and the effect of the component selection method with the normalization procedure, a snapshot of the system was taken at the first time when the observation node is seen as “SL” (a reactive maintenance is required) after a sufficiently long time, i.e, $t = 125$. In Table 5.3, efficiency measure calculation for each component of the RAH system using the FEL_{fp} and FEL_{wp} method are shown where P_i, ψ_i, ψ_i^N denote the posterior probability, the maintenance cost and the normalized maintenance cost of component i respectively at time $t = 137$ where the system is first stopped for reactive maintenance after a specified time period, $t = 125$. In the table, both ef_{it}^U and ef_{it} which represent unnormalized efficiency measure and normalized efficiency measure respectively are evaluated according to Table 3.2. However, in ef_{it}^U, the unnormalized (the original) maintenance cost is used whereas in ef_{it} the normalized cost calculated as in Equation (3.11) is applied.

	BB1	**WI1**	**RS1**	**HRG1**	**BB2**	**WI2**	**RS2**	**HRG2**	**Hc**	**RI**	**Max**	**Min**
						FEL_{wp}						
P_{it}	0.7990	**0.4863**	0.7148	0.9046	0.8245	0.5527	0.7490	0.7790	0.9457	0.6413	0.9457	0.4863
ψ_i	**27,000**	115,000	101,500	52,000	**27,000**	115,000	101,500	52,000	151,600	50,100	151,600	27,000
ψ_{it}^N	**0.4863**	0.8108	0.7610	0.5785	**0.4863**	0.8108	0.7610	0.5785	0.9457	0.5715	0.9457	0.4863
ef_{it}^U	**21,573**	55,925	72,552	47,039	22,262	63,561	76,024	40,508	143,368	32,129	143,368	21,573
ef_{it}	0.3886	0.3943	0.5439	0.5233	0.4009	0.4481	0.5700	0.4506	0.8944	**0.3665**	0.8944	0.3665
						FEL_{fp}						
P_{it}	0.0848	**0.5137**	0.2852	0.0954	0.0739	0.4473	0.251	0.221	0.0543	0.2922	0.5137	0.0543
ψ_i	**27,000**	115,000	101,500	52,000	**27,000**	115,000	101,500	52,000	151,600	50,100	151,600	27,000
ψ_{it}^N	**0.0543**	0.3788	0.3290	0.1465	**0.0543**	0.3788	0.3290	0.1465	0.5137	0.1395	0.5137	0.0543
ef_{it}^U (x10^{-6})	3.141	4.470	2.810	1.830	2.740	3.890	2.470	4.250	0.3582	**5.832**	5.832	0.3582
ef_{it}	1.5634	1.3563	0.8671	0.6513	1.362	1.1811	0.763	1.5089	0.1056	**2.0952**	2.0952	0.1056

Table 5.3: Details of the efficiency measure calculations.

In FEL_{wp}, WI1 has the worst posterior best working state probability. If cost was not important and hence not considered in determining the maintenance activities, one would select WI1 to maintain at $t = 137$. BB1 is the fourth best among the ten components according to the posterior best-working state probabilities. Nevertheless, since its cost is the minimum, ef_{it}^U of BB1 is dominated by this cost value resulting in the minimum efficiency value probably unduly. On the other hand, ef_{it} enable to evaluate also the components other than the one with the minimum cost due to using the normalized maintenance costs which are scaled in the domain of the posterior probabilities. As a result of this, RI, which is the third worst among the ten components according to the posterior best working state probabilities, is proposed to be maintained with the minimum efficiency value.

In $\mathrm{FEL}_{\mathrm{fp}}$, WI1 has the maximum posterior worst state probability and BBs have the minimum maintenance cost. Though, both efficiency measures propose RI to be maintained. It is important to note that the efficiency measure of $\mathrm{FEL}_{\mathrm{fp}}$ is more affected by the posterior worst state probabilities than the costs of the components when compared to $\mathrm{FEL}_{\mathrm{wp}}$ measure. This is because of the fact that the worst state probabilities are mainly smaller than the best working state probabilities. Hence, they differ proportionally more compared to the cost values and are more dominant in the calculations of the efficiency measure without normalization. To avoid this, the effect of probabilities and costs are balanced with the help of normalization. Although both efficiency measures propose the same component, when subsequent components in the respective ranks are examined, it is observed that probabilities are more effective in the efficiency measure without normalization whereas this unfair effect reduces while the cost effect increases in the normalized efficiency measure.

To emphasize the importance of the normalization procedure, all proposed cost-effective methods were run with 30 replications for a 300-day planning horizon without normalization procedure firstly . The random selection method (RND), where the component to be maintained is randomly selected when a reactive maintenance is required, was also used to analyze the performance of the proposed methods. The results are given in Table 5.4, where the average total maintenance number of each component, the average total number of maintenance and the average total maintenance cost are reported.

Method	BB1	WI1	RS1	HRG1	BB2	WI2	RS2	HRG2	Hc	RI	**Total Number**	**Total Cost**
RND	1.67	2.40	1.97	1.93	2.27	1.60	1.83	2.03	1.77	1.80	19.27	1.467.477
$\mathrm{FEM}_{\mathrm{fp}}$	1.80	1.10	0.50	2.80	1.70	1.00	0.50	2.70	0.00	2.10	14.20	828,710
$\mathrm{FEL}_{\mathrm{fp}}$	1.80	1.00	0.60	2.90	1.80	1.10	0.40	2.70	0.00	2.30	14.60	846,630
$\mathrm{REM}_{\mathrm{fp}}$	22.00	0.00	0.00	0.60	21.50	0.00	0.00	0.70	0.00	0.20	45.00	1,252,120
$\mathrm{REL}_{\mathrm{fp}}$	21.80	0.00	0.00	0.60	21.20	0.00	0.00	0.40	0.00	0.10	44.10	1,218,010
$\mathrm{FEM}_{\mathrm{wp}}$	20.50	0.00	0.00	0.60	21.40	0.00	0.00	0.90	0.00	0.10	43.50	1,214,310
$\mathrm{FEL}_{\mathrm{wp}}$	20.70	0.00	0.00	0.80	20.40	0.00	0.00	0.70	0.00	0.20	42.80	1,197,720
$\mathrm{REM}_{\mathrm{wp}}$	21.80	0.00	0.00	0.60	19.70	0.00	0.00	0.30	0.00	1.00	43.40	1,217,400
$\mathrm{REL}_{\mathrm{wp}}$	20.80	0.00	0.00	0.30	19.80	0.00	0.00	0.30	0.00	1.00	42.20	1,177,500

Table 5.4: Average replication results of the proposed methods.

Replication results show that in all methods except FEM_{fp} and FEL_{fp}, the ball bearing is selected at almost every reactive maintenance time. This is because the cost of the ball bearing is less than the other components. Although selecting the component with the lowest maintenance cost is seen as an advantage for the specific time interval in which maintenance is performed, it will cause more financial losses in the long run, especially when the interested component does not contribute to the reliability of the entire system. Therefore, cost and probability effects need to be balanced when making maintenance decisions.

In FEM_{fp} and FEL_{fp}, the efficiency measure is largely affected by the posterior worst state probabilities, but less affected than the cost values. Therefore, these methods do not tend to choose the ball bearing at each reactive maintenance time, although it costs the least. In contrast, the efficiency measures of FEM_{wp} and FEL_{wp} are not affected by the aforementioned posterior probabilities. So, the cost is dominant in these selection methods and causes the ball bearing to be considered in almost all maintenance times.

In replacement effect methods, all efficiency measures are based on the posterior probability of the observation node when it is assumed that each component is maintained in a given time period. Therefore, the posterior probabilities of the observation node are not very different from each other and have a small max-min ratio compared to the max-min ratio of the maintenance costs of the components. After all, these methods are greatly influenced by the cost factor and lead to select ball bearings for almost all maintenance times. These results justify the necessity of the normalization procedure.

5.1.2.2 Replication Results with Normalization Procedure

Before the normalization procedure, the probability factor is more effective than the cost factor in the FEM_{fp} and FEL_{fp} methods while in other methods, the opposite is true. The normalization procedure brings the effect of the posterior probabilities and the effect of the cost of the components to the same significance level in all methods. Each normalized method were run 50 replications over the 300-day planning horizon, and the results are given in Table 5.5. After this procedure, it is seen that the distribution is more stable when selecting the components during the reactive maintenance times and the methods also select components apart from ball bearing for maintenance. According to the results, it is clear that the normalization procedure helps to improve all methods when the total maintenance cost is considered.

Method	BB1	WI1	RS1	HRG1	BB2	WI2	RS2	HRG2	Hc	RI	**Total Number**	**Total Cost**
RND	1.76	2.12	2.18	1.86	2.16	1.76	1.96	2.00	1.74	1.60	19.14	1,516,914
$\mathrm{FEM_{fp}}$	5.78	0.72	0.28	2.82	5.08	0.48	0.10	2.42	0.00	1.62	19.30	823,432
$\mathrm{FEL_{fp}}$	5.76	0.62	0.06	2.68	5.32	0.54	0.16	2.66	0.00	1.58	19.38	811,728
$\mathrm{REM_{fp}}$	0.18	1.56	0.90	3.72	0.20	1.40	0.88	3.66	0.00	2.88	15.38	1,059,378
$\mathrm{REL_{fp}}$	0.44	1.56	0.40	3.70	0.42	1.64	0.38	3.78	0.00	2.84	15.16	1,001,634
$\mathrm{FEM_{wp}}$	2.52	1.06	0.64	2.32	2.48	1.06	0.64	2.32	0.00	1.98	15.02	849,198
$\mathrm{FEL_{wp}}$	2.56	1.00	0.60	2.10	2.62	1.22	0.72	2.36	0.00	1.92	15.10	857,252
$\mathrm{REM_{wp}}$	0.32	1.26	0.90	3.38	0.16	1.26	0.70	3.12	0.00	5.48	16.58	1,077,708
$\mathrm{REL_{wp}}$	0.44	1.28	0.32	3.24	0.36	1.26	0.30	3.12	0.00	5.22	15.54	968,872

Table 5.5: Average replication results of the proposed methods after normalization procedure.

