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M.S. Thesis

2019

ANALYSIS OF DIFFERENT MAINTENANCE POLICIES ON A MULTI-COMPONENT SYSTEM USING DYNAMIC BAYESIAN NETWORKS

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M.S., Industrial Engineering, IŞIK UNIVERSITY, 2019

Submitted to the Graduate School of Science and Engineering
in partial fulfillment of the requirements for the degree of
Master of Science
in
Industrial Engineering

IŞIK UNIVERSITY
2019

IŞIK UNIVERSITY
GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

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Abstract

Recently, system components and interactions between them have become more complex and this situation has made it difficult to provide maintenance decisions. Herewith, determining effective decisions has played an important role. In multi-component systems, many methodologies and strategies can be applied when a component or a system has already broken down or when it is desired to identify and avoid pro-actively defects that could lead to future failure.

In dynamic systems, it is important for proactive maintenance to increase system reliability by performing early diagnosis-based maintenance activities without waiting for a problem. In this study, we focus on proactive maintenance of a complex multi-component dynamic system. Components are hidden although there exists partial observability to the decision maker. Components deteriorate in time. It is possible to replace or repair components with a given cost. We want to find a policy that minimizes the total maintenance cost in a predefined time horizon. We propose several maintenance policies and compare the performance of these by simulating them via Dynamic Bayesian Networks on an empirical model. Furthermore, a dynamic Bayesian network is constructed for the maintenance of an endo generator system to show how the proposed methods can be implemented in real life.

Keywords: Multi-component systems, Maintenance, Reliability, Policy analysis, DBNs

ÇOK-BİLEŞENLİ SİSTEMLER ÜZERİNDE DİNAMİK BAYESÇİ AĞLAR KULLANARAK FARKLI BAKIM POLİTİKALARININ ANALİZİ

Özet

Son zamanlarda, sistemlerin karmaşıklığı artmış ve bunun paralelinde bileşenler arasındaki etkileşimler gittikçe daha karmaşık hale gelmiş ve bu durum bakım kararlarını vermeyi zorlaştırmıştır. Dolayısıyla etkili bakım politikalarının belirlenmesi ve uygulanması büyük önem kazanmıştır. Çok bileşenli sistemlerde, birçok metodoloji ve strateji bir bileşen veya sistem bozulduğunda veya bir arızaya neden olabilecek proaktif olarak kusurları tanımlamak ve önlemek istendiği zaman uygunanabilir.

Dinamik sistemlerde, bir problem beklemeden erken tanıya dayalı bakım faaliyetlerini gerçekleştirerek sistem güvenilirliğini artırması proaktif bakım için önemlidir. Bu çalışmada, çok bileşenli dinamik bir sistem üzerinde çeşitli bakım politikaları oluşturup bunları sistem performansı ve bakım maliyetleri bakımından karşılaştırmayı hedefledik. Ele alınan sistem çeşitli bileşenler ve işlemlere sahiptir. Karar vermek için kısmi bir gözlemlenebilirlik olmasına rağmen, bileşenlerin durumları gizlidir gizlidir ve zaman içinde bozulmaktadır. Bileşenleri belirli bir zaman içerisinde değiştirmek mümkündür. amaç, belirli bir planlama ufkunda toplam bakım maliyetini en aza indirmektir. Empirik bir sistem için bakım politikaları önerip bunları çeşitli senoryalar altında Dinamik Bayesçi Ağlar ile planlama ufku boyunca benzeterek performanslarını karşılaştırıyoruz. Ayrıca, önerilen yöntemlerin gerçek hayatta nasıl uygulanabileceğini göstermek için bir endo jeneratör sisteminin bakımı için dinamik bir Bayesian ağı oluşturulmuştur.

Anahtar kelimeler: Çok bileşenli sistemler, Bakım, Güvenirlilik, Politika analizi, DBNs

Acknowledgements

Firstly, I would like to express my gratitude to my Supervisor Assist. Prof. Demet Özgür Ünlüakın for her positive supporting and encouraging the entire dissertation process. She has shown me her continual interest to the project. I fortunate to work with her and I am pleased.

Secondly, I would like to thank the thesis jury. Because they took part in my thesis defence and honoured me.

Finally, my project partners Assist. Prof. Demet Özgür Ünlüakın, Assoc. Prof. S. Çağlar Aksezer, Busenur Türkali and İpek Kıvanç should go to them with special thanks for they unceasing help and support. They always took care of me and solved all my troubles. I am grateful they for helping my path in the thesis.

In addition, I would like to thank my family and my friends for their unconditional supporting and continual love throughout my year of master. Also, I am thankful to my friends who have always encouraged me and are on my side.

This study was supported by The Scientific and Technological Research Council of Turkey (TÜBİTAK) Grant No: 117M587

To My Dear Readers

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List of Abbreviations

BN	**B**ayesian **N**etwork
FT	**F**ault **T**ree
DD	**D**esicion **D**iagram
DAG	**D**irect **A**cyclic **G**raph
DBN	**D**ynamic **B**ayesian **N**etwork
DD	**D**ynamic **D**ecision **N**etwork
DFT	**D**ynamic **F**ault **T**ree
BBN	**B**ayesian **B**elief **N**etwork
CPF	**C**onditional **P**robability **F**unction
JPD	**J**oint **P**robability **D**istribution
FB	**F**orward **B**ackward algorithm
BK	**B**oyen **K**oller algorithm
FF	**F**actored **F**orinter algorithm
LBP	**L**oopy **B**elif **P**ropagation
C1	**C**omponent node **1**
C2	**C**omponent node **2**
C3	**C**omponent node **3**
C4	**C**omponent node **4**
A1	**A**ction node **1**
A2	**A**ction node **2**
A3	**A**ction node **3**
A4	**A**ction node **4**
P1	**P**rocess node **1**
P2	**P**rocess node **2**

P3	**P**rocess node **3**
O1	**O**rocess node **1**
Y	**Y**ellow state
N	**N**o state
W	**W**ork state
NW	**N**ot work state
D	**D**egradate state
F	**F**ault state
G	**G**reen state
Y	**Y**ellow state
R	**R**ed state
FEM	**F**ault **E**ffect **M**yopic Method
FEL	**F**ault **E**ffect **L**ook-aHead Method
REM	**R**eplacement **E**ffect **M**yopic Method
REM	**R**eplacement **E**ffect **L**ook-aHead Method
CM	**C**orrective **M**aintenance
PM	**P**roactive **M**aintenance
CIPM	**C**anstant **I**nterval **P**roactive **M**aintenance
DIPM	**D**ynamic **I**nterval **P**roactive **M**aintenance
ThPM	**T**hreshold **P**roactive **M**aintenance
OPP	**O**pportunistic
OPPCM	**O**pportunistic **C**orrective **M**aintenance
OPPPM	**O**pportunistic **P**roactive **M**aintenance
OPPCIPM	**O**pportunistic **C**anstant **I**nterval **P**roactive **M**aintenance
OPPDIPM	**O**pportunistic **D**ynamic **I**nterval **P**roactive **M**aintenance
OPPThPM	**O**pportunistic **T**hreshold **P**roactive **M**aintenance
i^*	The component selected for replacement
$Cost_i$	Total maintenance cost for node i
RC_i	Replacement cost for node i
dt_i	Downtime for node i

LP_i	Production lost cost for node i
T	Set of time periods
F	Failure probability
R	Reliability probability
ef_{it}	Efficiency measure of component i in period t
${ef_{it}}^{FEM}$	Efficiency measure of FEM method
${ef_{it}}^{FEL}$	Efficiency measure of FEL method
${ef_{it}}^{REM}$	Efficiency measure of REM method
${ef_{it}}^{REL}$	Efficiency measure of REL method
C_{it}	State of component i in period t, $i \in I$
O_t	State of observation node in time t
F_{it}	Failure probability of component i in period t, $i \in I$
I	Set of replaceable components
C_{it}	State of component i in period t, $i \in I$
mt	Maintenance end time
O_t	State of observation node in time t
ε	Accumulated evidence consisting of the replacement history
pmt	Maintenance period
pci	Constant interval maintenance period
$abmt$	Constant interval maintenance periods array
pdi	Dynamic interval maintenance period
thr	Threshold level
$OppList$	Opportunistic replaceable component
Opp_{thr}	Opportunistic threshold level

Chapter 1

Introduction

In recent years, systems had a more complex structure and have increased maintenance cost by means of evolving technology and industry. Following this, there have become more and more complex interactions between components and this situation make it difficult to give their maintenance decisions. Consequently, the importance of determination and implementation of effective maintenance policy to decrease maintenance cost and time has increased. In multi-component systems, effective maintenance policies are more important than single-component systems. Maintenance is a very important aspect of controlling the system. Systems are becoming more complex, but in a way that takes a very high intention of researchers. Many methodologies and strategies have been proposed and implemented in this area.

Also, maintenance stands at the center of strategical plans for economic and social development. First, of foremost, it provides rational and long-term usage of all productive resources with the protection of the environment, economic feasibility and also it provides more effective management [1]. The industrial revolution has made a major contribution to the development of the maintenance and its principles in the maintenance field. However, it is still hard to apply them due to a lot of reasons and factors like size, cost and complexity [2]. While a maintenance action means of a basic maintenance intervention, a set of rules that describe the triggering mechanism for various maintenance actions is defined as maintenance policy [3].

1.1 Maintenance Strategies

Maintenance actions are classified as shown in Figure 1.1 [4]. Maintenance actions are basically divided into two parts which are reactive and proactive strategies in system health monitoring and estimation. Reactive maintenance actions are known as breakdown maintenance and it repairs when the equipment has already broken down. It focuses on bringing the component back to the normal situation. Reactive maintenance consists of corrective maintenance and emergency maintenance.

- Corrective maintenance is an activity that is performed to remove the fault and make the system perform its functions after a fault has occurred in the system.
- Emergency maintenance is a maintenance activity that must be done immediately to prevent serious consequences [5].

On the other hand, during proactive or scheduled maintenance, maintenance activities are scheduled without waiting for the system failure. Proactive maintenance is a maintenance action that monitors the deterioration of components and avoids failures by undertaking minor repairs [6]. Proactive maintenance activity is examined under two main headings. These are preventive maintenance and predictive maintenance. With these activities, the likelihood of unexpected equipment failures is reduced. Preventive maintenance is use-based maintenance. In other words, maintenance activities are performed in proportion to the amount of use of the machine or at the end of a certain period. [7, 8].

Regular and routine maintenance helps to keep the component run and prevent unexpected interruptions of equipment failure and to hinder the high maintenance cost. This type of maintenance is based on the probability of the equipment failure in the specified interval. The benefits of preventive maintenance include reducing equipment failures and extending equipment life. The disadvantage of preventive maintenance is that production must be interrupted at scheduled intervals to perform the work. In addition, it is necessary to plan maintenance on the component before the failure occurs in component or system. Preventive maintenance can be very complex, especially for companies with a lot of components.

Preventive maintenance strategy is examined under three main headings. These are constant interval maintenance, age-based maintenance and imperfect maintenance as shown in Figure 1.1.

- Constant interval maintenance is the maintenance of the relevant system or components at a predetermined fixed time interval. Intervals are selected according to mean time to failure of the system. The components are regularly reviewed and any detected failures or degradations that can cause failures are corrected in the system [9, 10].

- Age-based maintenance is one of the most widely used maintenance strategies in terms of component age. The main idea is that the component is

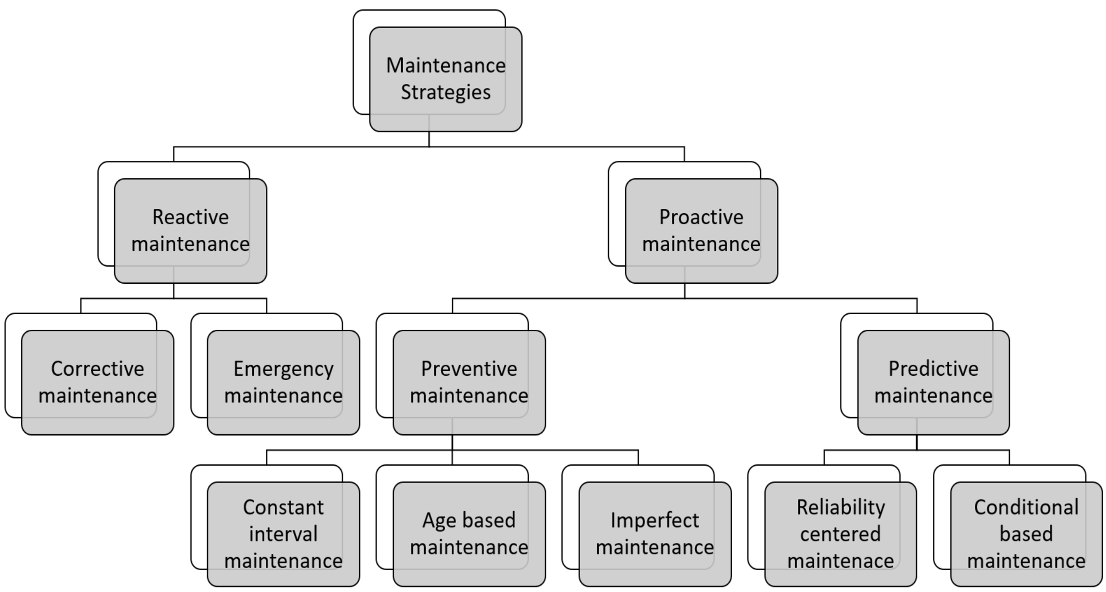

Figure 1.1: Taxonomy of maintenance strategies.

changed or repaired at the time of specific age t at $t \in T$ or at the first failure many T time horizon. Then, next preventive maintenance is scheduled to t units later [11, 12].

- Imperfect maintenance is defined as an action where the system is somewhere between "as good as new" state and "as bad as old" state. Maintenance of a system that is broken is generally insufficient. After maintenance has been completed the system will be new, but not as good as younger. Imperfect maintenance studies show an important improvement in reliability and maintenance theory [13, 14].

On the other hand, predictive maintenance differs from preventive maintenance at the point of scheduling of maintenance activities without degradation or failure. Preventive maintenance activities occur at fixed time intervals, while predictive maintenance activities happen on the dynamic times' intervals. They determined adaptability in predictive maintenance. Predictive maintenance strategy predicts the state of the components when maintenance needs to be carried out. Prediction of future faults ensures that maintenance is planned before failure occurs [15].

Predictive maintenance is divided into two parts as reliability centered maintenance and condition-based maintenance as shown in Figure 1.1.

- Reliability- maintenance is a technique used to develop cost-effective maintenance plans and evaluation criteria to perform, repair and maintain the functional capability of the equipment. Its main purpose is to reduce the cost of maintenance by planning appropriate preventive maintenance work to achieve these functions by focusing on the most essential functions of the system. [16, 17].

- Condition-based maintenance is a decision-making strategy in which maintenance decisions are determined by observing the state of the system or components. The system state is continuously monitored and measured by the specific parameters of the system or application. In other words, conditionally-based maintenance is a way of maintenance that is produced according to the measured values on the component or measurements made on the observation [18, 19].

Nowadays, It is expected to have a direct effect on the maintenance strategy is expected as the availability of new maintenance techniques and the economic consequences of maintenance actions are understood. Various maintenance strategies can be considered to trigger proactive or reactive maintenance interventions in one form or in another. [3].

1.2 Multi-Component Systems

In the complex system, components affecting each other and the system becomes complicated and it gets difficult to take a maintenance decision. Complex systems have many components that are dependent or not. To reduce maintenance cost and time, it is important to specify which types of dependencies exist between components. Dependency on the components can be divided into three different types: one of them is structural, the others are stochastic and economic [20].

- Stochastic dependency
  This dependency considers the effect of a component's degradation on the lifetime distribution of other components. It is divided into two categories. These are Type I failure interaction and Type II interaction. In the case of Type II failure interaction, if a component has a failure, other components may to certain failure probability. In Type II failure interaction, if a component has a failure, this affects the failure rate of one or more component(s) or cause over-dimensional stochastic damage (shocks) on them.

- Structural dependency
  According to this dependency, before the replacement or maintenance of defective components, it requires the replacement of some other working

components. If components have structural dependencies, they cannot be repaired independently. Therefore, this is not a dependency on failure, it is a dependency on repair.

- Economic dependency
  This is the type of dependence that causes grouping maintenance on components to result in either cost savings or higher costs compared to individual maintenance. This dependency is divided into two categories based on the cost of grouping maintenance: Positive economic dependency provides cost savings, negative economic dependency causes cost increase. Both positive and negative economic dependency corresponds k out of n systems. In the case of $n = k$ serial system, there is a positive economic dependency, $(n > k)$ means that there is a positive economic dependency when a component fails. And following this there is redundancy. Also, there is a negative dependency on the system as long as it is run. When optimizing maintenance in k out of n systems, the calculation of downtime costs is a problem. Because failure of a component does not lead to direct system failure.

In multi-component complex systems, it is quite conspicuous to define and model the dependency between components and the cause-effect relationship of this dependency. This is very important to identify dependencies between components and cause-effect relationships for reliability, safety analysis, and maintenance. Many methodologies have been applied and experienced for static and dynamic systems. There are Bayesian networks (BNs) [21], fault tree (FT) [22] and decision diagrams (DDs) [23, 24] using static models. Most of the methodologies mentioned are based on the combination between probability theory and graphical presentation theory. Within these, generally directed acyclic graphs (DAGs) are used to represent the system using nodes and arrows; where the nodes represent the variables in the system and the arrows define the relationship between the nodes through conditional and transition probabilities.

In real life, most of the systems are dynamic, so these methodologies have been expanded with time. Expanded methodologies include: Dynamic Bayesian networks (DBNs) [25], Dynamic decision networks (DDNs) [26], Dynamic fault trees (DFT) [27]. The main different point between static and dynamic systems is the existence of the concept of ageing or deterioration of the components in a dynamic system. In other words, the state of the variables may change from one state to another according to the probability distribution in the time. Also, DBNs use transition possibilities and have the flexibility to model dependencies between components easily, it is very easy to implement in complex systems.

1.3 Thesis Objective

The objectives of the project are different from the maintenance problems discussed in the literature. Also, the assumption that component states are fully observable may not be realistic for most systems. In this thesis, our aim is to develop original developed corrective, proactive and opportunistic maintenance strategies for a multi-component system where partial observations and dependencies among its components can be seen. Another objective of the thesis is to analyse the performances of the proposed strategies on an empirical multi-component system with partial observations in a finite planning horizon with Dynamic Bayesian networks (DBNs). We will also develop a DBN model for a real-life maintenance problem and give insights for the implementation of the proposed strategies and methods.

1.4 Thesis Motivation

In order to understand the state of multicomponent complex systems, we first realize the possibility of failure of components without any maintenance. Figure 1.2 shows the results of this prognosis without any maintenance. As expected, the possibility of failure increases when no maintenance is planned. We see a decrease in the probability of failure of the components undergoing a maintenance operation. Figure 1.3 shows the prognosis results. Because a replacement is assumed to be perfect maintenance when a component is changed over a period of time, the failure probability of this component is reset as shown in Figure 1.3. This result shows us how important it is to take maintenance decisions. The result provides us with the motivation of creating different maintenance strategies in this thesis.

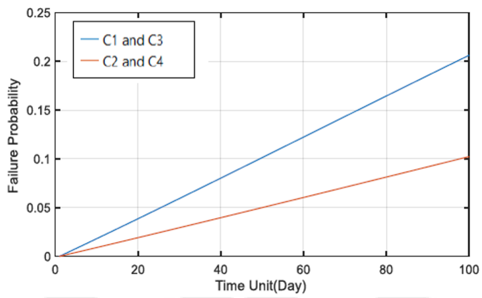

Figure 1.2: Component failure trend without maintenance

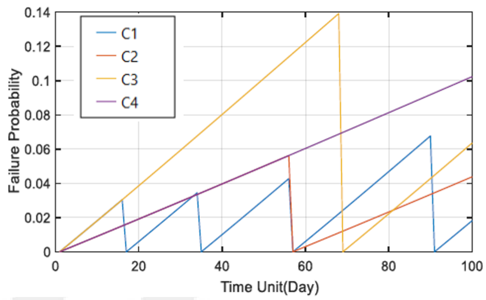

Figure 1.3: Component failure trend with maintenance

1.5 Thesis Outline

This study is organized as follows. In Chapter 2 presents related literature about the maintenance, reliability, maintenance strategies, applying them on a multi component complex system, dependencies between the components and approaches. We will give details about the methodology in Chapter 3, including the BNs and DBNs. In Chapter 4 we will give the details of the definition of the problem, presentation of the multi-component system with its main components, and assumptions made. Then, we will present the proposed solutions related to the maintenance strategies in Chapter 5. We will give our computational results and we examine these in Chapter 6. We develop a DBN model for a real-life maintenance problem in Chapter 7. Finally we conclude our work in Chapter 8.