The box plot showing the total maintenance costs of all methods according to the replication results is given in Figure 5.4. The figure clearly indicates that the RND method is the most costly method. ANOVA analysis is applied on the proposed methods and gives a p-value of zero which demonstrate that at least one of the proposed methods is statistically different from the others. Before post-ANOVA analysis, residuals were checked for model adequacy and it is understood that although the residuals are almost normally distributed, they can violate the constant variance assumption. Residual plots are given in Figure 5.5. Thereupon, Bartlett's test was applied to determine whether the residuals of the methods were evenly distributed and the p-value was found to be 0.003. This value shows that the constant variance assumption required for ANOVA test does not occur at the significance level of 0.05. Therefore, the analyzes are continued with the Welch test and Games-Howell tests, which can be used when the sample does not have constant variances. Table 5.6 and Figure 5.6 present the Games-Howell test results.

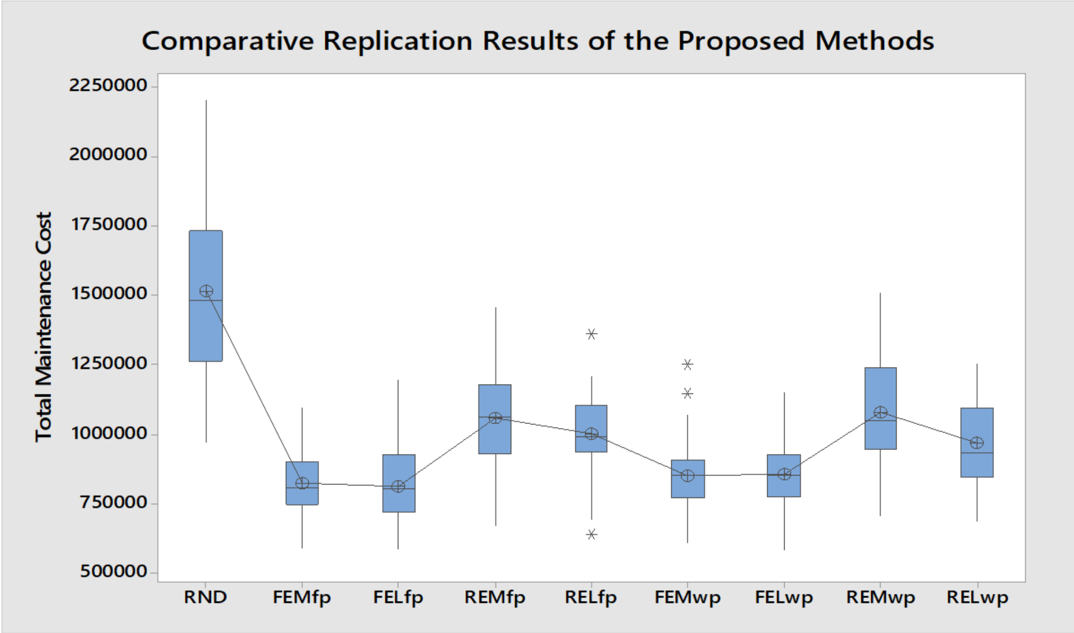


Figure 5.4: Comparative box plots of the methods.

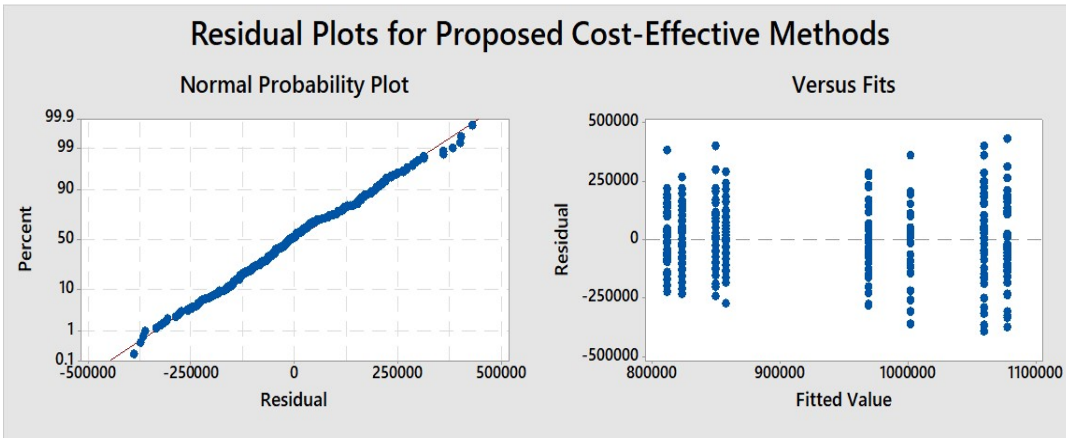


Figure 5.5: Residual plots for model adequacy for proposed methods.

According to the results, all failure effect methods are the best ones and they are not significantly different from each other. Among the replacement effect methods, REM_{wp} gives significantly higher cost value than REL_{wp}. However, Figure 5.6 shows that pairwise confidence interval of these methods does not include zero barely at $\alpha = 0.05$ significance, so it can be said that this significance may not be valid if replication number is increased. In addition to the conclusion that FEM and FEL methods give the least average maintenance cost, these methods are also superior to REM and REL methods in terms of simulation time perspective.

Method	Avg. M. Cost	SD	95% CI	GH
REM_{wp}	1,077,708	185,427	(1,025,010; 1,130,406)	A
REM_{fp}	1,059,378	179,497	(1,008,365; 1,110,391)	A,B
REL_{fp}	1,001,634	139,627	(961,952; 1,041,316)	A,B
REL_{wp}	968,872	152,335	(925,579; 1,012,165)	B
FEL_{wp}	857,252	120,054	(823,133; 891,371)	C
FEM_{wp}	849,198	125,957	(813,402; 884,994)	C
FEM_{fp}	823,432	113,416	(791,200; 855,664)	C
FEL_{fp}	811,728	132,478	(774,078; 849,378)	C

Table 5.6: Post-hoc test results of the normalized methods when Downtime Cost=25,000 TL.

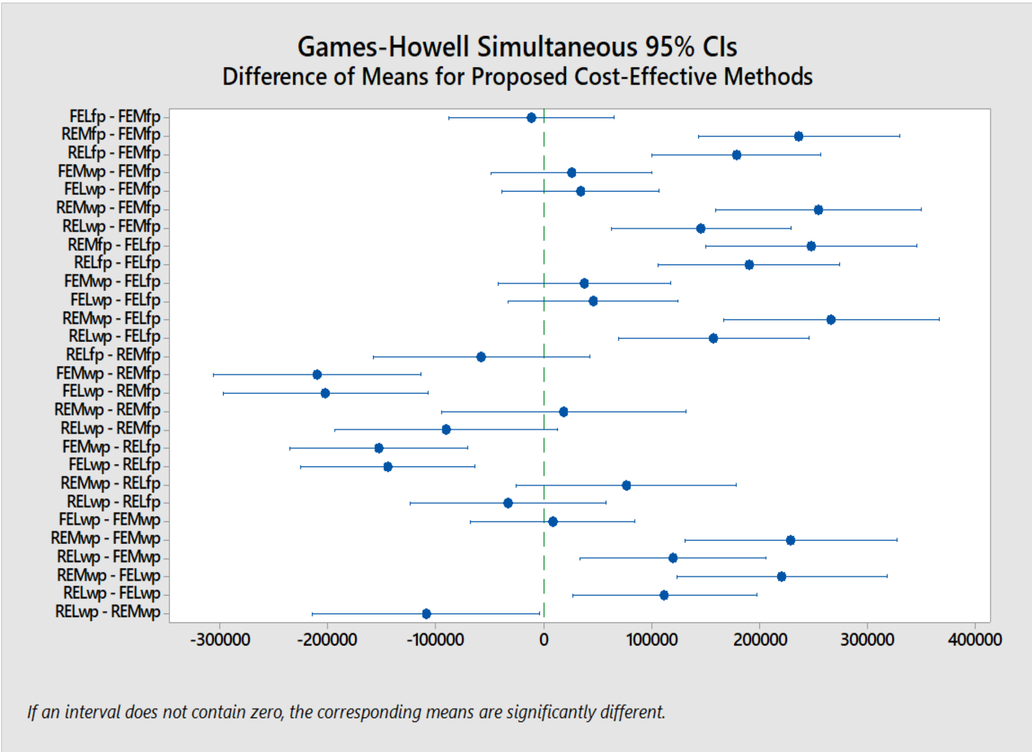


Figure 5.6: Confidence intervals for the average differences of the proposed methods for maintenance cost.

5.1.2.3 Sensitivity Analysis of the Proposed Methods according to Hourly Downtime Cost

Total downtime cost is part of the total maintenance cost and is obtained by multiplying the action duration of a component by the hourly downtime cost. Hourly downtime cost is based on the hourly profit loss of the thermal power plant due to a malfunction in one of the air gas lines, and this loss may vary depending on some factors that cannot be controlled internally, such as coal expense and electricity price. Four different hourly downtime costs are considered for the RAH system: 12,500, 25,000, 37,500 and 50,000 TL/hour. The current estimated hourly downtime cost is 25,000 TL while the others are used for sensitivity analysis. It should not be forgotten that the air gas system consists of two parallel lines and if one of them fails, the thermal power plant can continue to operate with 50% performance. So, the above-mentioned downtime costs are half of the downtime cost when thermal power plant stops completely. 50 replications were run for each downtime cost to measure the sensitivity of them in each proposed methods. Games-Howell test results showing whether the classification of the methods are different under each downtime cost are given in Table 5.7.

Cost=12,500 TL					**Cost=25,000 TL**				
Method	Mean	SD	95% CI	Group	Method	Mean	SD	95% CI	Group
REM$_{fp}$	561,100	91,601	(535,067; 587,133)	A	REM$_{wp}$	1,077,708	185,427	(1,025,010;1,130,406)	A
REM$_{wp}$	534,008	71,812	(513,599; 554,417)	A	REM$_{fp}$	1,059,378	179,497	(1,008,365;1,110,391)	A,B
REL$_{wp}$	523,396	74,157	(502,321; 544,471)	A	REL$_{fp}$	1,001,634	139,627	(961,952; 1,041,316)	A,B
REL$_{fp}$	517,928	79,355	(495,376; 540,480)	A	REL$_{wp}$	968,872	152,335	(925,579; 1,012,165)	B
FEM$_{wp}$	453,092	55,758	(437,246; 468,938)	B	FEL$_{wp}$	857,252	120,054	(823,133; 891,371)	C
FEL$_{fp}$	446,376	66,599	(427,449; 465,303)	B	FEM$_{wp}$	849,198	125,957	(813,402; 884,994)	C
FEL$_{wp}$	443,902	54,721	(428,351; 459,453)	B	FEM$_{fp}$	823,432	113,416	(791,200; 855,664)	C
FEM$_{fp}$	431,974	57,309	(415,687; 448,261)	B	FEL$_{fp}$	811,728	132,478	(774,078; 849,378)	C
Cost=37,500 TL					**Cost=50,000 TL**				
Method	Mean	SD	95% CI	Group	Method	Mean	SD	95% CI	Group
REM$_{wp}$	1,566,308	279,473	(1,486,883; 1,645,733)	A	REM$_{wp}$	2,033,002	303,499	(236,959; 414,964)	A
REM$_{fp}$	1,516,380	318,330	(1,425,912; 1,606,848)	A	REM$_{fp}$	2,015,694	344,428	(268,915; 470,926)	A
REL$_{wp}$	1,512,410	263,491	(1,437,527; 1,587,293)	A	REL$_{wp}$	1,985,284	295,771	(230,926; 404,399)	A
REL$_{fp}$	1,449,248	223,847	(1,385,631; 1,512,865)	A	REL$_{fp}$	1,931,700	342,080	(267,082; 467,716)	A
FEM$_{wp}$	1,288,022	193,420	(1,233,053; 1,342,991)	B	FEL$_{wp}$	1,713,494	216,545	(169,069; 296,075)	B
FEL$_{wp}$	1,262,766	158,064	(1,217,845; 1,307,687)	B	FEM$_{wp}$	1,637,058	262,559	(204,995; 358,989)	B,C
FEM$_{fp}$	1,190,410	170,166	(1,142,049; 1,238,771)	B	FEM$_{fp}$	1,547,436	209,411	(163,499; 286,321)	C
FEL$_{fp}$	1,184,158	167,223	(1,136,634; 1,231,682)	B	FEL$_{fp}$	1,543,092	181,540	(141,739; 248,214)	C

Table 5.7: Sensitivity results of the normalized methods at different downtime costs.

According to the Games-Howell test results, using different downtime costs change the order of the methods. However, it is seen that the grouping does not change significantly in the smallest three downtime costs (12,500, 25,000, 37,500) and all failure effect methods give the minimum total maintenance cost. When the downtime cost is 37,500 TL, there is a considerable difference between the costs of the FEL$_{fp}$ and FEM$_{wp}$ methods, although the failure effect methods do not differ significantly among themselves. When the cost of downtime is 50.000 TL, it is seen that FEM$_{fp}$ and FEL$_{fp}$ are dissociated from the others as the best methods with the minimum total maintenance cost. Accordingly, it can be said that these two methods will continue their superiority in terms of total maintenance costs under higher downtime costs.

5.1.2.4 Trade-off Analysis: Maintenance Cost vs Maintenance Number

Minimizing the total maintenance activities in a planning horizon is easier because it does not require consideration of maintenance costs. It can be fully concentrated to increase system availability. However, this will most likely result in high costs. On the contrary, while considering the minimization of the total cost in maintenance planning, the number of maintenance cannot be ignored. The reason is that the total maintenance cost that occurs in a planning horizon is directly related to the number of total maintenance activities performed. Therefore, since it is important to find a balance between the effects of cost and number in making maintenance decisions, the normalization procedure has been proposed to balance the effects of maintenance costs and posterior probabilities of the components in efficiency measures. After applying this procedure, it is observed that all methods consider all components, as opposed to non-normalized methods.

However, it may be interesting to analyze the total number of maintenance, as well as the total maintenance cost incurred in the planning horizon for normalized methods. Table 5.5 shows the maintenance distribution and total maintenance cost of the components for each method when the hourly downtime cost is 25.000 TL. According to the results, the $\mathrm{FEL}_{\mathrm{fp}}$ method, which has the lowest maintenance cost, has the highest number of maintenance. When single factor ANOVA analysis is applied with considering the maintenance number, p-value is found as 0.00, which means that at least one of the methods has a statistically different number of maintenance than the others. Since the normal distribution and constant variance assumptions in the ANOVA model are provided, Tukey test was applied to find out which methods are different and the results are given in Table 5.8.

Method	Avg. M. Number	SD	95% CI	GH
FEL_{fp}	19.38	3.602	(18.356, 20.404)	A
FEM_{fp}	19.30	2.936	(18.465, 20.135)	A
REM_{wp}	16.58	2.548	(15.856, 17.304)	B
REL_{wp}	15.54	2.305	(14.885, 16.195)	B,C
REM_{fp}	15.38	2.440	(14.686, 16.074)	B,C
REL_{fp}	15.16	2.074	(14.571, 15.749)	B,C
FEL_{wp}	15.10	1.992	(14.534, 15.666)	C
FEM_{wp}	15.02	2.199	(14.395, 15.645)	C

Table 5.8: Statistical analysis results based on maintenance number.

Fault effect methods which use the posterior worst state probability of components, FEM_{fp} and FEL_{fp}, give the highest total maintenance number and they are statistically different from other methods. However, these two methods are the best in terms of total maintenance cost. This result shows that in order to reduce the total maintenance cost in a planning horizon, it is needed to accept a reasonable increase in the total number of maintenance.

5.1.2.5 Analysis of Number - Based and Cost - Based Methods at Component Level

In order to evaluate the impact of cost-based approaches under the reactive maintenance strategy, the results were compared with the results of the number-based methods where costs were not considered in efficiency measures. Figure 5.7 shows the cost-based (orange bin) and number-based (blue bin) distribution of components for the 50 replication averages of each method.

In FEM_{fp} and FEL_{fp} methods, it is seen that there are significant differences in the total number of maintenance of some components when number-based and cost-based approaches are applied. When cost is not considered, ball bearing maintenance is not preferred at all, while it is the most preferred component due to the lowest cost when cost is considered. On the other hand, the maintenance numbers of WI and RS have decreased significantly in cost-based approaches. In REM_{fp} and REL_{fp} methods, there are important differences between cost-effective