Chapter 2

Literature Survey

Recently, there has been a great concern in the maintenance and solving the problems of complex systems. The reason is that the industry has started to be composed of very complex systems with highly interactive components. In order to measure the success of complex systems, some aspects have been defined as reliability and usability. Reliability is the probability that a system (part or component) performs its intended task under specified conditions for a given time interval. Availability is the percentage of time that a component or system is in its required function state.

This chapter provides a review of the following topics: Maintenance decisions, maintenance strategies, dependencies among components and probability modelling in complex systems.

2.1 Maintenance Decisions and Maintenance Strategies in Complex Systems

Reliability and maintenance are two basic concepts to be used in industry. There are many strategies and approaches that are recommended in the literature retailed with these fields.

Gupta et al. [28] studied the issue of allocation of repairable components as a multi-objective optimization problem. They discussed two different models.

These are reliability effective model and maintenance (cost and time spent), effective models. These two models have been formulated as multi-objective nonlinear programming (NLP) and solved by a fuzzy goal programming algorithm in the mathematical programming solver LINGO.

Chockie et al. [29] examined four organizations (U.S. Air Force program, U.S. Navy ballistic submarine program, U.S. commercial aviation industry, and the Japanese nuclear power industry) to assess the system and component ageing degradation in the nuclear industry. The selection of critical components defined as system analysis, performance analysis and observation of system ageing through the development of appropriate preventive (time-based) and forecasting (condition-based) maintenance tasks in the system. Lapa et al. [30] purposed to increase the availability of the nuclear power plant by optimizing the preventive maintenance plan. They used the genetic algorithm and probabilistic security in the optimization. The genetic model has unrestricted optimization that allows changes in maintenance plans.

Carazas et al. (2009) proposed a method for assessing the reliability and usability of gas turbines in power plants. The method seemed appropriate for interrelated components in systems. The method is based on reliability concepts. These concepts allowed the identification of critical components for maintenance and they defined the system reliability and usability. They used reliability-centered maintenance to improve system reliability and reduced unexpected failures of critical components [31].

Kothamasu et al. considered prognosis and it was a difficult task that required precise, adaptive and intuitive models to predict future machine health conditions. A large number of modelling techniques have been proposed in the literature and applied in practice. This article reviews the philosophies and techniques that focus on improving reliability and reducing unscheduled downtime by monitoring and predicting the health of the machine [4].

In recent years, the prognosis has been fulfilled frequently in maintenance planning. Lebold et al. defined prognosis as one of the most important methods for proactive maintenance. It is used to estimate the remaining life of a component or a system [32]. Also, Muller et al. proposed a new prognostic model for the resolution of metal coils life experience. This prognostic model included both probabilistic approach and dynamic monitoring [33]. Besides this, Tiddens et al. also discussed prognostic methods as they have been extensively studied, but are rarely used by companies. The authors explain how companies can apply prognostic technologies [34].

In another study, a prognostic model used dynamic Bayesian networks was proposed for a system [35]. It was also used to ensure prognosis, reliability, performance, and safety of complex systems. An evaluation model was developed using Dynamic Bayesian Networks (DBNs) for a gas turbine compressor system. The ant colony algorithm is also used to obtain propagation paths of errors [36].

Sharma et al. studied a literature review and future perspectives on maintenance optimization. These activities were preventive maintenance, corrective maintenance, and predictive maintenance. Also, these maintenance models included the analytical hierarchy process, the Bayesian approach, the Galbraith information processing, and genetic algorithm. There was a new trend towards the use of simulations for maintenance optimization that changed the appearance of maintenance [37].

A survey was conducted to investigate maintenance policies in degradation systems [38]. An effective maintenance strategy has been developed by establishing various maintenance policies in terms of system performance, maintenance costs, maintenance times and system reliability. The purpose of maintenance policies was to increase the average time between failures and the frequency of failure that cause maintenance to reduce system reliability, availability, and downtime. In this paper, the authors examined the stochastic behavior of the system under various stock policies and determined the optimal maintenance policies. In general, the most appropriate maintenance policy determined by achieving minimum maintenance costs, maximum system reliability and minimum maintenance time.

An opportunistic predictive maintenance-based DBN-HAZOP model implemented for a multi-component system in real life [39]. Two approaches presented, as a local predictive maintenance approach and a global opportunistic predictive maintenance approach. Then, an effective maintenance policy that integrated these approaches ensured optimum maintenance time, reliability and maintenance cost. Also Hu et al studied DBN based failure prognosis method considering the response of protective layers for the complex industrial systems. This study about failure prognosis which generally considers only dependencies of components. But it was important that defining protective layers and its effects on the system to make the failure prognosis analysis more accurate [40].

The article by Verbert et al. was about condition-based maintenance but his article was studied on last-minute maintenance and consider only one thing such as maintenance type, maintenance time or grouping maintenance etc. In this article, a model which included all of the above parameters was studied. Thanks to this method, what type of maintenance action was required and what time it should have been done could be decided at the same time. Besides this, combining or spreading components to maintain could be considered. This means that this article approached the maintenance both economic dependence and structural dependence of components [41]

Melani et al. studied on Criticality-based maintenance of a coal-fired power plant. In this article, the authors handled the components risks in a lot of ways such as human life risk, environmental risk, loss of production, dependency risk etc. Also, they show how many of methodologies cpıuld be combined. Besides, as the multi-criteria optimization method, they used the Analytic Network Process instead of Analytic Hierarchy Process which was easier [42].

2.2 Dependencies among the Components and Probability Modelling in Complex Systems

In recent years, increasingly complex systems have become important in the maintenance of policies. Therefore, studies on maintenance policies are increasing in the literature. Because of the complexity of systems, dependencies between components have increased. In a study, they developed a dynamic predictive maintenance policy for complex multi-component systems using different dependencies between components. This policy collected information about the useful life of a component and its degradation. Then, schedule of the maintenance policy was updated according to new information [43]. In another study, they proposed maintenance policy optimization for multi-component systems. They considered the degradation of components and imperfect maintenance actions. They used a clustering method to group components with stochastic economic dependencies [44].

There are three dependencies between components. These are structural, economical and stochastical dependencies. One of the most studied in the literature is economic dependence [45]. In the literature, the number of studies for more than one type of dependence is quite low. Scarf and Deara discussed structural and economic dependence together [46]. In addition, almost all of them made maintenance autonomy under the assumption of an infinite planning horizon in the studies on maintenance of multi-component systems to facilitate mathematical analysis. Thus, it was possible to extract analytical expressions for optimal control parameters and optimal cost. The finite-horizon model could be solved within a reasonable period of time [47, 48] but using the intuitive methods increased the size of the problem increases [49, 50, 51].

Up to now, none of the above-mentioned studies related to maintenance of multi-component systems have used predictive maintenance models that use forecasting, predictive information, or predictive useful life estimation. Last studies began to be encountered in times. Tian and Liao studied the situation-based maintenance optimization of multicomponent systems that were economically dependent on the components [52]. Bouvard et al. developed a dynamic conditional-based maintenance planning model for multi-component systems [53]. Hong et al. developed an optimal status-based maintenance strategy for multi-component systems with dependent stochastic failures [54]. In particular, Camcı showed that when the systems with interdependent components are taken into consideration, predictive maintenance methods using predictive information instead of threshold maintenance policies were more advantageous [55].

Determining the dependencies between components in complex systems is very important. They consider cause-effect relationships themselves. They are particularly important in reliability, safety analysis, and maintenance. In this area, researchers developed various approaches. These approaches were used to describe these relationships, such as event tree, fault tree and bow tie in literature. In a study, they developed fuzzy fault tree analysis for failure probability analysis. This method determined the main cause of accidents in chemical storage tanks[56]. In another study, they proposed a new methodology that was used production paths and the most dangerous equipment of accidents. They were used event tree in the process industry based on the example of the tank farm case study [57]. The other approach was bow-tie. It was used for dynamic risk analysis in another study in literature [58].

Recently, Bayesian Networks (BNs) become very popular in addition to all these approaches. Many researchers compare BNs with all of the aforementioned approaches. The reason is that the other aforementioned approaches compare different analysis methods such as reliability, safety, and maintenance. Bayesian networks provide the possibility of failure, predict the future of systems and allow them to update the probabilities of failure easily. Moreover, the modelling capacity of BNs is more flexible than other approaches. In a study, authors compared differences between bow-tie and BNs approach to dynamic safety analysis of process systems [59]. They indicated that the approaches such as bow tie, event tree, and fault tree were based only on the static nature of the components and that was very difficult to update the probability of events.

In other respects, the structure of BNs aren't based on a single output and include probabilistic dependency relationships of all variables in the system. BNs provide a great advantage in the analysis of complex systems with particular uncertainty. In a study, they used BNs modelling for maintenance planning in a manufacturing industry. They provided the simultaneous effect of various parameters such as average downtime, the arrival rate of defects, failure rate, inspection period and dependencies between components at the same time [60]. Also, another study provided a diagnostic advisory framework for improved operational availability in complex nuclear plants. Systems used the Bayesian Belief networks (BBN) [61]. In another study, authors represented a nuclear system using the BNs. They offered a solution to BNs as a log-linear model [62].

Dynamic Bayesian Networks (DBNs) are extended forms of BNs by adding the time dimension to describe the dynamic behavior of random variables [25]. Li et al. proposed a new methodology for a multi-state element reliability modelling and analysis based on the integration of the Markov process and DBNs. They used the Markov process to determine the state of transition relations and then according to these relations, they built a DBN model considering perfect repair, imperfect repair, and conditional based maintenance [63]. Also, Hu et al. had a series of studies on this subject. One of these was about planning opportunistic predictive maintenance for a gas turbine compressor system using HAZOP and DBN. HAZOP was used to analyse and learn the system, and then a DBN model was created based on these information [39].

Chapter 3

Methodology

Probabilistic graphical models (PGMs) are strong frameworks for representing complex areas using probability distributions with numerous applications in computer vision, machine learning, computational biology, and natural language processing. These models provide a flexible framework for modelling large random variable collections with complex interactions by combining probability theory and graph theory. In this chapter, we explain Bayesian Networks and Dynamic Bayesian Networks which are to be used for representing deterioration and dependencies among system components.

3.1 Bayesian Networks

Bayesian Networks (BNs) are known as belief networks. They are members of the family of PGMs which are used to represent information about the imprecise definition of the set of the problem of interest. In these models, nodes refer to random variables, while the edges between the nodes indicate the probabilistic dependencies between random variables. BNs have a Directed Acyclic Graph (DAG) structure. They provide an efficient representation of the multivariate probability distribution of a set of random variables and the ability to perform various calculations via this representation. Bayesian networks are an important method in expert systems, which allows unquestioned expert opinions to enter the system [64].

A BN represents the causal probabilistic relationship of the set of random variable. It provides the representation of a joint probability distribution [65]. BNs include directed acyclic graph and a set of conditional probability distributions. They have the qualitative and quantitative part. Qualitative part is a directed acyclic graph and quantitative part constitute the conditional probability distributions. $X = (X_1, X_2, ..., X_n)$ be random variables having a set of conditional probability functions (CPFs). The joint probability function of the random variable X [66] can be formulated as in Equation 3.1.

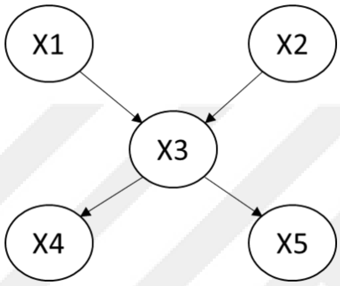

Figure 3.1: An example BNs over the nodes

$$P(X_1, ..., X_n) = \prod_{i=1}^{n}(P(X_i|pa(X_i))) \tag{3.1}$$

An example of a BN over the variables $X = (X_1, X_2, X_3, X_4, X_5)$ is shown in Figure 3.1. X_1 and X_2 are the parents of X_3 or X_3 is the child of X_1 and X_2. Similarly X_3 is teh parent of X_4 and X_5. X_1 and X_2 don't have ancestors, also X_4 and X_5 don't have descendants. Considering the conditional property of BNs, we can define joint probability as in Equation 3.2.

$$P(X_1, X_2, X_3, X_4, X_5) = P(X_1) * P(X_2) * P(X_3|X_1, X_2) * P(X_4|X_3) * P(X_5|X_3) \tag{3.2}$$

There are various inference algorithms to calculate the marginal probabilities for each unobserved node that is informed of the state of the nodes that are not monitored. Bayesian networks have three important inferences. There are "Causal or

Top-Down Inference", "Diagnostic or bottom-up inference" and "Explaining away inference" [67]. Bottom-up inference collects observations to determine current conditions. Top-Down inference uses current situations as evidence to identify future situations. Explaining away inference is a common reasoning model in which alternative reasons to verify the cause of an observed or believed event diminishes the need for search. [68].

3.2 Dynamic Bayesian Networks

Dynamic Bayesian networks are the added form of the time dimension to Bayesian networks and direct graphical models of stochastic processes. They generalize hidden Markov models and linear dynamic systems by representing the complex state in terms of state variables that can have complex dependencies. The graphical structure provides an easier way of specifying this conditional independence. Hence, the compact parameterization of the model is ensured. [69].

The BNs formulation involves a joint probability distribution (JPD) $P(X)$ of a set of random variables $X = \{X_1, ..., X_n\}$. The joint probability distribution expands with dynamic processes in the DBNs. This dynamic process includes the joint probability distribution of the set of the variables $X[t] = \{X1[t], ..., Xn[t]\}$. In the DBNs, JPD is represented similarly as in BNs. Equation 3.3 formulates the JPD for the dynamic process $X[t]$ in the finite time interval $[1, T]$.

$$P(X_1[1], ..., X_n[T]) = \prod_{t=1}^{T} \prod_{i=1}^{n} (P(X_i[t]|pa(X_i[t])) \tag{3.3}$$

The graphical structure of DBNs can be seen with a combination of many BNs associated by temporal arcs. Each of these static networks is called a time slice of the DBNs. DBNs have an initial network and a transition network. Transition networks provide the dynamic process. In these networks, initial network is represented as B_1 and transition network is prepresentd as $B_{\rightarrow}$. By definition, DBNs are based on the stationary assumption. Therefore, DBNs are identical according to structure and parameters for each time slice. DBNs move to the next time interval by the transition network $B_{\rightarrow}$. This network encodes the time-change transition probability distribution in the two time slots $P(X[t]|X[t-1])$ for $t > 1$. Because of the first order Markov assumption, we can define the transition network on two time slices of variables. B_1 defines the structure at time $t = 1$ and encodes the distribution on variable $X_{[1]}$. In a certain finite planning horizon, unrolling the transition network provides a joint probability distribution. JPD is calculated as in Equation 3.4 [70].

$$P(X[1], ..., X[T]) = P_{B_1}(X[1]) \prod_{t=2}^{T-1} (P_{B_{\rightarrow}}(X[t]|X[t-1])) \tag{3.4}$$

Markovian processes use the Markov property to make the inference mechanism easier. The Markov property means that when the current situation is given, future situations are independent of past situations. Thanks to this property, posterior probability can be calculated using the prior probability with transition probability. The DBN is modelled, as shown in Figure 3.2.

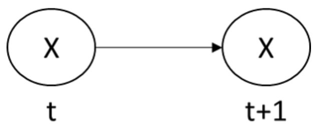

Figure 3.2: An example DBNs with the two time slice

In the example given by Figure 3.2, the DBN model has a variable with two-time slices. The first time slice shows the variables in the current time t and the second time slice shows the variables in the next time period $(t + 1)$. This model allows calculating the distribution of the variable by inference. A variable ${X_i}^{(t+1)}$ is defined by the current state in the current time ${X_i}^{(t)}$. The CPT is defined by the transition probability matrix which is represented in Table 3.1.

For calculating the marginal probability for every node, several different inference algorithms can be benefited. The main type of query for the model calculates

Table 3.1: CPT defining the transition probability matrix of markovian process.

${X_i}^{(t)}$	$P({X_i}^{(t+1)} = 0)$	...	$P({X_i}^{(t+1)} = n_i)$
0	$P({X_i}^{(t+1)} = 0)\|{X_i}^{(t)} = 0)$	...	$P({X_i}^{(t+1)} = n_i)\|{X_i}^{(t)} = 0)$
...	...	...	...
n_i	$P({X_i}^{(t+1)} = 0)\|{X_i}^{(t)} = n_i)$	...	$P({X_i}^{(t+1)} = n_i)\|{X_i}^{(t)} = n_i)$

the marginal distribution of a node X_i at a time-dependent on other nodes in times $1, ..., T$ [71]. The most common type of query is "filtering, "smoothing" and "prediction" of which the explanations are given below.

- If $T = t$, the query is a filtering.
- If $T > t$, the query is a smoothing.
- If $T < t$, the query is a prediction.

There are several exact and approximate inference algorithms in the DBNs. Exact inference is used when the analytical form of the problem exists and when the calculation state is possible. It can be used with directional acyclic graphs. The main exact inference algorithms are a forward-backward algorithm (FB), frontier algorithm, interface algorithm. Approximate inference is used when the analytical form is not available or the time required for the final solution is too long. The main approximate inference algorithms are The Boyen-Koller (BK) algorithm, The factored frontier (FF) algorithm and Loopy belief propagation (LBP) [25].

Chapter 4

Problem Definition and Empirical Model

In multi-component systems, there are relationships and dependencies to be defined between components. These can be very complex. A smaller empirical dynamic model was developed to examine the performance of the designed maintenance strategies. In this section, a DBN model is designed to reflect the relationships between the components. Also, the problem definition and the assumptions used in the model are given in this chapter. According to these assumptions, the detailed construction of the DBN model and all the components of it are explained in detail. The probabilities of each component are calculated according to the MTBF. Besides this, we also consider the costs related to the maintenance of the components.

4.1 Problem Definition

In a complex multi-component system, maintenance decisions are difficult to plan and implement. In addition, high costs arise by reason of the downtime and maintenance costs of the system caused by reactive maintenance. Reducing maintenance costs and developing proactive or opportunistic maintenance are very important for complex systems. Probability chart models can be used to determine to stop time and subsequent downtime. These models are quite difficult and complex processes. Thanks to the flexibility of modelling DBNs, we can easily model multi-component complex systems. The assumption that component states are fully observable in multi-component DBN models may not be realistic for most systems. In this study, reactive, proactive and group maintenance policies for a multi-component complex system have been developed. Their performances are analysed on an empirical DBN model on a finite planning horizon.

4.2 Assumptions of the Empirical Model

The assumptions made in the experimental DBN model are as follows:

1. One of the assumptions of the thesis is a multi-component complex system where partial observations and structural and random dependencies between components can be seen.

2. In the thesis, we assumed that the components and processes are hidden and can be inferred only from the observation node.

3. In the DBNs, it is not possible to define the actions. But we define actions with probabilistic nodes in the DBN model.

4. Also all components have certain maintenance durations. The ageing of the components continues to progress in the DBN model as long as the system is running in real life. However, when the system halts, ageing of the components is given a break. That's why we have assumed that DBN and system time are separate. With this assumption, when the system stops due to maintenance, the ageing times of the components also stop.

5. The system starts at its best state at the beginning of the planned maintenance horizon.

6. Since the planned maintenance horizon begins between the two revision maintenances, it is quite possible to assume the constant failure rate. Also, we know the MTBF of each component. We are able to use the DBN model with a constant failure rate.

4.3 DBN Modelling

Multi-component systems can be very complex based on the relationships and dependencies among the components. A small sized empirical dynamic model was developed to examine the performance of the designed maintenance strategies. We construct the model in the GeNie modular [72]. The initial, causal and the transitional probabilities of the components are defined rationally. In the empirical model, the maintenance costs are determined by using both the literature and real-life problems.