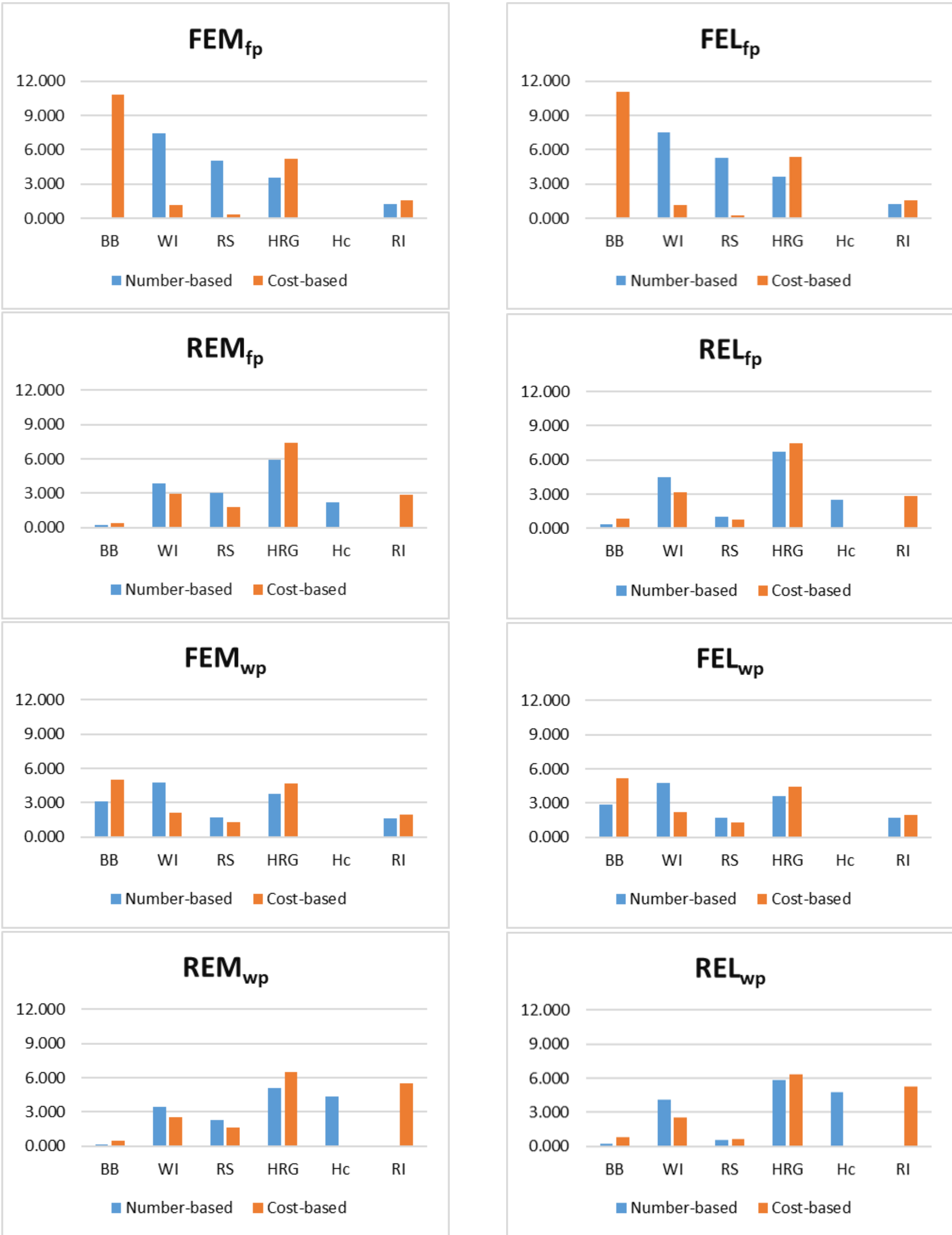


Figure 5.7: Distribution of the components in cost based and number based methods.

and number-effective approaches only for Hc and RI. In number-based approaches, while Hc is maintained, RI is never maintained due to the structural dependence between the two components. However, while RI is maintained in the cost-based approach, Hc is never maintained because it is a more expensive component.

In addition, comparing the methods according to “fp” and “wp” efficiency measures also gives interesting results. When $\mathrm{FEM_{fp}}$ and $\mathrm{FEM_{wp}}$ methods are compared, it is observed that in fault effect methods “fp” tends to consider the cost more than probability, whereas the probability effect is more dominant in “wp” measure. This inference is the result of that when cost is considered in $\mathrm{FEM_{fp}}$, the total maintenance number of high cost components such as WI and RS reduces while low cost components such as BB are maintained more. On the other hand, in $\mathrm{FEM_{wp}}$, there is no significant difference in the maintenance number of components between number-based and cost-based approaches. In replacement effect methods, the “fp” and “wp” measures behave more similar in terms of the distribution of the components.

Figure 5.8 and Figure 5.9 show the total maintenance cost and total maintenance number respectively in the planning horizon for all methods, under cost-based and number-based approaches. According to these figures, the largest difference between the total maintenance cost and the total amount of maintenance activities in the number-based and cost-based scenarios belongs to $\mathrm{FEM_{fp}}$ and $\mathrm{FEL_{fp}}$ methods. In these methods, when cost is considered in the efficiency measure, the total maintenance cost decreases, while the total number of maintenance increases. This also proves that $\mathrm{FEM_{fp}}$ and $\mathrm{FEL_{fp}}$ are the methods which focus cost impact mostly. On the other hand, in Figure 5.8, the minimum total maintenance cost difference belongs to the $\mathrm{FEM_{wp}}$ and $\mathrm{FEL_{wp}}$ methods, and similarly, according to Figure 5.9, there is no significant difference between the two approaches for these methods depending on the total number of maintenance. Also, when cost is considered in Figure 5.8, $\mathrm{REM_{wp}}$ and $\mathrm{REL_{wp}}$ improve more than $\mathrm{REM_{fp}}$ and $\mathrm{REL_{fp}}$ compared to the number-based approach.

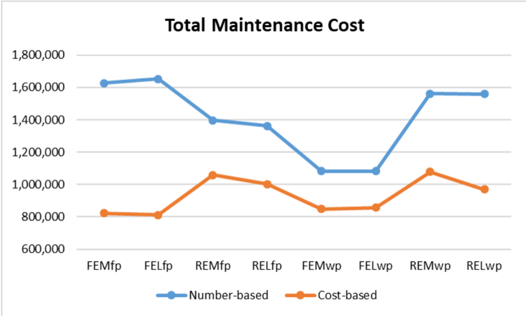


Figure 5.8: Total maintenance cost.

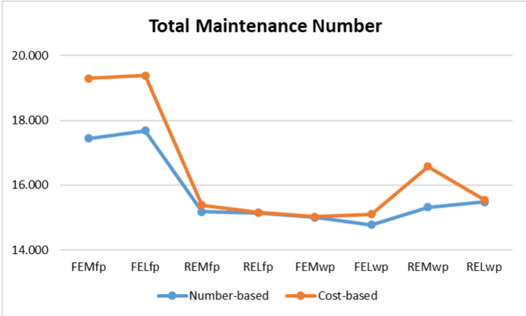


Figure 5.9: Total maintenance amount.

5.2 Results of Proactive Maintenance Modeling

Two main scenarios and three sub-scenarios based on the cost and duration of reactive maintenance are considered for the analysis of proactive maintenance results. Since the RAH system has two parallel engine groups, the system does not need to be stopped if a component in these engine groups is maintained in a proactive maintenance time and the RAH can continue to operate with a single engine group. Based on this, the two main scenarios are designed according to the need to stop the system during proactive maintenance. In each scenario, different levels of parameters (pci, pdi, thr) used for proactive strategies (CIPM, DIPM, ThPM) are evaluated. Increasing pci and pdi values or decreasing thr value brings the results of proactive maintenance strategies closer to the reactive maintenance results. Therefore, the upper limit for the pci and pdi parameters and the lower limit for the thr parameter are defined as the points where the respective proactive strategy reaches the reactive maintenance cost of the scenario under investigation. On the other hand, since very low pci and pdi values and very high thr values cause unnecessary proactive maintenance, they result in a higher total maintenance cost than the cost incurred with using the closest parameter value of the respective strategy. According to these parameter values, lower limit for the pci and pdi parameters and upper limit for the thr parameter are determined.

A tabu procedure detailed in Section 3.3 is applied to prevent to select same component consecutively in cases where proactive maintenance is frequent. When determining the tabu duration, it should be taken into consideration that tabu duration is not too large (then it becomes too restrictive) or too small (then it may become meaningless). Therefore, after some experimental trials, the tabu time is taken as 5 days in all analyzes.

In each maintenance strategy, FEL_{fp} is used to select the component to be maintained both at reactive and proactive maintenance times. 30 replications were run in MATLAB environment using the BNT-toolbox on a 300-day planning horizon for each proposed strategy, scenario, and parameter. The performance of the strategies are evaluated according to the average total cost of maintenance in the planning horizon.

ANOVA model is used to compare the performance of the strategies. Model adequacy is checked and all models are found to meet the assumption of normality. However, some ANOVA models violate the constant variance assumption. In these cases, Games-Howell (GH) was used. Otherwise, the Tukey (Tk) test was used.

5.2.1 Scenarios Based on Independent Parallel Engine Groups

This scenario represents the real situation where there are two parallel engine lines, and the system does not need to stop for proactive maintenance of a component selected from these engine groups, thereby a downtime cost does not occur. However, since reactive maintenance is required only when both engine groups stop, the advantage of parallel lines is not valid in this case. Under this main scenario, three sub-scenarios are created based on different unit reactive downtime costs, keeping the proactive maintenance cost constant.

5.2.1.1 Scenario DC_R25

This scenario is the basic scenario where the reactive and proactive maintenance costs of all components are taken as in Table 4.4. Since the ANOVA model violates the constant variance assumption, the Games-Howell post-hoc test is applied to compare the parameters of each maintenance strategy. Results for the average total maintenance cost in a planning horizon for 30 replications are provided in the "Mean" column of Table 5.9. In the table, "GH" represents Games-Howell groups, "Mean" denotes the average total maintenace cost and and "RM" represents the reactive maintenance results. The factor levels are tabulated in decreasing values of the average total cost.

CIPM				DIPM				ThPM			
Factor	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**
RM	812,990	113,176	A	RM	812,990	113,176	A	RM	812,990	113,176	A
pci=90	729,100	84,829	B	pdi=90	800,813	107,055	A	thr=0.85	794,085	136,550	A
pci=60	658,547	116,149	B,C	pdi=60	783,510	108,792	A	thr=0.90	604,953	182,613	B
pci=30	571,187	107,290	C,D	pdi=30	714,440	138,026	A	thr=0.99	463,040	28,197	C
pci=2	569,843	49,779	D	pdi=2	560,233	53,831	B	thr=0.95	343,057	101,168	D
pci=15	396,257	98,882	E	pdi=15	509,553	128,893	B	thr=0.97	303,420	58,434	D
pci=5	339,410	56,662	E	pdi=5	339,828	75,966	C				

Table 5.9: Post-Hoc test results of scenario DC_R25.

The results show that there is at least one parameter that provides significantly lower cost than the reactive maintenance for all proactive maintenance strategies. For constant and dynamic interval proactive maintenance strategies 5 days, and for threshold based strategy 0.97 thresholds are the best parameters. This indicates that frequent proactive maintenance is needed for this scenario, but unnecessary maintenance should also be avoided.