4.3.1 Representation of the DBN model

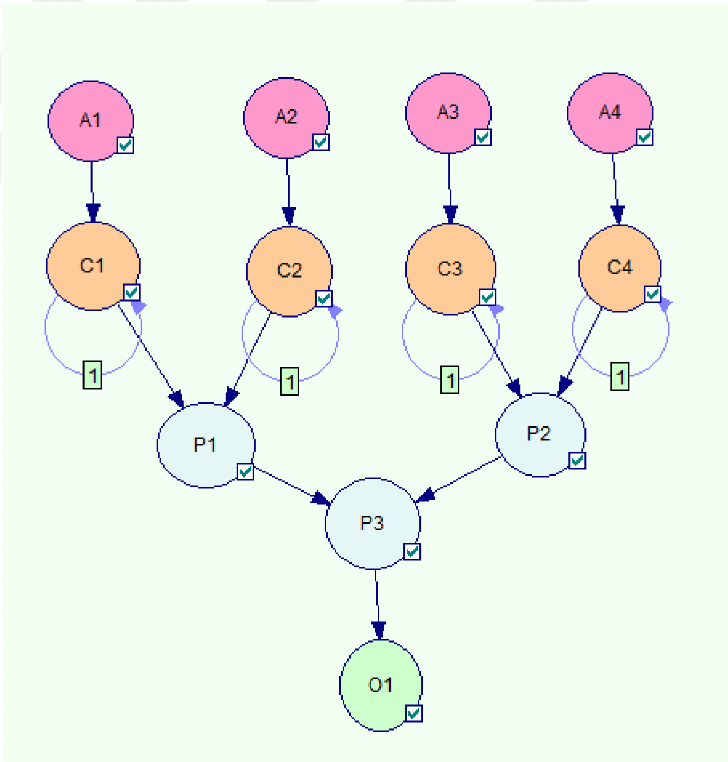

Figure 4.1: The empirical DBN model

In the empirical model, there are four components nodes, three process nodes, and one observation node. The model is shown in Figure 4.1. It is impossible to observe component nodes and manipulate nodes directly. However, the states of processes and components can be estimated via the observation node. It is configured that all components $C1$, $C2$, $C3$, $C4$ can be replaced with action nodes $A1$, $A2$, $A3$, $A4$ at any time interval. All component nodes and the observation node have three states, process nodes and action nodes have two states. The state space of all nodes are represented in Table 7.1.

Table 4.1: Information of Nodes in the empirical DBN Model

Node type	**Nodes**	**State space**
Action nodes	$A1$, $A2$, $A3$, $A4$	$\{Y, N\}$
Component nodes	$C1$, $C2$, $C3$, $C4$	$\{W, D, F\}$
Process nodes	$P1$, $P2$, $P3$	$\{W, F\}$
Observable node	$O1$	$\{G, Y, R\}$

In the model, Y represents the "yes" state and it means "replace", N represents the "no" state, it means "do nothing", W represents the "work", D represents the "degradation", F represents the "failure", G represents the "green", Y represents the "yellow" and finally R represents the "red" states according to the state space table. All components can be degraded over time, thus are modelled with temporal nodes. Temporal relations are modelling using the circular arrows represented with "1" in Figure 4.1. Components can be replaced with the help of the action nodes which are directly linked to the action nodes. The conditions of the intermediate process nodes $(P1, P2)$ are determined as the result of the interaction of the preceding components and their interactions. The observation node $O1$ is created to gather information provided by the main process node $P3$ in the model.

4.3.2 Probabilities in the DBN Model

Initially, all component nodes were started from their work states $(W = 1, D = 0, NW = 0)$. On the other hand, actions nodes have symmetric CPT $(Y = 0.5, N = 0.5)$. The conditional probability tables are given in Tables 4.2, 4.3, 4.4 and 4.5 for process nodes and the observation node respectively. The temporal property of the component nodes is defined in the transition probabilities of the components. Table 4.6 and Table 4.7 include the transition probabilities of C1, C3 and C2, C4 respectively. As can be seen in the table, the probability of degradation of C1 and C3 components is higher than the probability of degradation of C2 and C4 components.

Table 4.2: Conditional probability of P1

C2	**W**			**D**			**NW**		
C1	**W**	**D**	**NW**	**W**	**D**	**NW**	W	D	NW
W	1	0.4	0	0.8	0.2	0	0	0	0
NW	0	0.6	1	0.2	0.8	1	1	1	1

Table 4.3: Conditional probability of P2

C4	**W**			**D**			**NW**		
C3	**W**	**D**	**NW**	**W**	**D**	**NW**	**W**	**D**	**NW**
W	1	0.8	0	0.4	0.2	0	0	0	0
NW	0	0.2	1	0.6	0.8	1	1	1	1

Table 4.4: Conditional probability of P3

P2	**W**		N	
P1	**W**	**NW**	**W**	**NW**
W	0.999	0.4	0.8	0
NW	0.001	0.6	0.2	1

Table 4.5: Conditional probability of O1

P3	**W**	**NW**
G	0.9	0
Y	0.09	0.01
R	0.01	0.99

Table 4.6: Transition probabilities of C1 and C3

Reliated action node	**Y**			**N**		
(Self)[t-1]	**W**	**D**	**NW**	**W**	**D**	**NW**
W	1	1	1	0.994	0	0
D	0	0	0	0.004	0.996	0
NW	0	0	0	0.002	0.004	1

Table 4.7: Transition probabilities of C2 and C4

Reliated action node	**Y**			**N**		
(Self)[t-1]	**W**	**D**	**NW**	**W**	**D**	**NW**
W	1	1	1	0.997	0	0
D	0	0	0	0.002	0.998	0
NW	0	0	0	0.001	0.002	1

4.3.3 Maintenance Costs

The maintenance costs of each component, the production loss cost occurring when the system stops and the waiting periods during maintenance of the components are given in Table 4.8. Total maintenance cost is calculated using Equation 4.1. $Cost_i$ refers to the total cost of the maintenance performed to component i. This cost consists of the cost of repair applied to components and production loss cost. RC_i refers to the cost of the repair applied to components. This cost includes just maintenance-related costs. dt_i refers to maintenance duration time. This time shows the duration from the maintenance start time to the maintenance end time. LP_i refers to the cost of the production loss. Production is not possible due to system failure. Therefore, the daily profit of the production loss cost is unbeatable.

$$Cost_i = RC_i + dt_i * LP_i \tag{4.1}$$

Table 4.8: Maintenance costs and durations

	Reactive Maintenance			**Proactive Maintenance**		
Component	$RC_i(TL)$	$dt_i(day)$	$LP_i(TL)$	$RC_i(TL)$	$dt_i(day)$	$LP_i(TL)$
C_1	2,000	2	100,000	1,000	1	25,000
C_2	4,000	2	100,000	2,000	1	25,000
C_3	6,000	2	100,000	3,000	1	25,000
C_4	8,000	2	100,000	4,000	1	25,000

Chapter 5

Proposed Solutions

We have developed proactive and reactive maintenance strategies for the maintenance of a multi-component dynamic system and proposed four methods for deciding on the maintenance activity. Our goal is to minimize the total maintenance cost at a certain discrete time planning horizon. Then, we have simulated the developed maintenance strategies using the empirical DBN model and analysis their performances.

Proposed methods are implemented under different maintenance strategies to select the repairable component(s) to be maintained. Maintenance strategies determine the time periods at which reactive or proactive maintenance is going to be done. Each proposed method is implemented in each developed maintenance strategy to determine an effective maintenance activity.

In this chapter, we briefly give the general framework of the simulation and explain how to choose the selected repairable component or components in Section 5.1 and Section 5.2. Then, we examine the proposed methods, the developed algorithms and how they are applied in the model in Section 5.3. After that, we talk about the proposed to maintenance strategies in the Section 5.4.

5.1 General Framework of the Simulation

Figure 5.1 depicts the general simulation framework. In this framework of simulation, an observable node is simulated at each time period according to the probability distribution in this planning horizon. Undesirable means "R", this expression almost indicates a failure system state. Thus, at that time point, maintenance action(s) should be performed under reactive maintenance philosophy. on the other hand, maintenance decision is also taken at a time point if one of the proactive maintenance conditions occurs at that time. The component to be replaced is selected after a maintenance decision is taken. In the simulation, it applies one of the methods for selecting the repairable component(s), and the evidence is updated as maintenance is done. The time is updated by adding the maintenance duration to itself. Then, another observation is simulated, that takes into account the evidence, according to the probability distribution for the observable node. If this observation is not desired again, it verifies a different maintenance action from the replaceable components left at that time. In the other, it increases the time period one by one and continues with the next period until it reaches the end of the planning horizon.

5.2 DBN Time versus Real Time

In this section, the difference between DBN and real-time will be explained. This is due to the need for a certain repair time of the component to be serviced. Two different times are adapted to prevent ageing during the component repair period. At these times, ageing of the components is ceased while the planned time horizon of the system proceeds over real time. With this recommendation, the ageing of the components during the maintenance process has been stopped. With this adaption, real-life problems can be easily modelled with DBNs. The general mechanism of the DBN time and real-time is given in Figure 5.2. In this

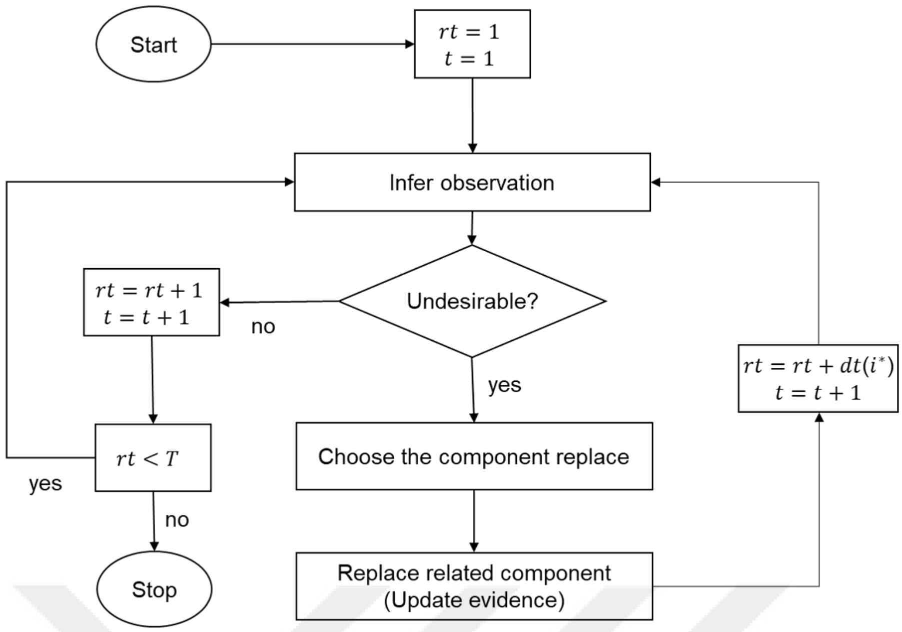

Figure 5.1: General framework of the simulation

mechanism, "t" represents "DBN time" and "rt" represents "real time". Also, "dt" represents duration time of the maintenance of the component selected.

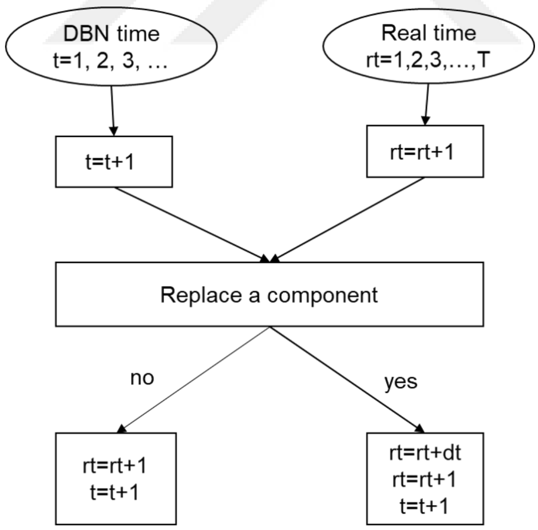

Figure 5.2: DBN Time vs Real Time

5.3 Proposed Methods

For a multi-component dynamic system, we proposed four approaches within the maintenance strategies and apply them in the empirical model presented in Chapter 4. Main goal in this study is to minimize the total cost of maintenance on a particular discrete time planning horizon. We simulate the proposed maintenance methods using the experimental DBN model. The proposed maintenance methods use a different efficiency measurement to select the most appropriate component(s) at a maintenance time to minimize the total maintenance cost in a given the planning horizon.

Proposed maintenance methods are based on fault effect or replacement effect. We consider each effect in two versions which are myopic and look-ahead. These methods are first encountered in [73, 74]. In this study, we extend these methods and apply them under various maintenance strategies in a given planning horizon.

Proposed maintenance methods select the component to replace using the efficiency measure ef_{it} when a maintenance decision is taken. This is realised either when a proactive maintenance is desired or when the system has an undesirable observation at a certain time in the planning horizon. Fault effect methods select the component for replacement as given in Equation 5.1. Replacement effect methods select the component for replacement as given in Equation 5.2.

$$i^* = argmax\{ef_{it}\} \tag{5.1}$$

$$i^* = argmin\{ef_{it}\} \tag{5.2}$$

5.3.1 Fault Effect Myopic Method (FEM)

The FEM method is one of the proposed methods for selecting the component to maintain when we take a maintenance decision. This maintenance method is based on fault effect. This method is searched by looking at myopic. The method of myopic is only looking at the relevant moment. Therefore, all maintenance activities are carried out instantly. The method chooses the component according to the maximum probability of conditional deterioration. The purpose of this method is to find the component that has the most explanatory power of the system malfunction and make maintenance to this component.

The method analyses the condition of system components when an undesirable observation is collected in t time period. This analysis considers the failure probability of the components based on the evidence accumulated and the condition that a red signal is observed. If take a maintenance decision, the method calculates an efficiency measurement for each component. The efficiency measurement is calculated in Equation 5.3 according to the objective of minimizing the total number of replacements and calculated as in Equation 5.4 according to the objective of minimizing the total maintenance cost. Detailed information about component selection is given in Algorithm 1.

$$ef_{it}^{FEM} = P(C_{it} = \text{“}F\text{”} | \varepsilon \cup \{O_t = \text{“}R\text{”}\}) \tag{5.3}$$

$$ef_{it}^{FEM} = \frac{ef_{it}^{FEM}}{Cost_i} \tag{5.4}$$

Algorithm 1 FEM pseudo-code

1: Calculate $F_{it} = P(C_{it} = \text{“}F\text{”} | \varepsilon \cup \{O_t \leftarrow \text{“}R\text{”}\}) \ \ \forall i \in I^{'}$
2: Calculate $ef_{it}{}^{FEM} \ \ \forall i \in I^{'}$
3: Select $i^{*} = argmax\{ef_{it}{}^{FEM}\}$
4: **return** i^{*}

5.3.2 Fault Effect Look - Ahead Method (FEL)

The FEL method is one of the proposed methods for selecting the components to maintain when we take a maintenance decision. This maintenance method is based on fault effect like the FEM method. This method is searched by looking at look-ahead. The method of look-ahead is looking at the next period. Therefore, all components are examined in period $t+1$ by considering the fault effect of the observation. The purpose of this method is to find and maintain the component that has the most explanatory power at period $t+1$ given a system malfunction.

As we apply this method, we assume the component has a probable failure just at period $t+1$. Therefore, this method takes into account future information. If a system has an undesirable observation in period t, the method selects the maintainable component with the maximum probability of failure in period $t+1$. In Equation 5.5, we calculate the efficiency measurement according to the objective of minimizing the total number of replacement. For the objective of minimizing the total cost, we calculate the efficiency measurement by using the Equation 5.6. The pseudo-code of this version of the selection method is given in Algorithm 2.

$$ef_{it}^{FEL} = P(C_{i,t+1} = \text{“}F\text{”} | \varepsilon \cup \{O_t = \text{“}R\text{”}\}) \tag{5.5}$$

$$ef_{it}^{FEL} = \frac{ef_{it}^{FEL}}{Cost_i} \tag{5.6}$$

Algorithm 2 FEL pseudo-code

1: Calculate $F_{it} = P(C_{i,t+1} = \text{“}F\text{”} | \varepsilon \cup \{O_t \leftarrow \text{“}R\text{”}\}) \ \ \forall i \in I^{'}$
2: Calculate $ef_{it}{}^{FEL} \ \ \forall i \in I^{'}$
3: Select $i^{*} = argmax\{ef_{it}{}^{FEL}\}$
4: **return** i^{*}

5.3.3 Replacement Effect Myopic Method (REM)

The REM method is one of the proposed methods for selecting the components to maintain when we take a maintenance decision. This maintenance method is based on the replacement effect. This method decides on the maintenance action by looking at myopic. The method of myopic is only looking at the relevant period. Therefore, all maintenance activities are carried out focusing on the current period. The method selects the component that improves the system given the condition that the component is replaced at that time period. The purpose of this method is to find and maintain the component that has the most improvement on the observation.

When the system has an undesirable observation based on the evidence accumulated until the period t, this method calculates the efficiency measure using Equation 5.7 if the objective is to minimize the total number of maintenance activities and Equation 5.8 if the objective is to minimize the total cost. If the system is observed in the red state, the method considers all maintainable components and selects the most relevant component that improves the system. The pseudo-code of this method is given in Algorithm 3.

$$ef_{it}^{REM} = P(O_t = \text{“}R\text{”} | \varepsilon \cup \{C_{it} = \text{“}W\text{”}\}) \tag{5.7}$$

$$ef_{it}^{REM} = ef_{it}^{REM} * Cost_i \tag{5.8}$$

Algorithm 3 REM pseudo-code

1: Calculate $F_{it} = P(O_t = \text{“}R\text{”} | \varepsilon \cup \{C_{it} \leftarrow \text{“}W\text{”}\})\ \ \forall i \in I^{'}$
2: Calculate $ef_{it}{}^{REM}\ \ \forall i \in I^{'}$
3: Select $i^* = argmin\{ef_{it}{}^{REM}\}$
4: **return** i^*

5.3.4 Replacement Effect Look - Ahead Method (REL)

The REL method is one of the proposed maintenance methods for selecting the component to be maintained. This maintenance method is based on the replacement effect. This method decides on the maintenance action by looking at look-ahead. The method of look-ahead is focusing the period $t+1$. Therefore, all maintenance activities are carried out by focusing on the next time period. The purpose of this method is to find and maintain the component that has the most improvement on the observation.

The REL method is applied when the system is observed at the red signal and decides to do maintenance under all the evidence accumulated. The component to be maintained is selected according to the minimum efficiency measurement. The efficiency criterion is calculated as in Equation refeq:RELformulawithmaintenancenumber if the objective is to minimize the total number of maintenance activities. On the other hand, if the objective is to minimize the total cost Equation 5.10 is used as the efficiency measure. The pseudo code of how the component selection is done with this method is given in Algorithm 4.

$$ef_{it}^{REL} = P(O_{t+1} = \text{“}R\text{”} | \varepsilon \cup \{C_{it} = \text{“}W\text{”}\}) \tag{5.9}$$

$$ef_{it}^{REL} = ef_{it}^{REL} * Cost_i \tag{5.10}$$

Algorithm 4 REL pseudo-code

1: Calculate $F_{it} = P(O_{t+1} = \text{“}R\text{”} | \varepsilon \cup \{C_{it} \leftarrow \text{“}W\text{”}\}) \;\; \forall i \in I'$
2: Calculate ${ef_{it}}^{REL} \forall i \in I'$
3: Select $i^* = argmin\{{ef_{it}}^{REL}\}$
4: **return** i^*

5.4 Maintenance Strategies

Maintenance is the total activity required to maintain the system or bring it back to the condition necessary for the fulfillment of the production function. Maintenance and its principles have taken an important place since the industrial revolution. It is impressively applied in the field of industry, but due to many reasons and factors such as size, cost, and complexity, it is still a great challenge to implement maintenance activities. Maintenance strategies vary with the basic philosophies used. For example, maintenance time is an important factor. Will the maintenance be made after the problem occurs or when will the maintenance be made if it is applied before the problem occurs? To answer this question is very important.