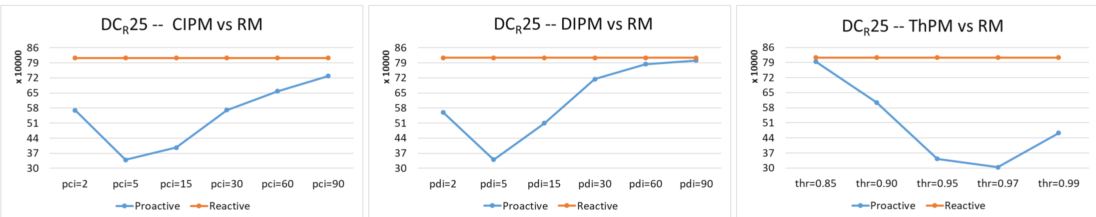


Figure 5.10: Results of the maintenance strategies for Scenario DC_R25.

Figure 5.10 plots the average total maintenance cost against increasing values of the experimented parameters for each strategy and compares them with the cost of reactive maintenance. While CIPM and DIPM behave similarly as parameter values increase, the ThPM strategy is like the mirror image of the two because of the reverse effect of their parameter: Inreasing (decreasing) the thr (pci or pdi) parameter enables proactive maintenance activities more and hence first reduces total horizon cost, but then increases the cost due to the unnecessary proactive maintenance. DIPM and CIPM give almost the same cost values in narrow proactive maintenance intervals, i.e., 2 and 5 days but as the range expands, the DIPM cost approaches the reactive maintenance cost faster. This is due to the fact that when using a dynamic interval strategy, proactive maintenance times are shifted whenever a reactive maintenance is needed between the planned two preventive maintenance times which results in less (higher) number of proactive (reactive) maintenance compared to the CIPM. So, the total maintenance cost increases due to the increasing reactive maintenance number.

5.2.1.2 Scenario $\mathrm{DC_R}50$

In the second scenario, a pessimistic approach in which the domestic market prices suddenly rise to a very high value of 0,65 TL/kw although the thermal power plant has already made an agreement with companies for a low electricity price (0.20 TL/kw). In this case, proactive and reactive downtime costs were calculated as approximately 20,000 TL/hour and 50,000 TL/hour, respectively. The results are shown in Table 5.10 and Figure 5.11.

CIPM				DIPM				ThPM			
Factor	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**
RM	1,508,150	181,300	A	pdi=90	1,568,133	205,506	A	thr=0.85	1,514,588	215,080	A
pci=90	1,383,025	162,591	A,B	pdi=60	1,553,275	266,095	A	RM	1,508,150	181,300	A
pci=60	1,247,132	213,617	B	RM	1,508,150	181,300	A,B	thr=0.90	1,093,598	286,436	B
pci=30	1,002,885	202,155	C	pdi=30	1,335,845	259,728	B	thr=0.995	767,653	82,401	C
pci=15	772,232	214,363	D	pdi=15	899,697	245,286	C	thr=0.95	585,782	201,297	D
pci=2	639,673	110,493	D	pdi=2	637,687	85,915	D	thr=0.99	520,915	67,143	D
pci=5	490,910	117,018	E	pdi=5	487,282	126,608	E	thr=0.97	447,710	167,359	D

Table 5.10: Post-Hoc test results of scenario $\mathrm{DC_R}50$.

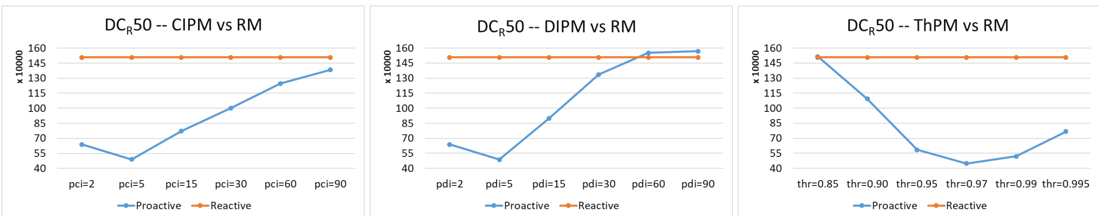


Figure 5.11: Results of the maintenance strategies for Scenario $\mathrm{DC_R}50$.

According to the results, the parameter value that gives the best results for both CIPM and DIPM is 5 days. In ThPM, 0.97 gives the minimum cost but threshold reliabilities of 0.99 and 0.95 are found not to be significant than 0.97 in terms of average total cost. On the other hand, in the previous scenario, when the reactive downtime cost is 25,000 TL, the thr values of 0.97 and 0.95 are the best and they are not statistically different from each other, but the thr value of 0.99 gives worse results than them. From this situation, it can be concluded that implementing more proactive maintenance becomes more advantageous as the unit downtime cost of the reactive maintenance increases and thus provides a lower total cost.

5.2.1.3 Scenario DC_R50 - 2*AD

Thirdly, a more pessimistic scenario is handled where unplanned reactive maintenance cannot be achieved quickly as a result of an economic crisis and layoffs. Accordingly, the durations of reactive maintenance actions is doubled. This causes an increase in the maintenance cost of each action. In addition to the doubled reactive maintenance durations, the reactive downtime cost was also taken as 50.000 TL/hour due to the reasons explained in the previous scenario. Table 5.11 shows the comparison results of replications and Figure 5.12 shows graphically the average total maintenance cost for each strategy.

CIPM				DIPM				ThPM			
Factor	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**
RM	3,072,683	475,618	A	RM	3,072,683	475,618	A	RM	3,072,683	475,618	A
pci=90	2,549,158	468,636	B	pdi=60	3,023,847	488,502	A	thr=0.85	3,028,380	561,275	A
pci=60	2,468,732	360,075	B	pdi=90	3,021,160	500,477	A	thr=0.90	2,473,207	648,184	B
pci=30	2,049,825	411,459	C	pdi=30	2,643,295	660,310	A	thr=0.999	1,539,012	129,953	C
pci=1	1,671,372	161,985	D	pdi=15	2,011,895	582,416	B	thr=0.95	1,214,898	518,435	D
pci=15	1,324,710	348,467	E	pdi=1	1,633,573	104,908	C	thr=0.97	833,015	264,002	E
pci=5	877,810	202,740	F	pdi=5	934,773	255,623	D	thr=0.995	812,990	118,105	E
pci=2	755,177	193,740	F	pdi=2	774,073	169,836	D	thr=0.99	651,698	196,147	E

Table 5.11: Post-Hoc test results of scenario DC_R50-2*AD.

According to the results, a proactive maintenance interval of 2 days is the best parameter for CIPM and DIPM, but this is not signicantly different from the 5 days parameter within the respective strategy. In ThPM, the threshold level

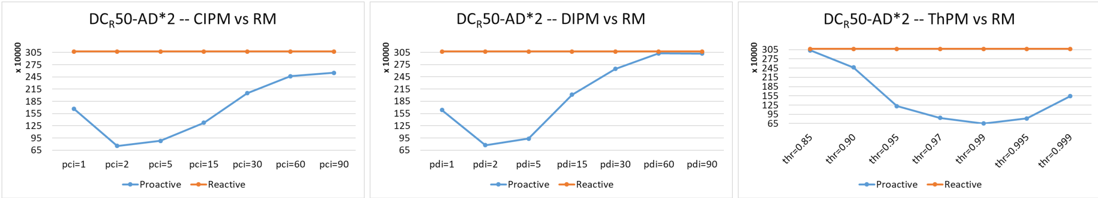


Figure 5.12: Results of the maintenance strategies for Scenario DC$_R$50-AD*2.

of 0.95 gives the lowest maintenance cost, but this is not significantly different from the cost values of thr=0.995 and thr=0.97. These results show that in such a pessimistic scenario where reactive maintenance result in a huge cost, more frequent proactive maintenance is needed to prevent reactive maintenance. However, using a reliability threshold more than 0.99 or taking pci and pdi as 1 day increases the total maintenance cost as a result of unnecessary proactive maintenance. It should also be noted that the ThPM strategy is more successful at achieving a lower minimum total cost than CIPM and DIPM. Comparisons with the best performing parameters among the strategies will be discussed in Section 5.2.3.

In all the scenarios discussed, DIPM and CIPM strategies behave similarly, but as proactive maintenance intervals expand, DIPM approaches the RM strategy faster. This is due to the need for more reactive maintenance as the time between proactive maintenance increases. Because of the dynamic interval used in DIPM, proactive maintenance times are postponed and need for reactive maintenance increases which results in an increase in total maintenance cost.

5.2.2 Scenarios Based on Dependent Parallel Engine Groups

In the scenarios handled in Section 5.2.1, it is necessary to stop the system to perform reactive maintenance, but not for proactive maintenance. In this case, proactive maintenance provides a great advantage in terms of reducing the total maintenance cost. To see if proactive maintenance will take advantage even in a dependent system, another scenario where the system must be stopped while performing proactive maintenance also has been designed. In this case, where the system cannot continue generating electricity during both proactive and reactive maintenance, all maintenance actions in both cases cause downtime costs. This scenario ran 30 replications for all sub-scenarios mentioned in Section 5.2.1 and for the three proposed proactive maintenance strategies.

5.2.2.1 Scenario depDC$_R$25

In this scenario, hourly proactive and reactive downtime costs of all components are taken as 20,000 TL and 25,000 TL, respectively. These downtimes are the same as those given in Table 4.4. Replication results for each strategy are shown in Table 5.12 and in Figure 5.13 where Tk represents Tukey test results.