The multi-component complex dynamic models discussed have addressed these problems. Thus, we have developed effective maintenance strategies to solve these problems and answer the questions. In the given empirical model, the following strategies are implemented:

1. Corrective maintenance (CM)
2. Constant interval proactive maintenance (CIPM)
3. Dynamic interval proactive maintenance (DIPM)
4. Threshold-based proactive maintenance (ThPM)

These strategies use proposed maintenance method to select the appropriate maintenance activity. Maintenance strategies, on the other hand, decide when to take maintenance. In addition, the corrective maintenance strategy has been developed under reactive maintenance modelling, but also CIPM, DIPM, and ThPM have been developed under proactive maintenance modelling. We are giving the details of the implementation and the application of all of these in this section.

5.4.1 Corrective Maintenance Strategy (CM)

Corrective maintenance is the activity to eliminate the malfunction and make the necessary functions of the system after a fault occurs in the system. In the empirical model, the deterioration of the system means that the observation node $O1$ is in the state of "red". Thus, Corrective maintenance methods that can be applied when the system is broken are planned. These maintenance methods are applied by taking into consideration the costs. When the costs are taken into account, the aim is to reach the time horizon at the minimum cost.

The purpose of the corrective maintenance strategy is to perform maintenance using one of the proposed maintenance methods when the system fails during a certain discrete planning horizon. In the corrective maintenance strategy, the system is simulated again after a component is maintained. If a failure is still observed in the system, other relevant components are serviced for replacement.

Furthermore, the system can take a maintenance decision if and only if the eligible component list is not empty. The eligible component list keeps the set of components that have not been maintained at that time point. Also, this maintenance strategy considers the maintenance duration time. Maintenance duration time should be smaller than the planned maintenance horizon. Corrective maintenance strategy can be included using the commands shown in Algorithm 5.

Algorithm 5 Corrective Maintenance pseudo-code

Set rt=1
while rt=1:T **do**
    Set $I^{'} = I$
    Simulate observation node O_t
    while (O_t is "R") and ($I^{'}$ is not empty) **do**
        Apply maintenance method (Algorithm 1, 2, 3, 4) to select i^*
        Calculate $mt = rt + dt_{i^*}$
        if $mt < T$ **then**
            Calculate $Cost_{i^*} = RC_{i^*} + dt_{i^*} * LP_{i^*}$
            Update $\varepsilon \leftarrow \varepsilon \cup \{C_{i^*t} \leftarrow W\}$ ▷ Update evidence list i^*
            Simulate observation node O_t
        Update eligible component list $I^{'} \leftarrow I^{'} | \{i^*\}$
    rt=rt+1

5.4.2 Constant Interval Proactive Maintenance (CIPM)

In this maintenance strategy, maintenance is scheduled at time points in a certain discrete planning time horizon. In this type of maintenance, constant maintenance intervals change according to the needs of the systems. The constant interval maintenance strategy maintains with fixed intervals determined throughout the planning horizon for the system. In addition, the system performs corrective maintenance in the event of failure before reaching the maintenance period. In this case, the maintenance strategy continues to proceed to the next maintenance period without taking into account the period of corrective maintenance.

The purpose of this maintenance strategy is to maintain the system at certain fixed intervals using one of the proposed maintenance methods taking into account the costs of the maintenance of components over a given planning horizon. In addition, this maintenance strategy aims to avoid unforeseen failures and it aims to reduce the maintenance costs caused by unexpected failures. Constant interval proactive maintenance strategy uses Algorithm 6.

Algorithm 6 Constant Interval Proactive Maintenance pseudo-code

Input pci ▷ pci represents constant interval maintenance period
Input $abmt = [pci * 1, pci * 2, ..., pci * \lfloor T/pci \rfloor]$ ▷ $abmt$ represents constant interval maintenance periods array
Set $rt = 1$
while $rt \leq T$ **do**
  Set $I' = I$
  Simulate observation node O_t
  while (O_t is "R" or $abmt(1) \leq t$) and (I' is not empty) **do**
    Update $abmt(1) = [\,]$ ▷ Delete first element of $abmt$
    Apply maintenance method (Algorithm 1, 2, 3, 4) to select i^*
    Calculate $mt = rt + dt_{i^*}$
    if $mt < T$ **then**
      Calculate $Cost_{i^*} = RC_{i^*} + dt_{i^*} * LP_{i^*}$
      Update $\varepsilon \leftarrow \varepsilon \cup \{C_{i^*t} \leftarrow W\}$ ▷ Update evidence list
      Update $rt = rt + dt_{i^*}$
      Simulate observation node O_t
    Update $I' \leftarrow I' | \{i^*\}$ ▷ Update eligible component list
  rt=rt+1

5.4.3 Dynamic Interval Proactive Maintenance (DIPM)

The dynamic interval proactive maintenance strategy maintains the system throughout the specific discrete planning horizon in certain dynamic intervals. The maintenance interval in this strategy changes depending on the last corrective maintenance taken. Due to this feature, after the corrective maintenance, the dynamic maintenance time is shifted. If a fail occurs in the system prior to the next proactive scheduled maintenance, the corrective maintenance of the system is performed. In this maintenance strategy, the next maintenance period is calculated by adding the dynamic interval proactive maintenance period to the current time after a maintenance period. In this way, we have reached a dynamic interval.

The purpose of the dynamic interval maintenance strategy is to prevent frequent maintenance in CIPM by shifting the maintenance period and to reduce maintenance costs resulting from corrective and/or proactive maintenance at certain times in the planning horizon. It also selects the component to be maintained using one of the proposed methods and calculates the maintenance cost of the component. DIPM uses the pseudo-code as shown in Algorithm 7

Algorithm 7 Dynamic Interval Proactive Maintenance pseudo-code

Input $pmt = pdi$ ▷ pdi represents dynamic interval maintenance period
Set $rt = 1$
while $rt \leq T$ **do**
    Set $I^{'} = I$
    Simulate observation node O_t
    while (O_t is "R" or $pmt \leq t$) and ($I^{'}$ is not empty) **do**
        Apply maintenance method (Algorithm 1, 2, 3, 4) to select i^*
        Calculate $mt = rt + dt_{i^*}$
        if $mt < T$ **then**
            Calculate $Cost_{i^*} = RC_{i^*} + dt_{i^*} * LP_{i^*}$
            Update $\varepsilon \leftarrow \varepsilon \cup \{C_{i^*t} \leftarrow W\}$ ▷ Update evidence list
            Update $rt = rt + dt_{i^*}$
            Update $pmt = mt + pdi$
            Simulate observation node O_t
        Update $I^{'} \leftarrow I^{'}|\{i^*\}$ ▷ Update eligible component list
    rt=rt+1

5.4.4 Threshold Based Proactive Maintenance (ThPM)

The threshold-based proactive strategy takes proactive maintenance decision if the system reliability falls below a certain threshold level during the specific planning horizon. This threshold level keeps the system at the desired level. While determining the threshold, a reliability level must be set to meet the system requirements. An unexpected failure may occur in the system even if the system does not fall below the specified threshold level and at that time corrective maintenance is also applied. The threshold level is directly controlled in the empirical system via the main process node $P3$.

This strategy allows us to make a predictive maintenance decision. In this way, the ThPM estimates when an equipment failure can occur and prevents system failure by proactive maintenance. Prediction of future faults ensures that maintenance is performed before a failure occurs. This maintenance strategy aims to reduce the maintenance costs associated with corrective maintenance, as in other proactive strategies. In addition, after it takes the decision on maintenance, it uses the proposed methods to choose the component to be maintained and calculates its cost. Algorithm 8 was used to implement the threshold-based proactive maintenance strategy.

Algorithm 8 Threshold Based Proactive Maintenance pseudo-code

Input thr ▷ thr represents reliability threshold
Set rt=1
while $rt \leq T$ **do**
  Set $I^{'} = I$
  Simulate observation node O_t
  while (O_t is "R" or $P(P_{3t} =$ "W"$|\varepsilon) \leq thr$) and ($I^{'}$ is not empty) **do**
    Apply maintenance method (Algorithm 1, 2, 3, 4) to select i^*
    Calculate $mt = rt + dt_{i^*}$
    if $mt < T$ **then**
      Calculate $Cost_{i^*} = RC_{i^*} + dt_{i^*} * LP_{i^*}$
      Update $\varepsilon \leftarrow \varepsilon \cup \{C_{i^*t} \leftarrow W\}$ ▷ Update evidence list
      Update $rt = rt + dt_{i^*}$
      Simulate observation node O_t
    Update $I^{'} \leftarrow I^{'} | \{i^*\}$ ▷ Update eligible component list
  rt=rt+1

5.5 Opportunistic Maintenance Approach

The opportunistic approach in maintenance is carried out primarily by implementing additional preventive maintenance activities at a maintenance time that will not cause a delay in the maintenance end time of the primary maintenance activity selected to be done. Opportunistic maintenance is the maintenance activity used to replace other components, even if they are not in a failure state when equipment or system has stopped for the maintenance of one or more deteriorated components. The ultimate goal of this maintenance approach is to maintain system functionality with the longest possible service life and at the same time to enable avoiding any dangerous malfunctions, bringing the machine to an optimum balance between downtime and maintenance costs. In general, the opportunistic maintenance approach aims to reduce the planned downtime for the systems as well as to maximize the life or reliability of the components. All of this is to provide the best possible life of the components and to avoid costly and risky failures during operation.

In this study, one of the proposed maintenance strategies is applied within the opportunistic maintenance approach. Furthermore, when the system encounters a failure one of the proposed maintenance methods are used to select the component to be maintained. During each failure period, the most probable defective components are properly repaired and at the same time, opportunistic maintenance is performed if the reliability of other components below a certain threshold. This ensures that all components are protected and restored to specific conditions. Thanks to this threshold, it is not forced to maintain the components in the system. Algorithm 9 is used to implement the opportunistic maintenance function.

An advantage of this opportunistic maintenance approach is to save on installation costs and production loss cost. It can also be easily applied to all maintenance strategies. We can implement an opportunistic maintenance approach with corrective maintenance or proactive maintenance. This application is given

Algorithm 9 Opportunistic Maintenance Function pseudo-code

Set $OppList = \{\ \}$
for $i' \leftarrow I'$ **do**
  if $(dt_{i'} < dt_{i^*})$ and $(P(C_{i't} = W|\varepsilon) \leq Opp_{thr})$ **then**
    Calculate $TCost_{i'} = TCost_{i'} + RC_{i'}$
    Update $OppList \leftarrow OppList \cup \{i'\}$
Update $I' \leftarrow I' \mid OppList$ ▷ Update eligible component list
Update $\varepsilon \leftarrow \varepsilon \cup \{C_{i't} = W\} \quad \forall i' \in OppList$ ▷ Update evidence list

in Algorithm 10. There are many situations in which opportunistic maintenance is effective. For example, when some components require stopping the entire system when corrective maintenance is applied, other components may be useful in implementing proactive maintenance in these components when performing corrective maintenance. Another example is that opportunistic maintenance on defective components may delay the next corrective maintenance period in a system.

Algorithm 10 Oppurtunistic Maintenance Approach Framework pseudo-code

Input Opp_{thr}
Input Maintenance strategy and parameter
Input Maintenance method
Set rt=1
while $rt \leq T$ **do**
  Set $I' = I$
  Simulate observation node O_t
  while (O_t is "R" or Proactive M. satisfied) and (I' is not empty) **do**
    Apply maintenance method (Algorithm 1, 2, 3, 4) to select i^*
    Calculate $mt = rt + dt_{i^*}$
    if $mt < T$ **then**
      Calculate $TCost_{i^*} = TCost_{i^*} + RC_{i^*} + dt_{i^*} * LP_{i^*}$
      Apply opportunistic maintenance approach function (Algorithm 9)
      Update $\varepsilon \leftarrow \varepsilon \cup \{C_{i^*t} \leftarrow W\}$ ▷ Update evidence list
      Update $t = t + dt_{i^*}$
      Simulate observation node O_t
    Update $I' \leftarrow I' | \{i^*\}$ ▷ Update eligible component list
  rt=rt+1

Chapter 6

Computational Analysis

The designed methods were simulated in the MATLAB environment using the BNT toolbox [65], which were run on a 300-day planning horizon and with 30 times. The performance of the methods under the maintenance strategies and also opportunistic maintenance approach were evaluated according to the cost of maintenance in the given planning horizon. In this part, we present the results of all maintenance policies proposed which are corrective maintenance, constant interval proactive maintenance, dynamic interval proactive maintenance and threshold-based proactive maintenance. Opportunistic maintenance approach is also included in all these strategies and the corresponding results are also discussed. Then, we compare these results statistically.

Inference calculations required during replications are performed by dynamic junction tree inference algorithm available in [65]. This algorithm implements the static junction tree algorithm to neighboring slices [75]. Also, the junction tree algorithm has exact inference and it ensures exact marginals can be computed.

Also, We use ANOVA models to compare the strategies and methods. There we have also checked the model adequacy by analysing the residual plots. Where ever we use ANOVA, the residual plots of all models developed to satisfy the normality, constant variance, and zero mean assumptions. So, we can say that the ANOVA models used in the analysis are adequate. All numerical experiments were run on four computers. The first computer has 64-bit windows, Intel(R) i5 processor at 1.60 GHz and 8 GB RAM. The second computer has 64-bit windows, Intel(R) i7 processor at 2.60 GHz, 256 GB SSD and 16 GB RAM. The third computer has 64-bit windows, Intel(R) Xeon processor at 2.40 GHz and 12 GB RAM. And the last computer has Intel(R) i7 processor at 2.80 GHz, 256 GB SSD, and 16 GB RAM.

6.1 Results of Corrective Maintenance Strategy

In this section, we applied corrective maintenance to eliminate unexpected failures encountered during the maintenance horizon to improve the system state then we compared the results in terms of both maintenance quantity and maintenance cost. The number of replacements for every component is also recorded for each method. Accordingly, inventory planning is given.

6.1.1 Results Based on the Maintenance Quantity and Cost

Corrective maintenance was applied to failures occurring in the empirical DBN model and replications results for four methods are presented in Table 6.1. In addition to these methods, a random maintenance method has also been developed to be compared to the performances of the others. The purpose of this method is to perform random maintenance without using any knowledge of the system. The maintenance results of the given horizon are shown in the table as two different response variables used in the study for 30 replications. Maintenance cost and maintenance quantity can be seen in the table for each method.

The results of all five methods, including random method, were compared using one-way ANOVA. The result of the test is a p-value of 0.000 for both maintenance quantity and maintenance cost. Thus, at least one method differs significantly from the others. We applied post-ANOVA and used the Tukey test [76]. Results

Table 6.1: Replication Results of Corrective Maintenance

Response	Method	Mean	Std. Dev.	95%CI
	FEM	4,847,467	459,103	(4,676,035; 5,018,898)
	FEL	4,948,000	521,441	(4,753,291; 5,142,709)
Cost	REM	5,130,067	455,494	(4,769,637; 5,060,096)
	REL	4,914,867	388,931	(4,959,982; 5,300,151)
	RND	5,958,200	605,614	(5,732,060; 6,184,340)
	FEM	23.767	2.254	(22.925; 24.608)
	FEL	24.267	2.559	(23.311; 25.222)
Quantity	REM	25.200	2.235	(24.366; 26.034)
	REL	24.133	1.907	(23.421; 24.845)
	RND	29.067	2.935	(27.971; 30.163)

are given in Table 6.2. In the table, we can see the behavior of the proposed method for maintenance quantity and maintenance cost.

Table 6.2: Post-ANOVA Results of Corrective Maintenance

Response	Method	N	Mean	Group
	RND	30	5,958,200	A
	REM	30	5,130,067	B
Cost	FEL	30	4,948,000	B
	REL	30	4,914,867	B
	FEM	30	4,847,467	B
	RND	30	29.067	A
	REM	30	25.200	B
Quantity	FEL	30	24.133	B
	REL	30	24.133	B
	FEM	30	23.767	B

Furthermore, we compared the difference between the means of maintenance quantity and maintenance cost. The results are given in Figure 6.1 and Figure 6.2 respectively. Two-way comparisons were made with a 95% confidence interval for the difference. If a range does not contain zero, the corresponding methods are significantly different. The random method, as expected, is significantly worse than any proposed method. However, no one can say that the performances of the four methods are significantly different.

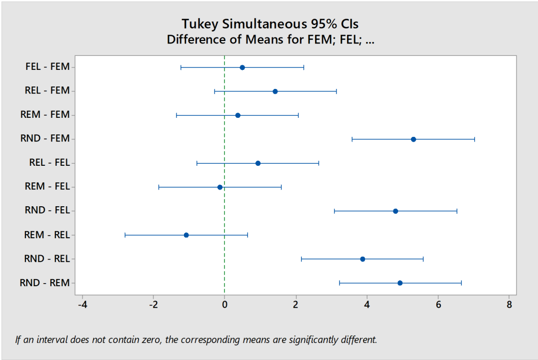

Figure 6.1: CM - Difference of Means of Quantity

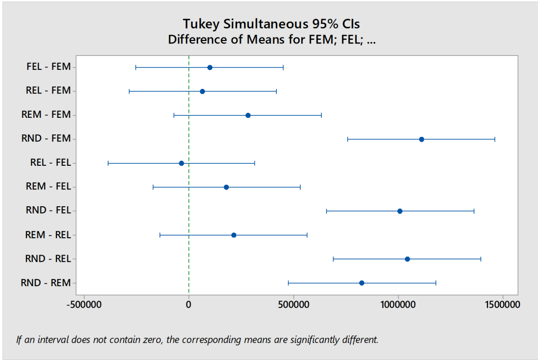

Figure 6.2: CM - Difference of Means of Cost

As a result, when four methods were examined with random methods, a significant difference was found both in terms of cost and quantity of changes. However, we cannot say that there is a significant difference between the four proposed methods. Each of the four proposed methods for corrective maintenance can be easily used and applied.

6.1.2 Results of the Selected Maintenance Method

Also, we compared the average total maintenance cost and maintenance quantity according to each component for each method except the random method. When we look at the total maintenance cost and maintenance quantity which is given Figure 6.3 and Figure 6.4. The FEM method seems better than the other methods, although there isn't any significant difference between them both in maintenance quantity and maintenance costs.

After that, we compare total maintenance cost, replacement cost, and loss production cost according to the FEM method. Most of the total maintenance cost is the loss of production cost. Replacement cost is very low compared to the loss production cost. Figure 6.5 gives this cost comparison. As the loss production cost occurs due to unexpected faults and the system has stopped because of these faults, production cannot be made. Because of this, penalty costs are included in the loss of production cost and this increases the total maintenance cost.

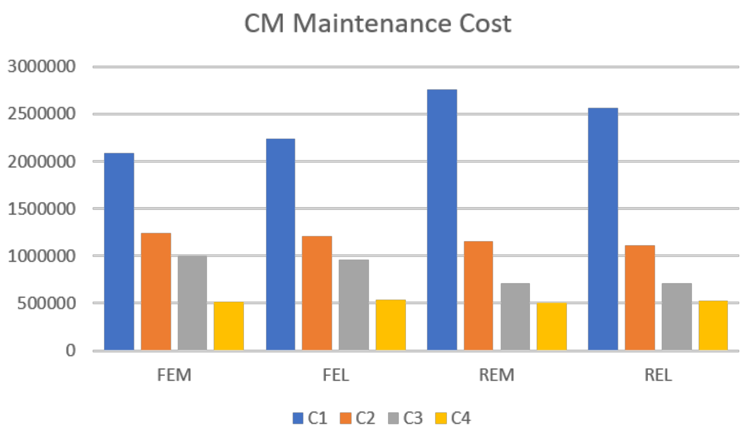

Figure 6.3: CM Cost Distribution among Components

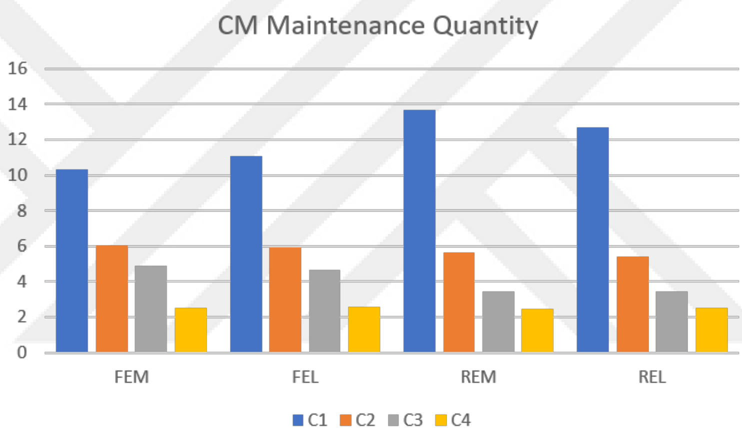

Figure 6.4: CM Quantity Distribution among Components

6.1.3 Resource Planning of the Selected Maintenance Method

When a system fails, assume we prefer to use the FEM method for maintenance. In order to do this, a resource must be provided urgently in case of failure. These resources are like spare parts, personnel, test equipment. This important spare part supply planning has great importance. Supply planning has been reported components with an average annual supply requirement. These requirements are given in Table 6.3 for each component C1, C2, C3 and C4.

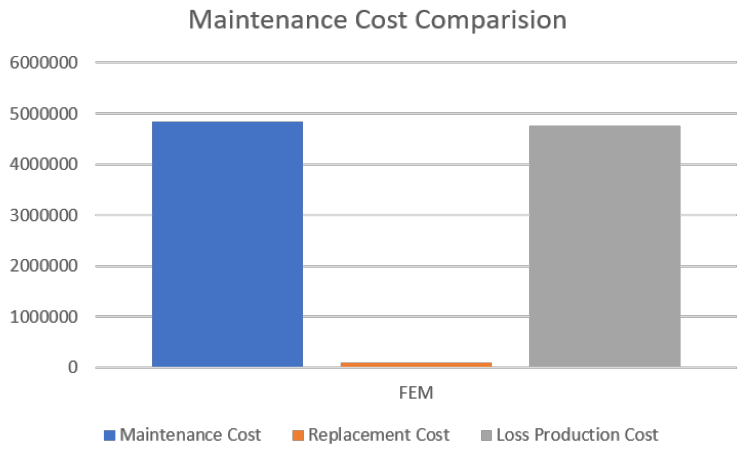

Figure 6.5: CM Cost Distribution

Table 6.3: CM Requirements of Components according to FEM

Component	**Quantity**	**Std. Dev.**
C1	10.333	1.240
C2	6.067	0.790
C3	4.867	0.630
C4	2.500	0.510

6.1.4 Effect of the Selected Maintenance Method on the System

Assuming that we implement the FEM method, its result is more suitable than the others due to low cost and maintenance quantity, when a corrective maintenance decision is made, we can forecast failure trends of the components. The effect of the FEM method on the components when the FEM method is applied in corrective maintenance is given in Figure 6.6 for one replication and a planning horizon of 300 days. As a result of this single replication, component C1, C2, C3, and C4 are maintained 11 times, 6 times, 4 times and 3 times respectively. Also, failure probability is 0.3447 of the system at 300th day.

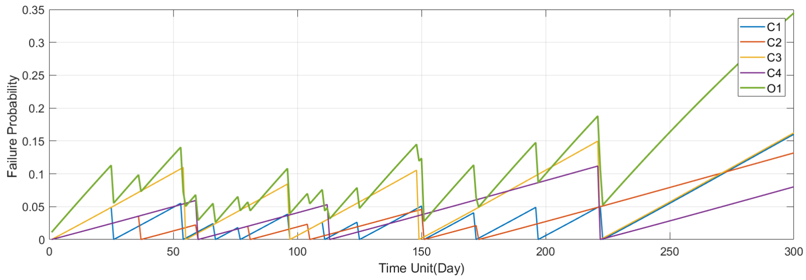

Figure 6.6: CM FEM Failure Trends

6.2 Results of Proactive Maintenance Strategies

In this section, we applied proactive maintenance strategies to eliminate probable future failures in addition to corrective maintenance. Numerical tests were performed in order to examine which of the methods detailed above will give better results in the DBN system. Maintenance strategies were examined separately according to both the maintenance costs and maintenance quantity. For the maintenance quantity and maintenance costs minimization, we performed each strategy and we used ANOVA according to 95% confidence level for comparisons. In this section, we showed results to maintenance cost, maintenance quantity, and resource planning, and the effect of them to be selected maintenance method on the system.

6.2.1 Results Based on the Maintenance Cost

The replication results of the proposed methods under proactive maintenance strategies are shown in Table 6.4 and Table 6.5. These results include the average of the total cost, standard deviation and 95% confidence intervals of 30 replication in the given planning horizon for each strategy and method.

Each maintenance strategy was compared by using two-way ANOVA according to the maintenance parameters and maintenance methods and the p-values for all strategies are shown in Table 6.6. Factors for the comparison of two-way ANOVA

Table 6.4: Replication Results of Proactive Maintenance Strategies

Strategy	**Method**	**Mean (TL)**	**Std. Dev.**	**%95 CI**
CIPM, $pci = 2$	FEM	5,098,667	352,923	(4,966,883; 5,230,450)
	FEL	5,250,033	567,519	(5,038,118; 5,461,948)
	REM	5,167,767	355,744	(5,034,930; 5,300,604)
	REL	5,150,300	435,909	(4,987,529; 5,313,071)
CIPM, $pci = 5$	FEM	3,810,833	629,264	(3,575,862; 4,045,804)
	FEL	3,757,033	419,793	(3,600,280; 3,913,787)
	REM	3,751,600	529,636	(3,553,831; 3,949,369)
	REL	3,935,700	650,135	(3,692,936; 4,178,464)
CIPM, $pci = 10$	FEM	3,968,633	587,370	(3,677,176; 4,099,357)
	FEL	3,881,233	601,524	(3,718,023; 4,100,177)
	REM	3,990,133	551,552	(3,794,222; 4,172,045)
	REL	3,948,633	631,213	(3,723,080; 4,119,854)
CIPM, $pci = 30$	FEM	4,361,467	516,418	(4,168,633; 4,554,300)
	FEL	4,470,833	648,141	(4,228,813; 4,712,853)
	REM	4,633,500	517,832	(4,440,138; 4,826,862)
	REL	4,504,067	502,639	(4,316,378; 4,691,755)
CIPM, $pci = 60$	FEM	4,573,333	452,045	(4,404,537; 4,742,130)
	FEL	4,647,833	447,089	(4,480,888; 4,814,779)
	REM	4,688,467	472,839	(4,511,906; 4,865,028)
	REL	4,857,333	419,962	(4,700,517; 5,014,150)
CIPM, $pci = 90$	FEM	4,620,133	491,095	(4,436,755; 4,803,511)
	FEL	4,867,033	511,795	(4,675,926; 5,058,141)
	REM	5,021,167	4,654,26	(4,847,374; 5,194,960)
	REL	4,792,233	465,310	(4,618,484; 4,965,983)
DIPM, $pci = 2$	FEM	4,019,733	453,305	(3,850,466; 4,189,000)
	FEL	4,031,033	412,435	(3,795,002; 4,137,065)
	REM	4,137,400	550,144	(3,927,133; 4,248,067)
	REL	4,001,233	469,549	(3,948,711; 4,290,289)
DIPM, $pci = 5$	FEM	3,595,900	602,180	(3,371,042; 3,820,758)
	FEL	3,368,300	474,820	(3,190,999; 3,545,601)
	REM	3,929,033	637,687	(3,690,917; 4,167,149)
	REL	3,807,133	514,642	(3,646,311; 4,166,022)
DIPM, $pdi = 10$	FEM	4,121,567	605,522	(3,895,461; 4,347,672)
	FEL	4,043,400	575,705	(3,828,428; 4,258,372)
	REM	4,334,100	358,293	(4,200,311; 4,467,889)
	REL	4,240,167	652,089	(3,996,673; 4,483,661)
DIPM, $pdi = 20$	FEM	4,554,633	535,556	(4,354,654; 4,754,613)
	FEL	4,617,900	603,298	(4,392,625; 4,843,175)
	REM	4,617,900	603,298	(4,376,491; 4,844,309)
	REL	4,739,433	578,913	(4,523,264; 4,955,603)

Table 6.5: Replication Results of Proactive Maintenance Strategies (cont'd)

Strategy	**Method**	**Mean (TL)**	**Std. Dev.**	**%95 CI**
DIPM, $pdi = 30$	FEM	4,736,600	482,377	(4,556,477; 4,916,723)
	FEL	4,928,400	583,217	(4,710,623; 5,146,177)
	REM	4,895,600	441,124	(4,730,881; 5,060,319)
	REL	4,989,000	421,467	(4,831,622; 5,146,378)
DIPM, $pdi = 60$	FEM	4,819,600	502,922	(4,631,806; 5,007,394)
	FEL	4,859,467	508,112	(4,669,735; 5,049,199)
	REM	5,029,667	461,425	(4,857,368; 5,201,966)
	REL	4,980,733	544,728	(4,777,329; 5,184,138)
DIPM, $pdi = 90$	FEM	4,968,533	396,319	(4,820,545; 5,116,521)
	FEL	4,915,000	599,577	(4,691,114; 5,138,886)
	REM	4,961,267	451,331	(4,792,737; 5,129,796)
	REL	4,953,067	452,440	(4,784,123; 5,122,010)
ThPM, $thr = 0.50$	FEM	4,819,400	437,225	(4,656,138; 4,982,662)
	FEL	4,913,733	520,137	(4,719,511; 5,107,956)
	REM	5,028,867	500,631	(4,841,928; 5,215,805)
	REL	4,859,067	403,518	(4,708,391; 5,009,743)
ThPM, $thr = 0.75$	FEM	4,887,333	486,590	(,4705,637; 5,069,029)
	FEL	4,988,667	492,003	(4,804,950; 5,172,383)
	REM	4,948,133	445,599	(4,781,744; 5,114,523)
	REL	4,914,067	429,752	(4,753,595; 5,074,539)
ThPM, $thr = 0.85$	FEM	4,844,500	361,017	(4,709,694; 4,979,306)
	FEL	4,891,067	573,160	(4,677,045; 5,105,088)
	REM	4,697,067	466,646	(4,522,818; 4,871,315)
	REL	4,949,133	519,767	(4,755,049; 5,143,217)
ThPM, $thr = 0.90$	FEM	4,210,267	515,104	(4,017,924; 4,402,610)
	FEL	4,664,633	592,916	(4,443,235; 4,886,032)
	REM	4,378,300	674,665	(4,126,376; 4,630,224)
	REL	4,508,400	663,324	(4,260,711; 4,756,089)
ThPM, $thr = 0.95$	FEM	3,554,800	560,758	(3,345,410; 3,764,190)
	FEL	3,778,233	566,699	(3,566,624; 3,989,842)
	REM	3,514,533	545,118	(3,310,983; 3,718,084)
	REL	3,715,533	705,211	(3,452,203; 3,978,864)
CIPM, $thr = 0.97$	FEM	3,811,900	482,325	(3,631,797; 3,992,003)
	FEL	3,513,700	404,478	(3,362,665; 3,664,735)
	REM	3,717,100	568,760	(3,504,722; 3,929,478)
	REL	3,753,633	604,003	(3,528,095; 3,979,172)

were selected from the parameters of the maintenance strategies and the proposed methods. We analysed the effect of the two factors on the total maintenance cost in the planning horizon. It was aimed to select the maintenance strategy with the most appropriate cost among the related parameter and related method.

Table 6.6: ANOVA Results of Proactive Maintenance Strategies

Strategy	**Factor**	**P-Value**
CIPM	Parameter $(2; 5; 10; 30; 60; 90)$	0.000
	Method $(FEM; FEL; REM; REL)$	0.000
	Parameter*Method	0.442
DIPM	Parameter $(2; 5; 10; 20; 30; 60; 90)$	0.000
	Method $(FEM; FEL; REM; REL)$	0.000
	Parameter*Method	0.415
ThPM	Parameter $(0.50; 0.75; 0.85; 0.90; 0.95; 0.97)$	0.000
	Method $(FEM; FEL; REM; REL)$	0.000
	Parameter*Method	0.060

When we look at the CIPM strategy, the period ranges are selected as 2, 5, 10, 30, 60 and 90 days and two-way ANOVA results are given in Table 6.6. According to the results, the p-value of the parameters is 0.000, the p-value of the methods is 0.000, and these values are lower than $\alpha = 0.05$. We can clearly say that the parameters and methods are significant and that the best interval time for CIPM is 5 days. We make a further analysis over costs after the two-way ANOVA results in Figure 6.7 and Figure 6.8 which are interaction and main effects plots respectively. The figures show that the cost results with the parameters from 5 to 90 are steadily increasing due to the convergence of the model to corrective maintenance as the interval time increases. On the other hand, when we select parameter 2, we are forced to do proactive maintenance, therefore, the system tends to do unnecessary maintenance. Besides, when we look at the interaction plot of CIPM, p-value is found to be 0,442. This value is higher than $\alpha = 0.05$. We can conclude that the parameter and method interaction is not significant in CIPM.

Following the CIPM main effect plots, we examined the corrective maintenance and proactive maintenance of the FEM method. When we look at Figure 6.9, we

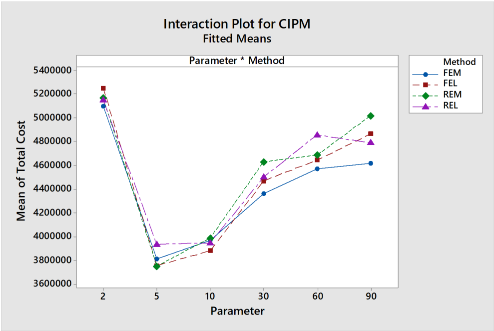

Figure 6.7: CIPM Interaction Plot

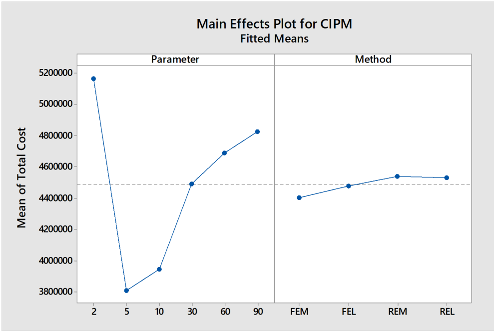

Figure 6.8: CIPM Main Effects Plot

can easily see that the average maintenance cost is converging to the average cost of corrective maintenance as the proactive maintenance intervals get larger. Also, it is not a very logical solution to keep the maintenance interval low though. This is because the system does more maintenance than it is required. This increases the maintenance cost.

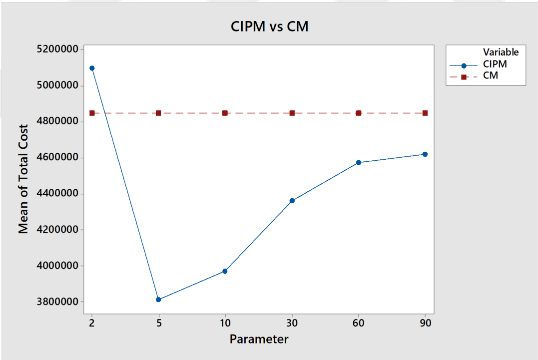

Figure 6.9: CIPM vs CM

The ranges of 2, 5, 10, 20, 30, 60 and 90 days are selected for the dynamic interval proactive maintenance strategy and two-way ANOVA is applied. The results are given in Table 6.6. P-value of the effects of parameter and method are both 0.000 and p-value of the effect of interaction between the parameters and the methods is 0.415. Parameters and methods have low s. So the parameters and methods considered in this strategy are significantly different. In addition, when we look at the interaction between the parameters and methods, p-value is higher than $\alpha = 0.05$. Therefore, this is not significant for the model. After the ANOVA results, we also obtained plots of interaction and main effects for further analysis in Figure 6.10 and Figure 6.11 where shows the best solution is founded as 5 days.

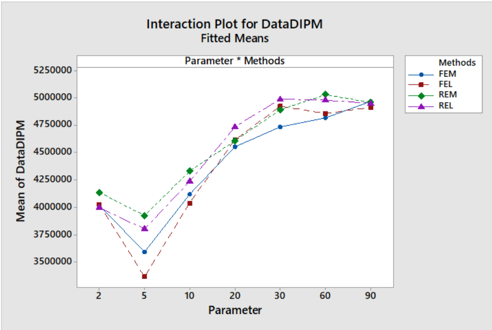

Figure 6.10: DIPM Interaction Plot

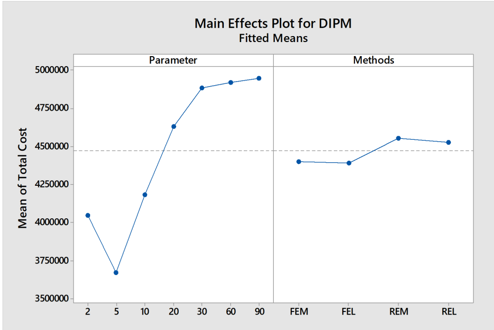

Figure 6.11: DIPM Main Effects Plot

After the ANOVA result, we compare corrective maintenance result to DIPM-FEM result. Figure 6.12 shows that the parameter 5 to parameter 90 are continuously leading to an increase in the average total maintenance cost due to the convergence of the model to corrective maintenance as the interval time increases. Also, we have used the t-test to understand whether it has a significant difference between proactive maintenance with parameter 90 and the corrective maintenance. And, we found that p-value is 0.279. The result shows that there is exist to the significant difference between them. When we select parameter 2, we are forced to do proactive maintenance therefore, the system tends to do unnecessary maintenance.

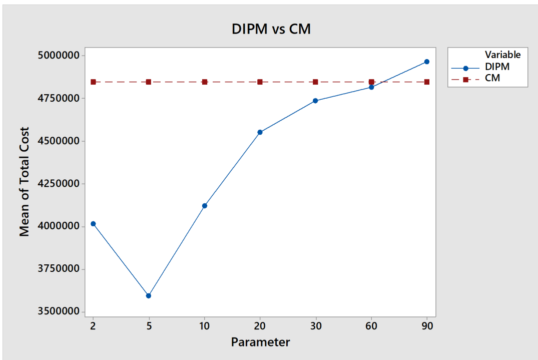

Figure 6.12: DIPM vs CM

When we look at the ThPM strategy, the threshold values are selected as 0.50, 0.75, 0.85, 0.90, 0.95 and 0.97 respectively. The result of ANOVA is given in Table 6.6. When the results are evaluated, the p-value of the parameters and methods are 0.000 from which we can say easily that parameters and methods are significant for the model. In addition, when we look at the interaction between parameters and methods p-value is 0.060. We examine this value is higher than $\alpha = 0.05$. We can conclude that it is not significant. We obtain plots of interaction and main effects in Figure 6.13 and Figure 6.14 after the ANOVA result. We find the best parameter is 0.95.

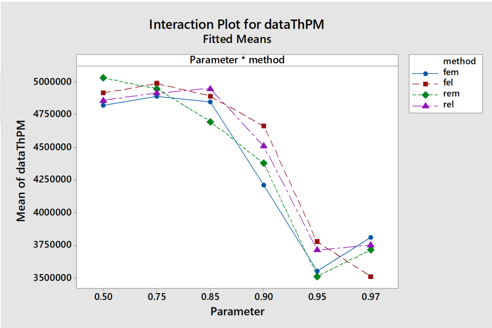

Figure 6.13: ThPM Interaction Plot

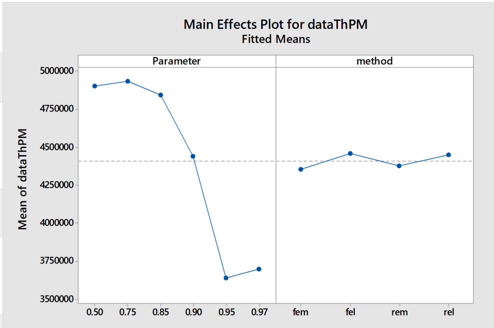

Figure 6.14: ThPM Main Effects Plot

After ANOVA analysis on the total costs, we compare corrective maintenance result to ThPM result using the FEM method. 0.50, 0.75, 0.85 and 0.90 have higher cost since proactive maintenance is very rare leaving the system doing almost only corrective maintenance. It gives the best result when the value is 0.95. Also, we have used the t-test to understand whether there exists a significant difference between the costs while using parameter 0.75. And, we found that p-value is 0.745 which means there is no significant difference between them.