CIPM				DIPM				ThPM			
Factor	**Mean**	**SD**	**Tk**	**Factor**	**Mean**	**SD**	**Tk**	**Factor**	**Mean**	**SD**	**Tk**
pci=5	1,371,632	84,708	A	pdi=5	1,314,080	71,977	A	thr=0.99	1,820,468	70,485	A
pci=15	896,750	118,529	B	pdi=15	860,923	128,510	B	thr=0.97	968,652	69,521	B
pci=90	861,858	133,908	B,C	pdi=45	835,497	144,658	B	thr=0.95	872,307	96,427	C
pci=30	853,227	123,612	B,C	pdi=60	833,427	114,897	B	thr=0.85	822,928	139,546	C
RM	812,990	113,176	B,C	pdi=30	817,995	107,112	B	RM	812,990	113,176	C
pci=60	781,005	126,373	C	RM	812,990	113,176	B	thr=0.75	806,593	104,865	C
pci=45	776,202	133,158	C	pdi=90	782,293	94,332	B	thr=0.90	800,207	123,541	C

Table 5.12: Post-Hoc test results of scenario depDC$_R$25.

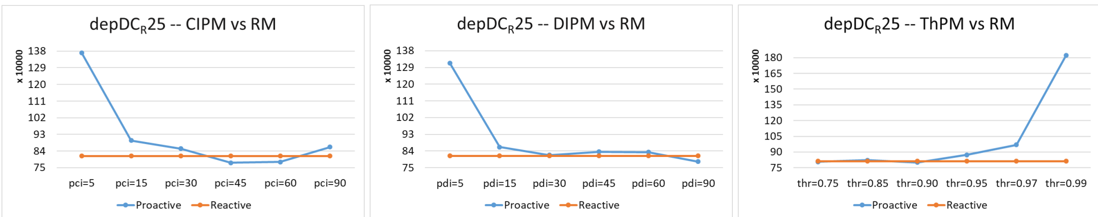


Figure 5.13: Results of the maintenance strategies for Scenario depDC$_R$25.

The results indicate that in all strategies there are no parameters that give a significantly lower cost than the cost of RM. On the contrary, some parameters of the strategies cause higher maintenance costs. In CIPM and DIPM, 5 days interval gives the worst result and it is seen that while the interval between proactive maintenance increases, the total cost decreases. The parameter pci=5, which gives the worst cost in CIPM, is significantly different from other parameters and reactive maintenance. In ThPM, parameters which result in more proactive maintenance, thr=0.97 and thr=0.99, are significantly different from RM and other threshold levels, as well as significantly different from each other and give the highest cost results. Other threshold parameters give almost the same cost with RM. Results show that using a proactive maintenance strategy does not provide any advantage under the cost structure given in this scenario.

5.2.2.2 Scenario depDC$_{\mathrm{R}}$50

In this scenario, all components need to be stopped for both reactive and proactive maintenance, and the cost of reactive downtime was taken as 50,000 TL because of the reasons described earlier. The results are given in Table 5.13 and Figure 5.14.

CIPM				DIPM				ThPM			
Factor	**Mean**	**SD**	**Tk**	**Factor**	**Mean**	**SD**	**Tk**	**Factor**	**Mean**	**SD**	**Tk**
pci=2	3,234,358	181,300	A	pdi=2	3,263,513	98,797	A	thr=0.99	1,912,942	149,836	A
pci=5	1,610,330	217,801	B,C	pdi=30	1,607,462	241,444	B	thr=0.85	1,606,567	229,963	B
pci=90	1,608,683	229,191	B,C	pdi=60	1,595,673	233,141	B	RM	1,508,150	181,300	B,C
pci=60	1,559,500	207,912	B,C	pdi=90	1,574,220	249,517	B,C	thr=0.90	1,397,760	244,947	C,D
pci=45	1,555,900	175,201	B,C	pdi=5	1,560,697	168,177	B,C	thr=0.95	1,260,420	220,126	D,E
RM	1,508,150	181,300	B,C	pdi=45	1,525,210	269,834	B,C	thr=0.97	1,228,858	217,561	E
pci=30	1,447,768	221,860	B,C	RM	1,508,150	181,300	B,C				
pci=15	1,400,557	186,110	C	pdi=15	1,395,637	236,102	C				

Table 5.13: Post-Hoc test results of scenario depDC$_{\mathrm{R}}$50.

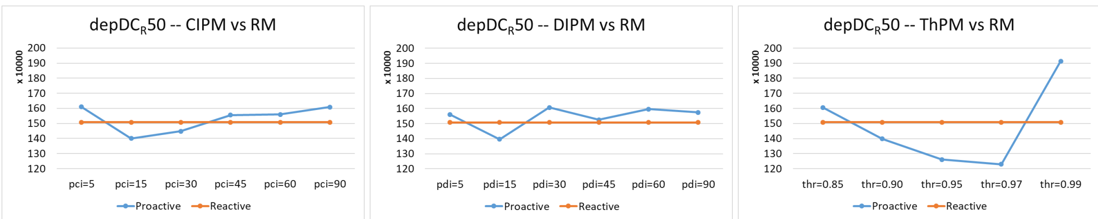


Figure 5.14: Results of the maintenance strategies for Scenario depDC$_{\mathrm{R}}$50.

For CIPM and DIPM strategies, there is no parameter resulting in significantly less cost than the reactive maintenance. However, the thresholds of 0.97 and 0.95 in ThPM are the best and give a significantly lower cost than RM. As threshold level increases, the maintenance cost decreases until thr=0.97. When the threshold level rises to 0.99, the cost increases greatly as a result of unnecessary proactive maintenance. It can be concluded that ThPM is the best strategy in this scenario since the threshold based proactive strategy achieves to give significantly lower cost than that of the RM.

5.2.2.3 Scenario depDC$_R$50-2*AD

In this scenario, in addition to the previous scenario, the reactive maintenance times of the components are also doubled due to the previously described arguments in Section 5.2.1.3. Replication results are shown in Table 5.14 and Figure 5.15.

CIPM				DIPM				ThPM			
Factor	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**	**Factor**	**Mean**	**SD**	**GH**
pci=2	3,411,912	271,384	A,B	pdi=2	3,459,180	261,008	A	RM	3,072,683	475,618	A
RM	3,072,683	475,618	B	RM	3,072,683	475,618	B	thr=0.85	2,991,852	546,488	A
pci=90	3,062,532	390,982	B	pdi=90	3,046,507	459,494	B	thr=0.90	2,675,882	620,795	A
pci=60	2,914,787	390,891	B,C	pdi=60	2,972,570	407,950	B	thr=0.99	2,089,465	268,921	B
pci=30	2,896,617	457,727	B,C	pdi=30	2,877,380	523,580	B,C	thr=0.95	1,833,235	497,400	B,C
pci=15	2,554,793	514,663	C	pdi=15	2,550,208	456,090	C	thr=0.97	1,777,223	415,788	C
pci=5	1,867,830	411,877	D	pdi=5	1,900,833	328,620	D				

Table 5.14: Post-Hoc test results of scenario depDC$_R$50-2*AD.

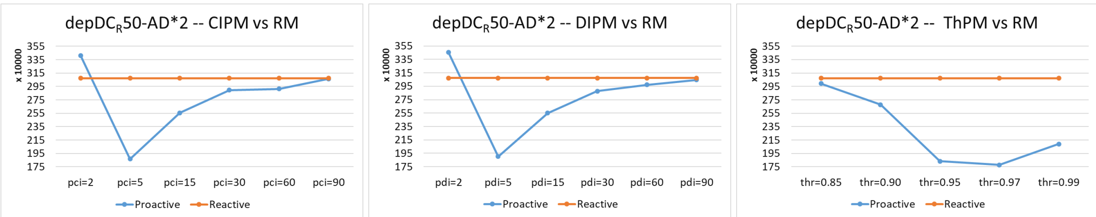


Figure 5.15: Results of the maintenance strategies for Scenario depDC$_R$50-2*AD.

According to the results, there is at least one parameter for each strategy that is significantly better than RM. The 5 days interval gives the lowest cost in CIPM and DIPM. Moreover, there is also another parameter value (pci=15 and pdi=15) that is significantly better than RM but significantly worse than pci=5 and pdi=5 in CIPM and DIPM respectively. Among the experimented values, the 2 days interval gives the highest cost in these strategies due to unnecessary proactive maintenance. ThPM gives the lowest cost at the threshold level of 0.97, and this threshold is statistically different from RM and other parameter values other than thr=0.95. Moreover, all parameter values give lower cost than RM in ThPM. These results show that even if the operation of parallel lines in the system is dependent, if the cost of reactive maintenance is sufficiently high, proactive maintenance provides an advantage in keeping the system sustainable while reducing the total maintenance cost.

5.2.3 Comparison of the Strategies using the Best Parameters

To understand which maintenance strategy is better, the best performing parameters of each strategy, which yield significantly lower costs than RM under the given scenarios, are compared to each other using ANOVA. The depDM$_R$25 scenario, where none of the strategies give significantly lower cost than RM, and depDM$_R$50 scenarios, where only some ThPM parameters give significantly lower cost than RM, are not considered in the comparisons. Table 5.15 shows the comparison results by both total maintenance cost and total maintenance number.