After each strategy was examined in detail, the best method in each strategy was examined with one-way ANOVA including also corrective maintenance results and a p-value of 0.000 was obtained. We can easily say that at least one parameter of the maintenance strategies is significantly different. After ANOVA, we compared all averages using Tukey's test [76]. The results in Table 6.7 are

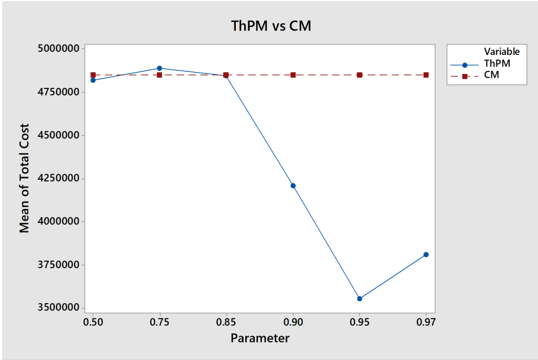

Figure 6.15: ThPM vs CM

obtained and the average differences of the selected proactive strategies in 95% confidence interval are shown in Figure 6.16. If a range does not contain zero, the corresponding policies are significantly different. As expected, the corrective maintenance strategy is significantly worse than all strategies applied since it has the highest average maintenance cost. However, we cannot say that the performances of the three strategies differ significantly because they are in the same group.

Table 6.7: ANOVA Results of Selected Proactive Strategies

Strategy	**Method**	**N**	**Mean**	**Group**
CM	FEM	30	4,847,467	A
CIPM $pci = 5$	FEM	30	3,810,833	B
DIPM $pdi = 5$	FEM	30	3,595,900	B
ThPM $thr = 0,95$	FEM	30	3,554,800	B

As a result, it is understood that there is no difference between the selected best proactive maintenance strategies. In addition, it is possible to implement any of these maintenance strategies in the given best parameters effectively.

6.2.2 Results Based on the Maintenance Quantity

Since we did not find any significant differences between the proposed maintenance strategies, we examined further the maintenance quantity. The results available in Table 6.8 where 95% Tukey groups are also shown as post-ANOVA

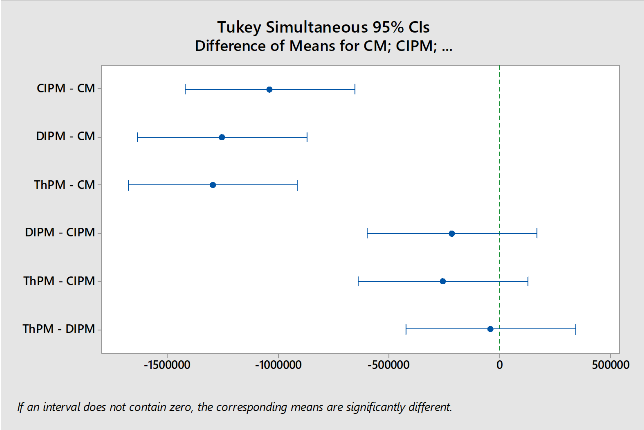

Figure 6.16: Difference of Means for Selected Proactive Strategies

analysis. according to maintenance quantity of selected maintenance strategies. If we look at the result, we can say that there are significant differences in the selected maintenance strategies. CIPM was worse than other strategies when compared with them. This is due to the maintenance of this strategy at fixed intervals. The DIPM has less maintenance than the CIPM because the maintenance intervals can be shifted because of next maintenance period changes. Since ThPM is dependent on the reliability of the component, it does not undertake unnecessary maintenance and has less maintenance quantity than other proactive maintenance strategies. Although there is no difference in terms of maintenance cost in these selected maintenance strategies, it is more logical to choose ThPM when considering the maintenance quantity.

Table 6.8: Post-ANOVA Results of Selected Proactive Strategies wrt Maintenance Quantity

Strategy	**Method**	**N**	**Mean**	**Std. Dev.**	**Group**
CIPM $pci = 5$	FEM	30	69.900	3.089	A
DIPM $pdi = 5$	FEM	30	52.433	1.305	B
ThPM $thr = 0,95$	FEM	30	49.100	0.712	C

6.2.3 Results of the Selected Maintenance Strategy

The ThPM strategy was selected to be analysed further according to proactive maintenance strategy results. Furthermore, the corrective maintenance cost and the proactive maintenance cost out of the total cost were examined based on the replication results. These results are shown in Figure 6.17. The average maintenance cost was 3,554,799.00 TL when the ThPM was applied. We can easily say that this cost includes average corrective maintenance cost as 2,576,133 TL and the average proactive maintenance as 978,666 TL. Also, we analysed the corrective part and found average replacement cost as 56,133 TL and loss production cost as 2,520,000 TL. In proactive part, we are found average replacement cost as 66,166.670 TL and loss production cost as 978,666 TL. Replacement Cost is included approximately 2% of total cost. This shows that loss production cost has great importance for the maintenance planning.

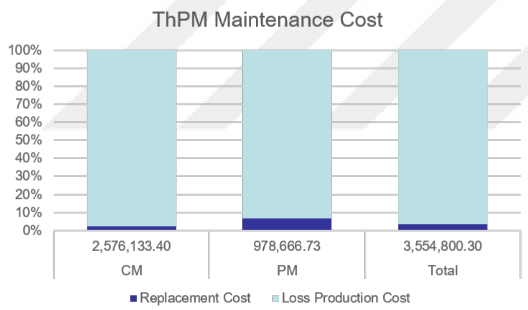

Figure 6.17: ThPM Maintenance Cost Distribution

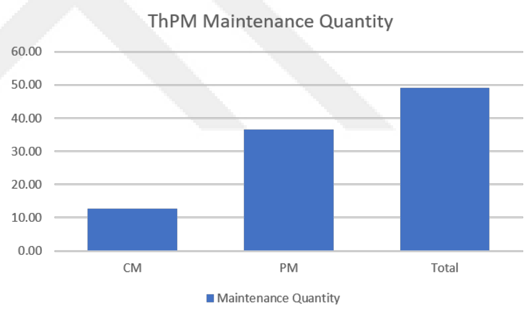

Figure 6.18: ThPM Maintenance Quantity Distribution

Furthermore, the maintenance quantity of ThPM is given in Figure 6.18. This maintenance quantity was found as 49 according to 30 replications results. This quantity indicates averagely as 49 times of maintenance per 300 days planning horizon. Approximately 12 of the maintenance quantities come from corrective maintenance, about 37 of them are proactive. Although the maintenance quantity is high, the maintenance cost is considerably lower than the maintenance cost when the corrective maintenance strategy is applied.

In Table 6.9, this comparison is given in detail. When we look at the table, there is a high cost in the corrective maintenance strategy. However, in terms of the maintenance quantity, the vice versa case is valid. Corrective maintenance has less number of activities. This is the reason why proactive maintenance is planned maintenance. Because of the planned maintenance, the cost of urgent procurement of spare parts is exempt from the costs that would incur additional penalty fees.

Table 6.9: CM vs ThPM

Response	**CM**	**ThPM**
Maintenance Cost	4,847,466.670	3,554,800.300
Replacement Cost	94,133.330	122,300.000
Loss Production Cost	4,753,333.330	3,432,499.600
Maintenance Quantity	23.770	49.100

6.2.4 Resource Planning of the Selected Maintenance Strategy

Planning of resources should be well controlled and planned in order to ensure that the system continues in a healthy manner, which will not hinder production and thus prevent capacity losses. In this case, the presence of backups of the components that may be needed in a possible or unexpected failure is very important both in terms of cost and maintenance duration. As we can calculate the average maintenance cost due to failures occurring in the system, resource planning can be done to keep the damage minimum. When we apply the ThPM strategy with FEM method, the amount of resources we need to keep is given in Table 6.10.

Table 6.10: PM Requirements of Components According to ThPM-FEM

Component	**Quantity**	**Std. Dev**
C1	23.233	0.570
C2	11.733	0.580
C3	9.000	0.370
C4	5.133	0.350

6.2.5 Effect of the Selected Maintenance Strategy on the System

After implementing the ThPM, we took 1 replication for 300 days planning horizon to see the effect on the system. The effect on components and the system when FEM method is applied that is given in Figure 6.19. As a result, C1 has 0.09282 failure probability, C2 has 0.05725 failure probability, C3 has 0.1329 failure probability, C4 has 0.107709 failure probability and the system has 0.2270 failure probability at the 300th day. Then, we compared the result according to the corrective maintenance result. And we can say the failure probability of components and the system have decreased at the end of the planning horizon.

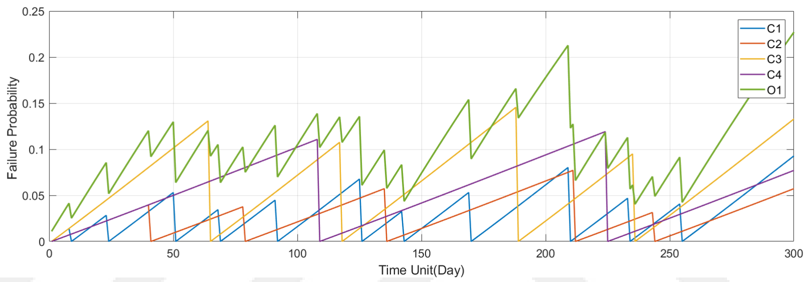

Figure 6.19: ThPM FEM Failure Trends

6.3 Results of Opportunistic Maintenance Approach

This Section examines the results of the opportunistic maintenance approach that we developed to prevent failure in the empirical DBN model. The opportunistic maintenance approach to maintenance is applied in both corrective and proactive maintenance strategies. 30 replications were taken for each strategy in the 300-day planned horizon. In this section, we discussed the result of opportunistic corrective maintenance and opportunistic proactive maintenance.

6.3.1 Results of Opportunistic Corrective Maintenance (OPPCM)

In this section, we applied OPPCM by using opportunistic maintenance approach to eliminate unplanned maintenance encountered during the maintenance horizon planned to improve the system state and compared the results in terms of both maintenance quantity and maintenance cost. Then, choosing the best from the maintenance methods encountered, the effects on the system and how much of the components are changed are given. Accordingly, inventory planning is given.

6.3.1.1 Results Based on the Maintenance Quantity and Cost

In the empirical DBN model, opportunistic corrective maintenance was applied and results of replications for the four methods are shown in Table 6.11. In addition to these methods, a random maintenance method has been developed. The purpose of this method is to perform random maintenance without any system knowledge. The given horizon is shown in the table for 30 replicates. The maintenance cost and maintenance quantity for each method can be seen in the table.

Table 6.11: Replication Results of Opportunistic Corrective Maintenance

Response	**Method**	**Mean**	**Std. Dev.**	**95%CI**
Cost	FEM	3,547,000	425,075	(3,388,274; 3,705,726)
	FEL	3,489,467	396,746	(3,341,319; 3,637,614)
	REM	3,580,867	677,291	(3,327,962; 3,833,771)
	REL	3,514,800	544,235	(3,311,579; 3,718,021)
	RND	3,598,600	414,667	(3,443,761; 3,753,439)
Quantity	FEM	46.933	3.676	(45.561; 48.306)
	FEL	46.067	3.667	(44.698; 47.436)
	REM	47.300	4.587	(45.587; 49.013)
	REL	46.967	3.952	(45.491; 48.442)
	RND	48.700	3.697	(47.320; 50.080)

The results of all five methods, including random method, were compared using one-way ANOVA. Results of the tests are a p-values of 0.914 and 0.136 for maintenance quantity and maintenance cost. This indicates that methods are not significantly different from the others. This is because the system has four components. Therefore, there are no differences among all methods, including the random method. If we examined the method result, every method has approximately 16 maintenance quantity with the non-opportunistic part, also these methods have approximately 30 maintenance quantity with the opportunistic part. Therefore, the results will always be the same as the statistics for the proposed methods. Distribution results of average total cost and quantity of OPPCM is shown Table 6.12.

Table 6.12: Cost and Quantity Distribution in OPPCM

Average Cost			
Methods	**Corrective**	**Opportunistic**	**Total**
FEM	3,365,133.330	181,866.670	3,547,000.000
FEL	3,310,800.017	178,666.650	3,489,466.667
REM	3,396,533.337	184,333.330	3,580,866.667
REL	3,405,133.340	109,666.660	3,514,800.000
RND	3,444,999.940	153,600.060	3,598,600.000
Average Quantity			
Methods	**Corrective**	**Opportunistic**	**Total**
FEM	16.633	30.300	46.933
FEL	16.367	29.700	46.067
REM	16.800	30.500	47.300
REL	16.467	30.500	47.000
RND	16.800	31.900	48.700

As a result, when four methods were examined with random methods had a not significant difference was found both in terms of cost and quantity of changes. However, we cannot say that there is a significant difference between the four proposed methods. Each of the five proposed methods for corrective maintenance can be used and applied.

6.3.1.2 Results of the Selected OPPCM Method

Also, we compared total cost and maintenance quantity for all method without random method according to the component. When we look at the total cost and maintenance quantity are given Figure 6.20 and Figure 6.21. We found that there isn't any significant difference between them both in maintenance quantity and maintenance costs.

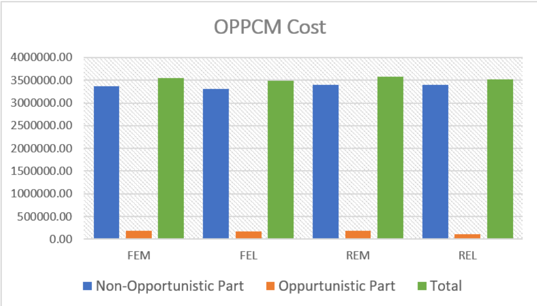

Figure 6.20: Corrective Maintenance Total Cost

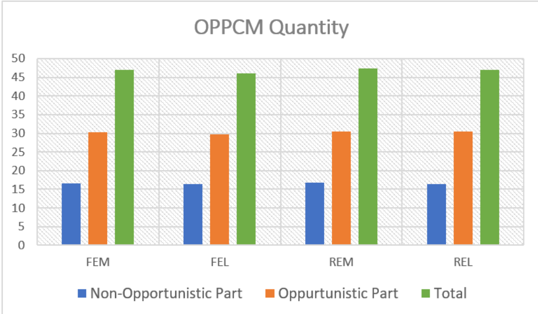

Figure 6.21: Corrective Maintenance Quantity

After that, we compare total cost according to opportunistic cost and non opportunistic cost in the FEM method. This cost is 3,489,467 TL and it include cost of opportunistic part as 178,666.650 TL and cost of Non-opportunistic cost as 3,310,799.720 TL. Also, every method has approximately 16 maintenance quantity with non-opportunistic part and approximately 30 maintenance quantity with opportunistic part. Although the opportunistic part has a very high quantity, they incurred very little cost due to this cost doesn't include loss production cost. This results are given in Figure 6.22 and 6.23.

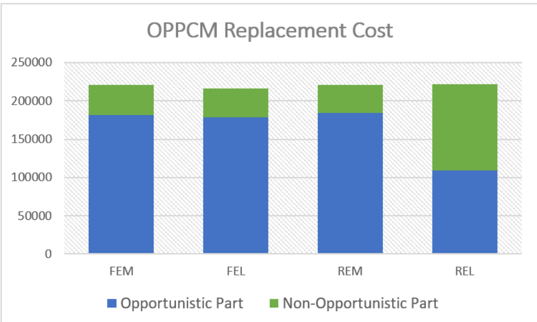

Figure 6.22: OPPCM Replacement Cost Distribution

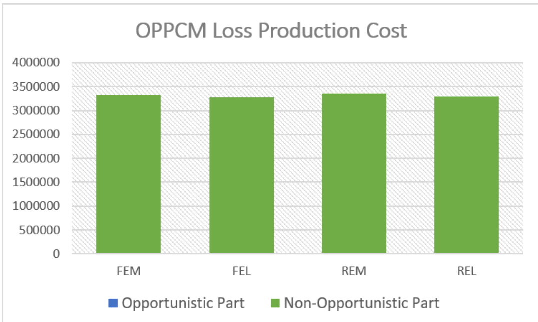

Figure 6.23: OPPCM Loss Production Cost Distribution

6.3.2 Results of Opportunistic Proactive Maintenance Strategies (OPPPM)

In this section, we applied proactive opportunistic maintenance strategies to eliminate probable future failures in addition to the corrective maintenance. Numerical tests were performed in order to examine which of the methods detailed above will give better results in the DBN system. OPPPM strategies were examined separately according to both the maintenance costs and maintenance quantity. For the maintenance quantity and maintenance costs minimization, we performed each strategy and we used ANOVA according to 95% confidence level for comparisons. In this section, we showed results to maintenance cost, maintenance quantity, and resource planning, and the effect of them to be selected maintenance method on the system.

6.3.2.1 Results Based on the Maintenance Cost

The replication results of the proposed maintenance strategies under opportunistic maintenance approach are shown in Table 6.13 and Table 6.14. These results include the total planning cost average, standard deviation, and intervals of 30 replication in the given planning horizon for each strategy and method.

Each opportunistic maintenance strategy was compared by using two-way ANOVA according to the maintenance parameters and maintenance methods and the p-value for all strategies are shown in Table 6.15. Factors for the comparison of two-way ANOVA were selected from the parameters of the maintenance strategies and the proposed methods. We analysed the effect of the two factors on the total maintenance cost in the planning horizon. It was aimed to select the opportunistic maintenance strategy with the most appropriate cost among the related parameters and methods.

In OPPCIPM strategy, parameters are selected as 2, 5, 10, 30, 60 and 90 days for maintenance period and two-way ANOVA results are given in Table 6.15. According to the results, the p-value of the parameters and methods are 0.000.