Scenario	Parameter	Avg. Cost	SD	Tk	Parameter	Avg. Number	SD	GH
DC$_R$25	pdi=5	339,410	56,662	A	pci=5	65.00	1.702	A
	pci=5	339,828	75,966	A	pdi=5	62.20	1.243	B
	thr=0.97	303,420	58,434	A	thr=0.97	51.30	4.348	C
DC$_R$50	pci=5	490,910	117,018	A	pci=5	65.57	1.716	A
	pdi=5	487,282	126,608	A	pdi=5	62.77	1.524	B
	thr=0.97	447,710	167,359	A	thr=0.97	49.20	3.624	C
DC$_R$50-2*AD	pdi=2	774,073	169,836	A	pci=2	150.67	1.155	A
	pci=2	755,177	193,740	A,B	pdi=2	150.27	0.785	A
	thr=0.99	651,698	196,147	B	thr=0.99	100.50	3.481	B
depDC$_R$50-2*AD	pdi=5	1,900,833	328,620	A	pci=5	63.00	2.197	A
	pci=5	1,867,830	411,877	A	pdi=5	61.40	1.276	B
	thr=0.97	1,777,223	415,788	A	thr=0.97	40.93	2.116	C

Table 5.15: Comparison of the best parameters of strategies for different scenarios.

The results show that although threshold-based maintenance gives the lowest cost, there is no significant difference between the strategies based on maintenance cost. On the other hand, when strategies are compared based on the total number of maintenance, ThPM is the best. Since threshold-based maintenance is a predictive strategy that considers the actual state of the system when making maintenance decisions, proactive maintenance is only performed when it is necessary. Thus, it reduces both the maintenance number and the maintenance cost. These results show that the threshold-based maintenance strategy is the best under these scenarios.

5.2.4 Justification of Using Tabu Procedure

In order to confirm the usage of tabu procedure within the maintenance decision making process, we also replicate the ThPM strategy without using the tabu procedure for 30 replications. The total maintenance cost for the parameters of the ThPM strategy in the scenario DC_c25 is shown in Figure 5.16 for the two related situations. In addition, the reactive maintenance cost is also plotted in the figure. According to the cost value, the biggest difference between the two cases belongs to thr=0.97, which gives the lowest cost with the tabu procedure. At all parameter levels, after confirming the normality of the model, t-test was used to statistically compare with (w/) and without (w/o) tabu procedure. In the t-test, zero p-value is obtained for the threshold levels of 0.97 and 0.99, while the other values are not significantly different from each other. When it is considered that as the reliability threshold value decreases, the frequency of proactive maintenance reduces and this results in an empty tabu list during almost all proactive maintenance times, the results can be said to make sense. On the other side, although the p-value is zero when thr=0.99, the cost difference is smaller compared to the previous threshold value because due to too much proactive maintenance, 5-days tabu duration causes a long tabu list and it makes the tabu very restrictive.

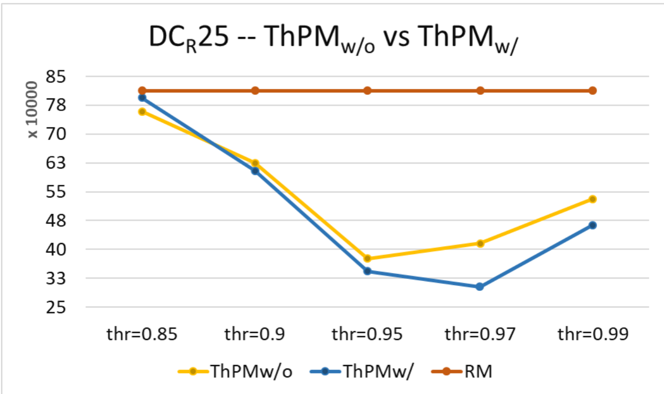


Figure 5.16: Comparison of with and without tabu procedure at thr=0.97.

We also analyze the distribution of the components that undergo maintenance within the planning horizon for the thr=0.97 case with and without tabu procedures. Results of both proactive and reactive maintenance within the ThPM strategy are given in Table 5.16. The results are really remarkable since a huge number of proactive maintenance is applied to RS in w/o tabu case. At thr=0.97, proactive maintenance is frequently performed, so the reliability levels of the components often remain high. This makes cost values more effective during proactive maintenance periods. Since the component with the lowest proactive maintenance cost is the RS, this component is repeatedly selected during such times which causes the solution procedure to be stuck at proactive maintenance times. When w/ tabu results are analyzed, the distribution is more balanced because prohibitions (henceforth the term tabu) are introduced to discourage the maintenance activity search from repeating the recently selected components.

		Components											
		BB1	**WI1**	**RS1**	**HRG1**	**BB2**	**WI2**	**RS2**	**HRG2**	**Hc**	**RI**	**Total**	**SD**
w/o Tabu	PM	0.00	3.23	50.47	6.23	0.00	2.97	48.87	6.60	0.00	1.13	127.17	24.83
	RM	2.90	0.00	0.00	0.30	2.53	0.00	0.00	0.10	0.00	1.83		
w/ Tabu	PM	1.73	4.37	8.77	6.77	1.77	4.03	9.43	7.03	0.00	3.27	51.30	4.35
	RM	1.47	0.03	0.00	0.13	1.40	0.00	0.00	0.37	0.00	0.73		

Table 5.16: Distribution of the components with and without tabu procedure at thr=0.97.

5.2.5 Number and Cost Distribution of the Components

Figure 5.17 and 5.18 show the number and cost distribution of the RAH components under ThPM (with thr=0.97) and reactive maintenance strategies in the scenario DC_c25. In the figures, the blue and light orange bins represent the proactive maintenance and reactive maintenance within the ThPM proactive maintenance strategy while orange bins show the maintenance under the reactive maintenance strategy.

Figure 5.17 shows that when reactive maintenance is applied in both ThPM and reactive strategy, WI and RS are selected very seldomly for maintenance. Instead, BB stands out for maintenance as it has the lowest action duration and therefore the lowest maintenance cost. The most frequent proactive maintenance in ThPM

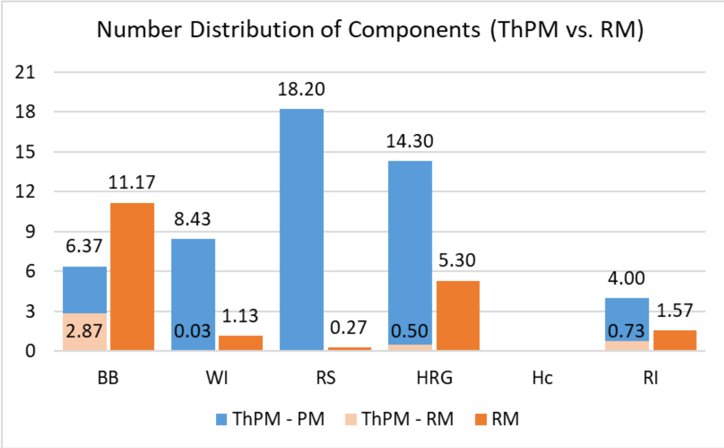


Figure 5.17: Number distribution of the components based on DC_R25.

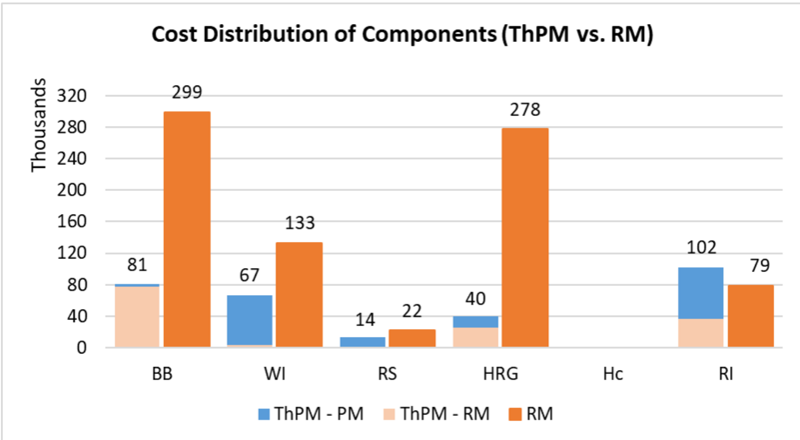


Figure 5.18: Cost distribution of the components based on DC_R25.

belongs to RS and HRG due to action costs and posterior probabilities. This is because in proactive maintenance, the cost of downtime does not occur, as the system does not need to stop during maintenance of components in parallel engine groups. Figure 5.18, which shows that these components provide the lowest proactive maintenance cost even though they have the highest maintenance number, also confirms this result. Although WI is also a component of the engine group, it is not preferred as much as RS and HRG in proactive maintenance times in ThPM strategy. However, since WI has the highest action cost, it has a higher share in cost distribution compared to RS and Hc.

Chapter 6

Conclusion

This study proposes a maintenance methodology for complex systems with multi-state hidden and dependent components. Due to their effectiveness in expressing structural and stochastic dependencies between components DBNs are selected to model the system. The methodology includes both reactive and proactive maintenance methods. Eight different maintenance methods with two different efficiency measures are proposed within the scope of corrective maintenance. These methods are considered in two ways: decreasing of maintenance number and decreasing of maintenance cost. When maintenance cost is considered, a normalization procedure is applied to the cost of maintenance activities with respect to the probability measures in order to balance the effect of the two. In proactive maintenance framework, two preventive, CIPM and DIPM, and one predictive, ThPM, maintenance strategies from a cost perspective are introduced using the tabu procedure. The purpose of these policies is to reduce maintenance cost and to increase the system reliability so as to avoid unexpected downtimes at the same time.

All the proposed methods are simulated in regenerative air heater system which is one of the critical subsystems of thermal power plants. The reason to select the RAH is that it is a complex multi-component system and the dependencies between its components are in accordance with the purpose of the study. In addition, maintenance optimization in power plants is critical due to the high losses incurred during downtime and maintenance interventions. Another important contribution of the thesis is that the system interaction and deterioration of the components of the RAH system are modeled with DBNs after a HAZOP analysis.