Table 6.13: Replication Results of OPPPM Strategies

Strategy	Method	Mean (TL)	Std. Dev.	%95 CI
OPPCIPM, $pci = 2$	FEM	4,937,567	519,651	(4,743,526; 5,131,607)
	FEL	5,187,433	4,91,876	(5,003,764; 5,371,103)
	REM	5,120,267	4,00,960	(4,970,546; 5,269,988)
	REL	5,090,800	4,63,566	(4,917,701; 5,263,899)
OPPCIPM, $pci = 5$	FEM	3,358,467	568,769	(3,146,085; 3,570,849)
	FEL	3,392,000	525,065	(3,195,938; 3,588,062)
	REM	3,384,633	482,637	(3,204,414; 3,564,853)
	REL	3,419,900	501,449	(3,232,656; 3,607,144)
OPPCIPM, $pci = 10$	FEM	2,869,667	479,247	(2,690,713; 3,048,620)
	FEL	2,903,500	443,971	(2,737,718; 3,069,282)
	REM	2,958,133	586,437	(2,739,154; 3,177,113)
	REL	2,979,067	518,969	(2,785,280; 3,172,853)
OPPCIPM, $pci = 30$	FEM	3,606,800	680,845	(3,172,644; 3,685,022)
	FEL	3,536,233	588,244	(3,099,617; 3,566,183)
	REM	3,498,367	615,035	(3,097,104; 3,550,163)
	REL	3,313,133	579,755	(3,284,836; 3,685,364)
OPPCIPM, $pci = 60$	FEM	3,362,033	590,516	(3,141,531; 3,582,536)
	FEL	3,420,400	462,954	(3,24,7530; 3,593,270)
	REM	3,388,200	540,747	(3,186,282; 3,590,118)
	REL	3,510,933	377,005	(3,370,157; 3,651,709)
OPPCIPM, $pci = 90$	FEM	3,602,167	499,460	(3,451,462; 3,840,472)
	FEL	3,625,567	485,275	(3,446,314; 3,951,286)
	REM	3,596,467	737,555	(3,302,607; 3,672,593)
	REL	3,623,500	540,334	(3,199,189; 3,648,211)
OOPDIPM, $pdi = 2$	FEM	3,971,600	454,132	(3,802,024; 4,141,176)
	FEL	3,954,267	433,218	(3,792,500; 4,116,033)
	REM	3,818,900	41,9752	(3,662,162; 3,975,638)
	REL	3,772,233	379,887	(3,630,381; 3,914,085)
OOPDIPM, $pdi = 5$	FEM	3,266,567	507,370	(3,077,112; 3,456,022)
	FEL	3,178,533	480,129	(2,999,250; 3,357,816)
	REM	3,133,700	478,502	(2,955,024; 3,312,376)
	REL	3,203,200	374,551	(3,063,340; 3,343,060)
OOPDIPM, $pdi = 10$	FEM	2,970,367	606,803	(2,743,783; 3,196,951)
	FEL	2,889,500	505,531	(2,7007,32; 3,078,268)
	REM	2,858,900	632,178	(2,622,841; 3,094,959)
	REL	3,045,233	572,113	(2,831,603; 3,258,864)
OOPDIPM, $pdi = 20$	FEM	3,128,033	506,745	(2,938,812; 3,317,255)
	FEL	3,213,233	554,847	(3,006,050; 3,420,417)
	REM	3,048,867	676,388	(2,796,299; 3,301,434)
	REL	3,184,567	613,779	(2,955,378; 3,413,755)

Table 6.14: Replication Results of OPPPM Strategies (cont'd)

Strategy	**Method**	**Mean (TL)**	**Std. Dev.**	**%95 CI**
OOPDIPM, $pdi = 30$	FEM	3,582,100	517,534	(3,388,850; 3,775,350)
	FEL	3,624,433	431,448	(3,463,328; 3,785,539)
	REM	3,485,733	512,799	(3,294,251; 3,677,216)
	REL	3,652,833	662,020	(3,405,631; 3,900,035)
OOPDIPM, $pdi = 60$	FEM	3,540,200	393,854	(3,393,133; 3,687,267)
	FEL	3,631,600	545,827	(3,427,785; 3,835,415)
	REM	3,646,200	469,800	(3,470,774; 3,821,626)
	REL	3,601,733	486,015	(3,420,252; 3,783,214)
OOPDIPM, $pdi = 90$	FEM	3,750,200	570,166	(3,537,296; 3,963,104)
	FEL	3,667,933	469,060	(3,492,783; 3,843,083)
	REM	3,496,133	412,526	(3,342,094; 3,650,173)
	REL	3,617,200	514,859	(3,424,949; 3,809,451)
OPPThPM, $thr = 0.50$	FEM	3,518,933	340,428	(3,391,815; 3,646,051)
	FEL	3,309,667	484,136	(3,128,887; 3,490,446)
	REM	3,523,067	528,753	(3,325,627; 3,720,506)
	REL	3,501,600	490,661	(3,318,384; 3,684,816)
OPPThPM, $thr = 0.75$	FEM	3,806,267	668,169	(3,556,768; 4,055,765)
	FEL	3,525,200	524,797	(3,329,238; 3,721,162)
	REM	3,508,933	492,190	(3,325,147; 3,692,720)
	REL	3,524,733	473,737	(3,347,837; 3,701,630)
OPPThPM, $thr = 0.90$	FEM	3,240,433	568,031	(3,028,327; 3,452,540)
	FEL	3,184,867	502,402	(2,997,267; 3,372,467)
	REM	3,207,633	552,015	(3,001,508; 3,413,759)
	REL	3,407,700	582,214	(3,190,298; 3,625,102)
OPPThPM, $thr = 0.95$	FEM	2,974,267	591,162	(2,753,523; 3,195,010)
	FEL	2,905,100	444,515	(2,739,116; 3,071,084)
	REM	2,902,067	557,000	(2,694,079; 3,110,054)
	REL	3,077,000	500,688	(2,890,040; 3,263,960)
OPPThPM, $thr = 0.97$	FEM	3,23,6167	670,114	(2,985,942; 3,486,391)
	FEL	3,362,500	447,250	(3,195,494; 3,529,506)
	REM	3,313,633	489,913	(3,130,697; 3,496,570)
	REL	3,173,200	405,261	(3,021,873; 3,324,527)

Table 6.15: ANOVA Results of OPPPM Strategies

Strategy	Factor	p-value
OOPCIPM	Parameter $(2; 5; 10; 30; 60; 90)$	0.000
	Method $(FEM; FEL; REM; REL)$	0.000
	Parameter*Method	0.826
OOPDIPM	Parameter $(2; 5; 10; 20; 30; 60; 90)$	0.000
	Method $(FEM; FEL; REM; REL)$	0.000
	Parameter*Method	0.944
OPPThPM	Parameter $(0.50; 0.75; 0.85; 0.90; 0.95; 0.97)$	0.000
	Method $(FEM; FEL; REM; REL)$	0.000
	Parameter*Method	0.246

These values show that the parameters and methods are significant. The best interval time for OPPCIPM is 10 days and that FEM method from the proposed methods gives the best results. We make a further analysis over costs after the two-way ANOVA results in Figure 6.24 and Figure 6.25 which are interaction and main effects plots respectively. The figures show that the results with that the parameter 10 to parameter 90 are increasingly deteriorating due to the converging of the model to corrective maintenance as the interval time increases. On the other hand, when we select parameter 2, we are forced to do proactive maintenance, therefore, the system tends to do unnecessary maintenance. Besides, when we look at the interaction plot of CIPM, p-value is found to be 0.826. We can conclude that the interactions plot of CIPM is not significant.

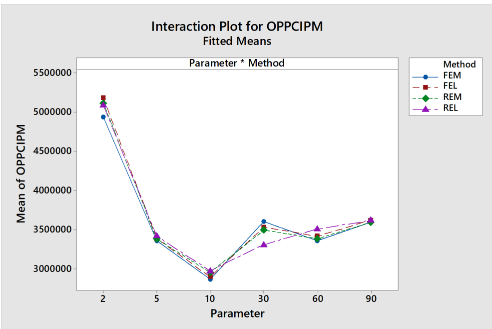

Figure 6.24: OPPCIPM Interaction Plot

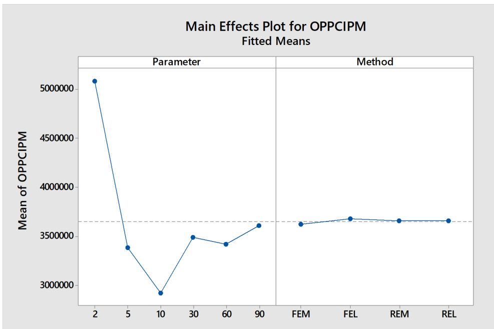

Figure 6.25: OPPCIPM Main Effects Plot

We analysed the OPPCM-FEM and OPPCIPM-FEM and comparison is given in Figure 6.26. We have used t-test to understand whether it has a significant difference between corrective maintenance to parameter 90. According to this comparison, we found that p-value is 0.424 between parameter 90 and OPPCM. Parameter 90 and OPPCM do not have significant differences. When we examine parameter 60 and parameter 30 to see why it decrease in parameter 60, p-value is 0.688 between parameter 60 and 30. There are not significant respectively. Lastly,

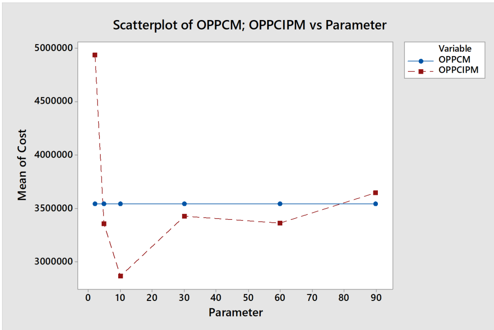

Figure 6.26: OPPCIPM vs OPPCM

The ranges of 2, 5, 10, 20, 30, 60 and 90 days are selected for the OPPDIPM strategy and two-way ANOVA is applied. The results are given in Table 6.15. P-value of the effects of parameter and method are both 0.000 and p-value of the effect of interaction between the parameters and the methods is 0.944. Parameters and methods have low p-values and they are significantly different. In addition, when we look at the interaction between the parameters and methods p-value is higher than $\alpha = 0.05$. Therefore, this is not significant for the model. After the ANOVA results, we also obtained plots of interaction and main effects for further analysis in Figure 6.27 and Figure 6.28 where the best solution is determined as 10 days from the main effects plot of OPPDIPM.

We compare OPPCM-FEM result to OPPDIPM-FEM result. Figure 6.29 shows the behaviour of the cost of decreasing values of the parameter. We have used the t-test to understand whether there exists a significant difference between the OPPCM and OPPDIPM with parameters 30, 60 and 90 respectively. Test results give p-values of 0.771, 0.948 and 0.424 respectively which indicate no significant difference. In addition, parameter 2 forces to do proactive maintenance many

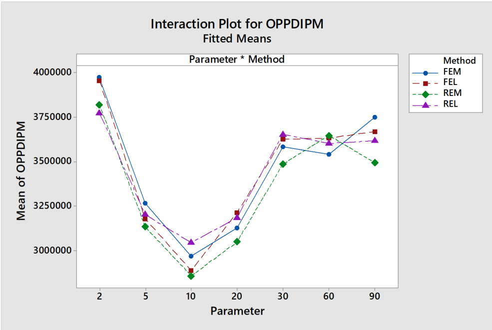

Figure 6.27: OPPDIPM Interaction Plot

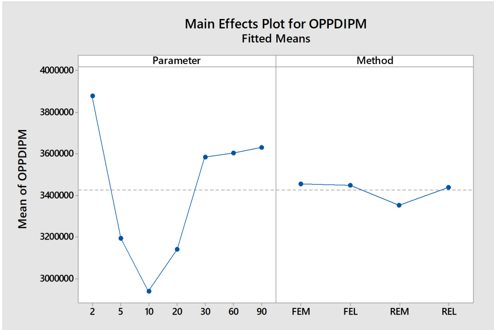

Figure 6.28: OPPDIPM Main Effects Plot

times. Therefore, the system tends to do unnecessary maintenance which is not desired.

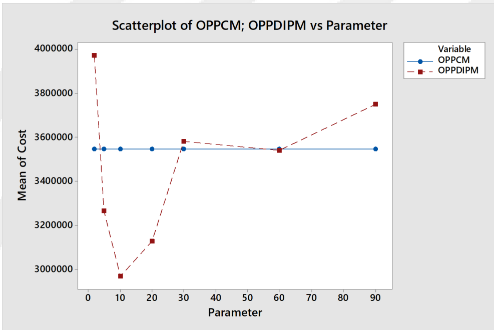

Figure 6.29: OPPDIPM vs OPPCM

In OPPThPM strategy, the threshold values are selected as 0.50, 0.75, 0.85, 0.90, 0.95 and 0.97 respectively. The result of ANOVA is given in Table 6.15. When the results are evaluated, the p-value of the parameters and methods are 0.000 from which we can say easily that parameters and methods are significant for the model. In addition, when we look at the interaction between the parameters and methods p-value is 0.246 from which we can conclude that interaction is not significant. We obtain plots of interaction and main effects in Figure 6.30 and Figure 6.31 after the ANOVA result. We find the best parameter is 0.95.

After ANOVA analysis of the total costs, we compare OPPCM to OPPThPM using the FEM method. The comparison graph is given in Figure 6.32. Parameters 0.50, 0.75, 0.85 and 0.90 have higher cost since proactive maintenance is very rare

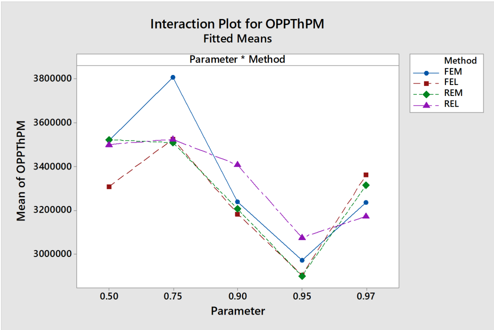

Figure 6.30: OPPThPM Interaction Plot

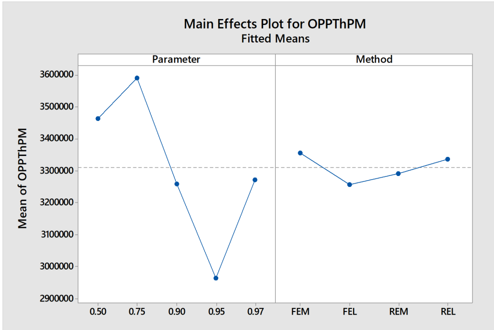

Figure 6.31: OPPThPM Main Effects Plot

leaving the system doing almost only corrective maintenance. Also, we have used the t-test to understand whether it has a significant difference between OPPCM to parameter 0.75. And, we found that p-value is 0.079. The result shows that there exists no significant difference between them.

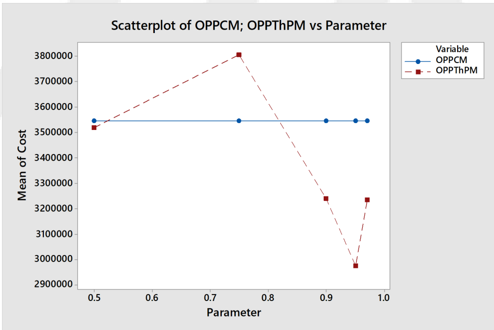

Figure 6.32: OPPThPM vs OPPCM

In addition, the best method in each opportunistic strategy was examined with one-way ANOVA including also corrective opportunistic maintenance results and a p-value of 0.000 was obtained. So, we compared these strategies also using Tukey's test [76]. The results are given in Table 6.16. As expected, the OPPCM strategy is significantly worse than all strategies applied since it has the highest average maintenance cost. However, we cannot say that the performances of the other three proactive strategies differ significantly from each other because they are in the same group.

Table 6.16: Post-ANOVA Results of Selected Oppurtunistic Maintenance Strategies

Strategy	Method	N	Mean	Group
OPPCM	FEM	30	3,547,000	A
OPPThPM $thr = 0.95$	FEM	30	2,974,267	B
OPPDIPM $pdi = 10$	FEM	30	2,970,367	B
OPPCIPM $pci = 10$	FEM	30	2,869,667	B

As a result, it is understood that there is no difference between the selected best OPPPM strategies. In addition, it is possible to implement any of these opportunistic maintenance strategies in the given best parameters easily.

6.3.2.2 Results Based on the Maintenance Quantity

We did not find any significant differences between the proposed opportunistic maintenance strategies, then we examined the maintenance quantity as our second objective. The results are given in Table 6.17. We can say that there is a significant difference among the selected maintenance strategies according to maintenance quantity. OPPThPM uses the system reliability to beside on the maintenance time, so it does not take unnecessary maintenance and consequently has less maintenance quantity than other OPPPM strategies. Although there is no difference in terms of maintenance cost in these selected maintenance strategies, it is more logical to choose OPPThPM when considering the maintenance quantity.

Table 6.17: Post-ANOVA Results of Selected OPPPM Strategies

Strategy	Method	N	Mean	Std. Dev.	Group
OPPCIPM $pci = 5$	FEM	30	79.200	2.124	A
OPPDIPM $pdi = 5$	FEM	30	73.033	2.498	B
OPPThPM $thr = 0,95$	FEM	30	69.033	2.593	C

6.3.2.3 Results of the Selected OPPPM Strategy

The OPPThPM-FEM strategy was applied according to OPPPM strategy results. Furthermore, the corrective maintenance cost part and proactive maintenance costs part were examined with the opportunistic part and non-opportunistic part on the results. These results are shown in Table 6.18. In the results, we found OPPThPM was 2,974,267 TL. In this cost, the corrective part has 2,296,066.67 TL and proactive part 678,200.00 TL. Also, we can look at the replacement cost, we can see that the effect of the cost of the opportunistic part. In addition, we found that ThPM was 3,55,480 TL in the previous section. The reason why OPPThPM is lower than ThPM due to it has an opportunistic part.

Table 6.18: Distribution of Cost in OPPThPM

Replacement Cost			
OPPThPM	**Opp part**	**NonOpp part**	**Total**
CM Part	42,333.33	33,733.33	76,066.67
PM Part	29,166.67	91,533.33	120,700.00
Loss Production Cost			
OPPThPM	**Opp part**	**NonOpp part**	**Total**
CM Part	0.00	2,220,000.00	2,220,000.00
PM Part	0.00	557,500.00	557,500.00

6.4 Comparison of the Maintenance Policies

After we found the best maintenance strategies, we selected them as policies and examined them under each method for total cost and quantity. The results are given in Figure 6.33 and 6.34. The significant of the method is most observed in the DIPM strategy where is in the other strategies. The maintenance methods behave indifferently according to the total cost.

In addition, we can say that the proactive maintenance group is better. In total quantity, the significance of the method is also observed in ThPM strategy. and methods behave indifferently in the other strategies. Corrective maintenance

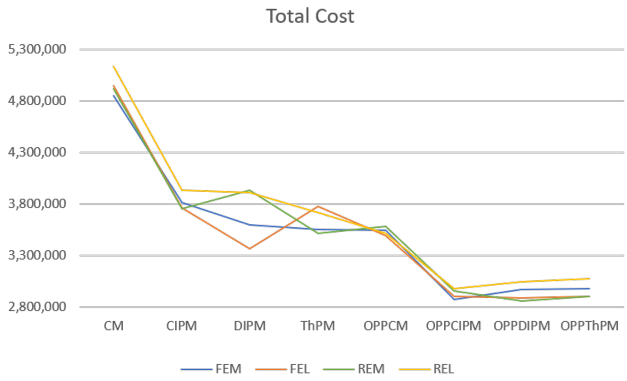

Figure 6.33: Comparison of Policies according to Total Cost

group is better. We take a consider proactive group, the best strategy is ThPM for proactive strategy and OPPThPM for opportunistic proactive strategy.

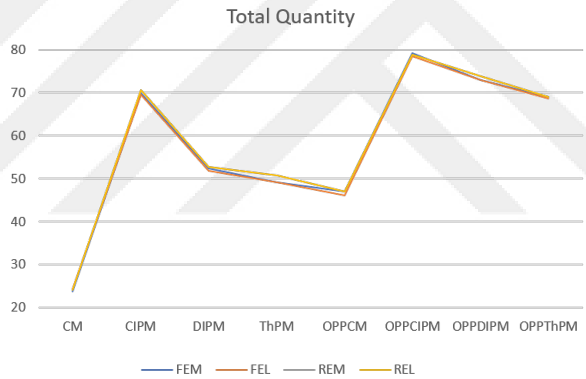

Figure 6.34: Comparison of Policies according to Total Quantity

We examined further best policy with one-way ANOVA. P-value was found 0.000. After ANOVA, we compared all averages using Tukey's test [76]. The results are available in Table 6.19. However, there exists a significant difference between the best-selected policies in terms of cost. Although it is quite indifferent with respect to the OPPCM, the results show that ThPM is significantly better than CM. As expected, OPPThPM policy is the best.

Table 6.19: Post-ANOVA Results of Selected Policies

Strategy	Method	N	Mean	Group
CM	FEM	30	4847467	A
ThPM $thr = 0.95$	FEM	30	3554800	B
OPPCM	FEM	30	3547000	B
OPPThPM $thr = 0.95$	FEM	30	2974267	C

6.5 Solution Time Analysis

The solution times of the methods and strategies are given in Table 6.20. When we examined the results, the random method did not run the inference due to select the component to be run randomly. Therefore, the solution time is shorter than the other methods. The parameters of the best selected maintenance strategies are taken as reference for the solution period of the proactive maintenance and proactive maintenance policies. These strategies don't use the random method.

Table 6.20: Distribution of Average Solution Time

	Average Solution Time (minute)		
Strategies	**FEM-FEL**	**REM-REL**	**RND**
CM	22.60	23.21	9.87
PM	24.20	24.84	$--$
OPPCM	14.53	14.62	9.62
OPPPM	14.53	15.02	$--$

Chapter 7

Real Life Model

In the previous sections, we modelled an empirical system and analysed different maintenance policies using DBNs. In this section, how to apply DBNs in real life problems is given. This real-life model is about to heat treatment. Heat treatment is applied in production plants to give a metal shape especially in the places where metal is used in products. Heat Treatment is the process of replacing the physical, chemical and mechanical properties of metals by being heated and cooled in a controlled manner. Heat treatment is carried out using the austempering furnace line. This furnace line is a complex system with interrelated components. Maintenance plans for the austempering furnace line must be developed and implemented. It is aimed to use proposed strategies to plan maintenance using DBNs.