Reactive maintenance methods are evaluated considering both maintenance number and maintenance cost. Replication results of reactive maintenance based on number-based methods show that FEM_{wp} and FEL_{wp} methods which consider posterior best working state probabilities of the components in fault effect methods give less maintenance number compared to other methods. On the other hand, when cost-based reactive maintenance methods are used, FEM_{fp} and FEL_{fp} methods which consider posterior worst state probability are superior than the other methods. Also, a sensitivity analysis of the methods with respect to the unit downtime cost is done and it shows that distinction of FEM_{fp} and FEL_{fp} gets more significant as downtime cost increases. According to these results, it can be said that fault effect methods are better for both number-based and cost-based reactive maintenance approach. These methods are also superior than the replacement effect methods in terms of simulation time because less inference calculations are required for component selection at each maintenance time in fault effect methods.

In addition, the performance of the methods under two scenarios which are number-based and cost based are evaluated. Annual reactive maintenance cost is considered in both scenarios. It can be concluded that considerable gains on the annual cost can be achieved by the proposed approach in the cost-based scenario compared to the number-based scenario in all maintenance methods.

To evaluate the performances of the proactive policies, they are compared to each other and also to the reactive maintenance strategy under six different scenarios using different policy parameters. These scenarios are designed based on the dependability of parallel motor lines during proactive maintenance and different reactive cost structures. Although all proposed proactive strategies provide satisfactory results, as threshold based maintenance is a predictive policy which decides the maintenance time by considering the system reliability, it gives the minimum cost for almost all scenarios. Moreover, the threshold based strategy gives significantly less number of maintenance than the other two in all scenarios where the three proposed proactive strategies yield significantly lower cost than the reactive strategy. Thus, all proposed proactive strategies are effective in reducing maintenance cost. However, the threshold based policy is also successful in decreasing maintenance number in addition to the cost which may position it as a more preferable policy in industries where the production should continue with minimum downtime.

Although the proposed reactive and proactive maintenance strategies and methods based on DBNs are simulated on the regenerative air heater system available in thermal power plants, the whole methodology can be applied in the maintenance problem of all partially observable systems which have dependable components.

As a future study, presented methods can be used under the opportunistic maintenance in a complex real-life system. In addition, imperfect maintenance methods, which can bring the repaired components to an intermediate state, to not the best state can be applied. Apart from these, different methods can be tried to make the normalization procedure used in cost efficiency measures to be more effective.

Appendix

Appendix A

Initial probabilities of the RAH DBN model

BB M.	Replace	Do Nothing
Normal	1	1
Loose	0	0
Locked	0	0

Table A.1: Initial probabilities of Ball Bearing.

WI M.	Replace	Do Nothing
Original	1	1
Burned	0	0

Table A.2: Initial probabilities of Winding-Insulation.

RS M.	Grind	Do Nothing
Normal	1	1
Unaligned	0	0

Table A.3: Initial probabilities of Rotor-Shaft.

HRG M.	Replace	Do Nothing
Normal	1	1
Broken	0	0

Table A.4: Initial probabilities of Hub Reduction Gear.

RAH I. M	Replace		Do Nothing	
Hc. M	**Clean**	**Do Nothing**	**Clean**	**Do Nothing**
Full I.	1	1	1	1
Medium I.	0	0	0	0
Low I	0	0	0	0

Table A.5: Initial probabilities of RAH Insulation.

Hc M.	Clean	Do Nothing
New	1	1
Cleaned	0	0
Dirty	0	0

Table A.6: Initial probabilities of Honeycomb.

Good	0.5
Bad	0.5

Table A.7: Initial probabilities of Coal Rank.

Coal Rank	Good	Bad
No	0.95	0.6
Yes	0.05	0.4

Table A.8: Initial probabilities of Slagging.

Appendix B

Transition probabilities of the RAH DBN model

BB M.	**Replace**			**Do Nothing**		
(Self) [t-1]	**Normal**	**Loose**	**Locked**	**Normal**	**Loose**	**Locked**
Normal	1	1	1	0.99916	0	0
Loose	0	0	0	0.0005	1	0
Locked	0	0	0	0.00034	0	1

Table B.1: Transition probabilities of Ball Bearing.

WI M.	**Replace**					
BB [t-1]	**Normal**		**Loose**		**Locked**	
(Self) [t-1]	**Original**	**Burned**	**Original**	**Burned**	**Original**	**Burned**
Original	1	1	1	1	1	1
Burned	0	0	0	0	0	0
WI M.	**Do Nothing**					
BB [t-1]	**Normal**		**Loose**		**Locked**	
(Self) [t-1]	**Original**	**Burned**	**Original**	**Burned**	**Original**	**Burned**
Original	0.99933	0	0.993	0	0.2	0
Burned	0.00067	1	0.007	1	0.8	1

Table B.2: Transition Probabilities of Winding - Insulation.

RS M.	Grind					
BB [t-1]	Normal		Loose		Locked	
(Self) [t-1]	Normal	Unaligned	Normal	Unaligned	Normal	Unaligned
Normal	1	1	1	1	1	1
Unaligned	0	0	0	0	0	0
RS M.	Do Nothing					
BB [t-1]	Normal		Loose		Locked	
(Self) [t-1]	Normal	Unaligned	Normal	Unaligned	Normal	Unaligned
Normal	0.99978	0	0.02	0	1	0
Unaligned	0.00022	1	0.98	1	0	1

Table B.3: Transition Probabilities of Rotor - Shaft.

HRG M.	Replace		Do Nothing	
(Self) [t-1]	Normal	Broken	Normal	Broken
Normal	1	1	0.99888	0
Broken	0	0	0.00112	1

Table B.4: Transition Probabilities of Hub Reduction Gear.

RI M.	Replace					
Hc M.	Clean			Do Nothing		
(Self) [t-1]	F. Integrity	M. Integrity	L. Integrity	F. Integrity	M. Integrity	L. Integrity
F. Integrity	1	1	1	1	1	1
M. Integrity	0	0	0	0	0	0
L. Integrity	0	0	0	0	0	0
RI M.	Do Nothing					
Hc M.	Clean			Do Nothing		
(Self) [t-1]	F. Integrity	M. Integrity	L. Integrity	F. Integrity	M. Integrity	L. Integrity
F. Integrity	1	1	1	0.99889	0	0
M. Integrity	0	0	0	0.00078	0.998	0
L. Integrity	0	0	0	0.00033	0.002	1

Table B.5: Transition Probabilities of RAH Insulation.

Hc M.	Clean					
(Self) [t-1]	New		Cleaned		Dirty	
Slagging [t-1]	No	Yes	No	Yes	No	Yes
New	0	0	0	0	0	0
Cleaned	1	1	1	1	1	1
Dirty	0	0	0	0	0	0
Hc M.	Do Nothing					
(Self) [t-1]	New		Cleaned		Dirty	
Slagging [t-1]	No	Yes	No	Yes	No	Yes
New	0.99967	0.99933	0	0	0	0
Cleaned	0	0	0.99944	0.99833	0	0
Dirty	0.00033	0.00067	0.00056	0.00167	1	1

Table B.6: Transition Probabilities of Honeycomb.

Appendix C

Conditional probabilities of the RAH DBN model

RS	**Normal**					
WI	**Original**			**Burned**		
BB	**Normal**	**Loose**	**Locked**	**Normal**	**Loose**	**Locked**
Rotate	1	0.5	0	0	0	0
Not Rotate	0	0.5	1	1	1	1
RS	**Unaligned**					
WI	**Original**			**Burned**		
BB	**Normal**	**Loose**	**Locked**	**Normal**	**Loose**	**Locked**
Rotate	0.3	0.1	0	0	0	0
Not Rotate	0.7	0.9	1	1	1	1

Table C.1: Conditional Probabilities of Rotor Rotation.

HRG	**Normal**		**Broken**	
Rotor Rotation	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**
Rotate	1	0	0	0
Not Rotate	0	1	1	1

Table C.2: Conditional Probabilities of Hub Reduction Gear Rotation.

HRG Rotation 2	**Rotate**		**Not Rotate**	
HRG Rotation 1	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**
Rotate	1	1	1	0
Not Rotate	0	0	0	1

Table C.3: Conditional Probabilities of RAH Rotation.

RI	F. Integrity					
Hc	**New**		**Cleaned**		**Dirty**	
RAH Rotation	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**
Normal	1	0	1	0	0.99877	0
Low	0	0	0	0	0.00067	0
Super Low	0	1	0	1	0.00056	1
RAH Insulation	**M. Integrity**					
Honeycomb	**New**		**Cleaned**		**Dirty**	
RAH Rotation	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**
Normal	0.9996	0	0.9992	0	0.96	0
Low	0.00032	0	0.00035	0	0.025	0
Super Low	0.00008	1	0.00045	1	0.015	1
RAH Insulation	**L. Integrity**					
Honeycomb	**New**		**Cleaned**		**Dirty**	
RAH Rotation	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**	**Rotate**	**Not Rotate**
Normal	0.0002	0	0.00019	0	0.0014	0
Low	0.66	0	0.68	0	0.69	0
Super Low	0.3398	1	0.31981	1	0.3086	1

Table C.4: Conditional Probabilities of RAH Exit Temperature.

RAH Exit Temperature	Normal	Low	Super Low
Normal	0.99989	0.00015	0.00005
Low	0.0001	0.99	0.0099
Super Low	0.00001	0.00985	0.99005

Table C.5: Conditional Probabilities of RAH Measured Temperature.

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