In this chapter, we will give information about the austempering furnace line and its subsystems. We will talk about why the endo-gas generator, the subsystem of the austempering furnace line, is chosen for modelling and how it is modelled with DBNs, the dependencies between the components, prior and transition probabilities, costs and procurement processes of these components. We will explain how the malfunctions in the endo-gas generator can affect production.

7.1 Austempering Furnace Line

Electric or gas heating system with the desired size, gas atmosphere, direct heating or air circulation can be produced. Thanks to its energy efficiency and homogeneous heat distribution, austempering furnaces ensure that the materials are subjected to high-quality heat treatment to achieve the desired hardness. There are nine subsystems of the austempering furnace line. These systems are serially connected to each other except the endo-gas generator. The endo-gas generator works in parallel with the austempering furnace. In Figure 7.1, sub-systems of the austempering furnace line are given.

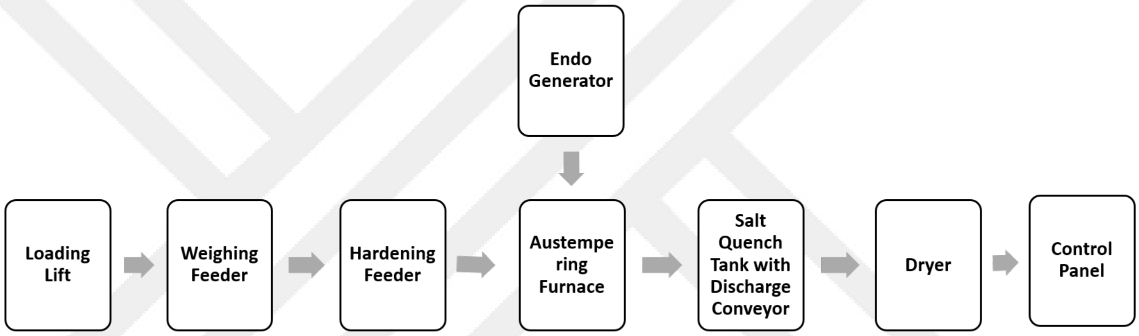

Figure 7.1: Sub-systems of Austempering Furnace Line

A typical austempering furnace line consists of nine main systems which are loading lift system, weighing feeder system, hardening feeder system, austempering furnace system, endo generator system, salt quench tank with discharge conveyor system, washing machines system, dryer system, and control panel system. This study focuses on the endo generator system. This is because the endo generator system has great importance for the austempering furnace line. Failures that may occur in this system completely stop the system and prevent production.

7.2 Endo Generator System

The decarburization layer on the steel surface forms a smooth area on this surface since it will not turn into martensite in the hardening process after cementation.

Decarburisation results in a reduction in surface hardness and fatigue strength. This is often undesirable. In order to prevent the formation of decarburisation layer, the endothermic gas mixture in the furnace atmosphere can be achieved and the surface of the steel part is protected from CO2, O2, and water vapour. This endothermic gas mixture is provided by endo generators. Endo generators provide a homogeneous atmosphere and provide atmosphere control heat treatment.

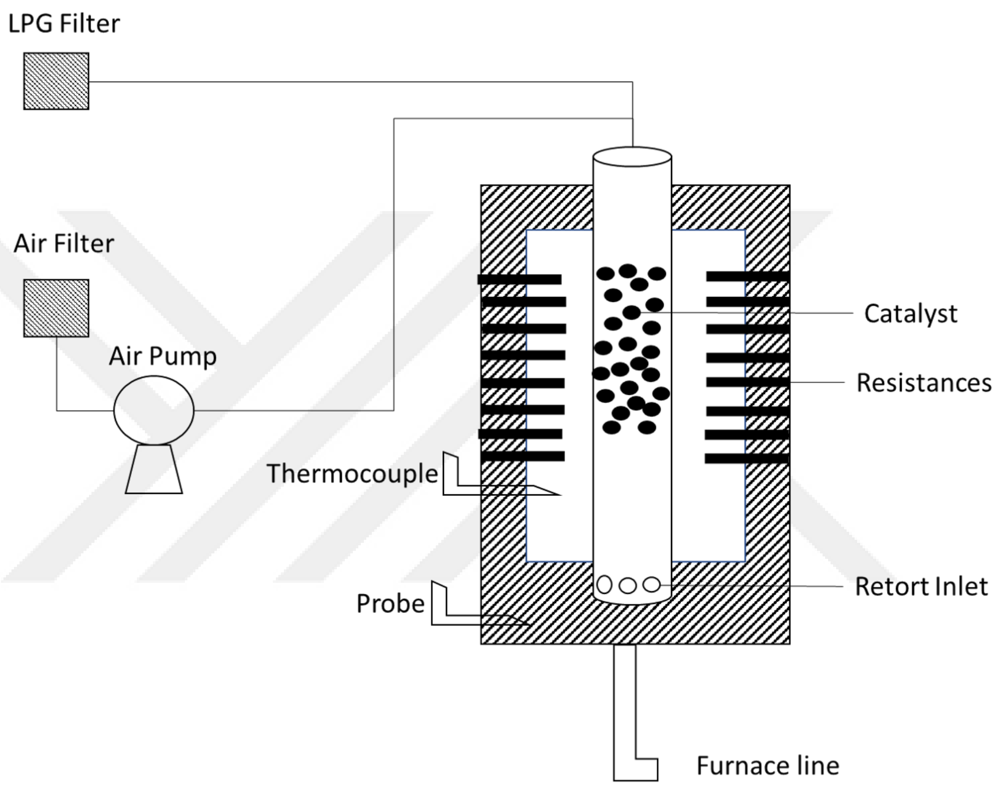

Figure 7.2: Diagram of Endo Generator System

Endo generator system consists of the air system, LPG system, and combustion system. The formation of endo-gas depends on the proper operation of these systems. The diagram of the endo generator system is given in Figure 7.2. Air system has an air pump and air filter. Air pump consists of a fan belt, the fan of motor and motor winding. These components draw the air required for combustion. Air is also controlled by air pressure measuring devices. In order to prevent air leakage, there are gaskets in the pipe joints. These gaskets consist of a mixture of hard plastic and paper.

In the LPG system, LPG is withdrawn from the main natural gas line. The LPG line and the transfer pipe contain the LPG filter. LPG pressure is monitored by measuring devices. If there is an LPG transfer at undesired pressure, a portion of LPG is discharged from the discharge regulator to reduce the pressure. In addition, there are gaskets to prevent LPG leakage from pipe joints. In the combustion system, there are resistance, thermocouple, and catalyst. The resistance gives a certain degree of heat and the heat is monitored by the thermocouple. Catalysts are contained in a retort. The combustion process takes place in this retort. Catalysts are combusted with the aid of air, LPG and resistances.

7.2.1 Technical Information of the Endo Generator

Endo generator is fitted directly on top of the furnace. It is heated by electrical heaters fitted inside a radiant tube. Operating temperature of the generator is 1025 C. The generator consists of heat resistant alloy retort inside which catalyst is filled. A mixture of gas and air is fed from the top into catalyst bed in a ratio of 1:4. a flow meter panel is provided with flowmeters and solenoid valves to control the gas flow. Gas is kept at 2 cub m/hr and air at 8 cub m/hr. The endo-gas generated enters the furnace through a pipe at the bottom of the generator. The gas potential is measured and controlled by a carbon controller which displays the MV. MV is maintained between 1000 and 1050 MV and this can be set from the panel. An oxygen probe is fitted on the top of the furnace to measure the MV value inside the furnace. Reference air panel is provided to give reference air to the probe. This air is kept at 2 to 3 cub ft/hr. A timer is provided to send purge air every 2 hr to clean the oxygen probe. To maintain the set MV, a separate flow of enrichment gas is let into the furnace directly through a flow meter. This flow is to be kept between 50 and 100 lph.

7.2.2 Working Principle of the Endo Generator

The processes of endo generator working principle is as follows:

- The air motor rotates the fan belt to rotate the fan and air enters the system through the air filter. The pressure of the incoming air is monitored.
- The air mixes with LPG to form a mixed gas and is released into the retort.
- The catalysts inside the retort are burnt by means of resistance and mix gas to form endo-gas.
- The resulting endo-gas is released from the holes under the retort into an empty chamber.
- With the emitted endo-gas probe, the CO2 value is measured and sent to the furnace at the desired level. If the amount of gas is too high, it is released through vent regulator. If the amount of gas is too low, the combustion process is repeated.

7.3 DBN Model of the Endo Generator System

While modelling the endo generator system, the data obtained from previous visits were used, such as the dependencies between the components, how a component degradation affects other components that depend on it, the cost of repair and replacement of each component, how long it lasts to repair or component and Mean Time to Failure of components. According to these, the model is constructed with the Genie Modeler [72] as given in Figure 7.3.

Endo generator consists of nine components which are air filter, motor winding, fan belt, LPG filter, resistances, thermocouple, endo-gas retort, ceramic catalyst, and probe. The model has three node types: dynamic nodes, process nodes, and observation nodes. In Figure 7.3, the arrows "1" refer to the temporal relationships which are effective after one time period. These arrows may locate between two different nodes or on the same nodes. Other arrows represent the causal relations among the nodes. Table 7.1 shows the node types and state spaces of all nodes in the DBN model. Endo gas CO_2 measurement is an observation

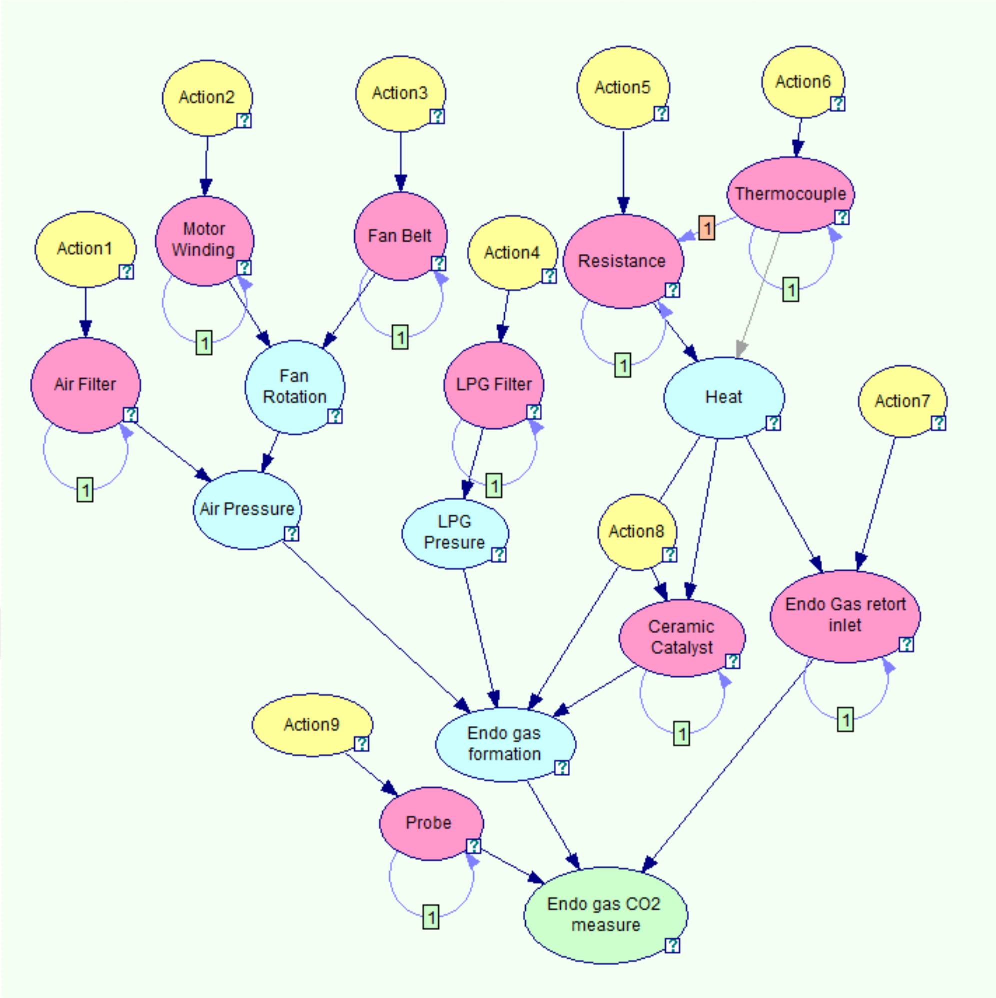

Figure 7.3: Endo Generator DBNs model

node, built in the endo generator system to model the observability that provides information on the amount of CO_2 of the rich gas generated.

7.3.1 Dependencies Among the Components

In the DBN model, components have relationships and dependencies of the Endo generator system. In the case of burn out of the motor winding in the air pump, the motor cannot rotate the belt and does not generate air. In this case, no air flow will occur even if the air filter is working. The formation of endo-gas arises from the air, LPG and catalytic combustion. The catalysts are burned with the help of resistances. Catalysts are likely to have 1025 degrees of heat

Table 7.1: Types of Nodes in the DBN Model

Nodes	**Node type**	**State space**
Air Filter	Component	{Normal, Fouling, Blocked}
Motor Winding	Component	{Normal, Burned}
Fan Belt	Component	{New, Corrosion, Failure}
LPG Filter	Component	{Normal, Fouling, Blocked}
Resistance	Component	{Normal, Degraded, Failure}
Thermocouple	Component	{Normal, Degraded Low, Degraded High}
Ceramic Catalyst	Component	{Normal, Low Quantity, Finished}
Endo Gas Retort Inlet	Component	{Normal, Fouling, Blocked}
Probe	Component	{Normal, Fouling, Blocked}
Fan Rotation	Process	{Rotate, Not Rotate}
Air Pressure	Process	{Normal, Low, Ultra Low}
LPG Pressure	Process	{Normal, Low, Not Available}
Heat	Process	{Normal, Low Level, High Level}
Endo Gas Formation	Process	{Normal, Low, Super Low}
Endo Gas CO_2 Measure	Observation	{Normal, Low, Super Low}

to be burned at the desired level. The resistances are heated at this level. The temperature inside the furnace is measured by the thermocouple. Resistances and thermocouple have a stochastic dependency between them. Because the failure of the thermocouple affects the resistances in the next period. For example, if the thermocouple is at the "Degraded Low" state, the resistance will be heated more and hence will work with a higher temperature and will be degraded due to high current. In this case, the temperature inside the furnace will increase and the catalysts will burn out faster than expected. The rapid consumption of catalysts will affect the endo-gas in the retort and will obstruct the endo-gas release by blocking the retort inlet. There is structural dependence between catalysts and retort inlet. In this case, a maintenance process that can occur in the retort or the catalysts leads to maintenance of both have to be maintained at the same time. In addition, LPG must be supplied at sufficient pressure for endo-gas formation. The decrease in LPG pressure is caused by the failure of the LPG filter.

7.3.2 Modelling of Maintenance Actions

In a DBN model, actions are not explicitly included in the model the influence diagram. Therefore, in this study, probabilistic action nodes were created for the replacement and repair of each component. The purpose of the action nodes is to ensure that the repair and replacement of the components do not affect the past and hence the current state of the other components.

Table 7.2 shows the action nodes and their state spaces. The action of "Do Nothing" is to leave that component in its case, without any changes, the action of "Replace" is to replace the component with a new, the action of "Non Calibrate" is to leave without any changes on the measurement device and the action of "Calibrate" is to calibrate the measurement device.

Table 7.2: Types of Action Nodes in the DBN Model

Component Nodes	**Action Nodes**	**State space**
Air Filter	Action 1	{Replace, Do Nothing}
Motor Winding	Action 2	{Replace, Do Nothing}
Fan Belt	Action 3	{Replace, Do Nothing}
LPG Filter	Action 4	{Replace, Do Nothing}
Resistance	Action 5	{Replace, Do Nothing}
Thermocouple	Action 6	{Calibrate, Non Calibrate}
Endo Gas Retort Inlet	Action 7	{Replace, Do Nothing}
Ceramic Catalyst	Action 8	{Replace, Do Nothing}
Probe	Action 9	{Calibrate, Non Calibrate}

7.3.3 Probabilities of the DBN Model

Mean Time to Failure (MTTF) was used to determine the failure probabilities of the components. This information is taken from factory employees. Table 7.3 shows the MTTF of each component and the working probabilities calculated in the next period accordingly. Initially, all components were started from their best condition. At later times, if the action node is in the "Replace" state, the component changes a new one and it backs to best condition.

Table 7.3: Average MTTF of Components

Component	MTTF (day)	Working Probability
Air Filter	365.0	0.997264
Motor Winding	1095.00	0.999087
Fan Belt	182.50	0.994536
LPG Filter	365.00	0.997264
Resistance	400.00	0.997503
Thermocouple	730.00	0.998631
Endo Gas Retort Inlet	60.83	0.983696
Ceramic Catalyst	60.83	0.983696
Probe	365.00	0.997264

All component nodes were started from their best states and actions nodes have symmetric CPT between each other ($Replace = 0.5, DoNothing = 0.5$) and ($Calibrate = 0.5, NonCalibrate = 0.5$). The transition probabilities of all component nodes are given from Table A.1 to Table A.9.The conditional probabilities of the process nodes and observation node resulting from causal relations are represented Table B.1to Table B.8.

Chapter 8

Conclusion and Future Study

A multi-component dynamic system consists of various components and subsystems interacting with each other. This system consists of various components and subsystem. Developing maintenance strategies for this system is quite challenging. We analyse a four-component the dynamic system under several maintenance policies. We model the system using DBNs. DBNs provide flexibility in modelling the dependencies in the system and efficient inference calculation.

For a four-component dynamic system, we propose four methods inspired by the literature to be used under all kinds of maintenance strategies to determine the most effective maintenance activity when a maintenance decision is taken. Our goal is to minimize the total cost. We also develop a random selection method that will be compared to the four methods. Each of these methods performed better than the random method and there is no significant difference between them.

We propose several maintenance policies under reactive, proactive and opportunistic maintenance strategies and implement them with different parameters. We simulate the policies within the framework of dynamic Bayesian networks and compare their performances using two criteria, total maintenance cost, and total maintenance quantity. The results show that all proactive maintenance policies are significantly better than the corrective maintenance policy. However, there exists no significant difference among the best selected proactive maintenance policies in terms of cost although they differ with respect to the quantity criterion. Threshold-based proactive maintenance is the best.

When the opportunistic approach is included in the policies, the performance of the policies is similar to respective cases without opportunistic approach except for the best parameter values. Proactive maintenance is preferred to be delayed to a later period when the opportunistic approach is used. Another interesting result about the policies including the opportunistic approach is that all proposed maintenance methods give similar performances with the random method in determining the maintenance action. This is not surprising in a four-component empirical system since more components than the necessary are replaced or repaired at any maintenance period within the opportunistic philosophy. Hence, the importance of determining the most effective component is lost which causes insignificance among all the component selection methods including the random method.

Furthermore, a dynamic Bayesian network is constructed for the maintenance of an endo generator system to show how the proposed methods can be implemented in real life. Endo generator system consists of several components having dependencies among them. The causal and temporal relations are represented with probabilities estimated based on the expert knowledge in the visited company. Once the dynamic Bayesian network model is constructed, the proposed policies can be efficiently implemented on such a real-life maintenance problem.

As a future study, we will analyse the performance of maintenance strategies on a more complex problem, the endo generator system, to reduce the total maintenance cost. The efficiency measures used in the maintenance methods can be improved and new efficiency measures can be developed. Systems giving more partial information with more than one observation can also be studied as the extension of this work.

In the current work during the integration of the opportunistic approach to maintenance policies, the reliability threshold value in the maintenance activity selection step is taken as 0.95. More extensive replications can be obtained including different reliability threshold values. Furthermore, sensitivity analysis of the performances of the policies to the loss production cost can be performed like a future study.

Appendix

Appendix A

Transition probabilities

Table A.1: Transition probabilities of Air Filter

Action 1	**Replace**			**Do Nothing**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	1	1	1	0.99726	0	0
Fouling	0	0	0	0.9	0.996	0
Blocked	0	0	0	0.00074	0.1	1

Table A.2: Transition probabilities of Motor Winding

Action 2	**Replace**		**Do Nothing**	
(Self)[t-1]	**Normal**	**Burned**	**Normal**	**Burned**
Normal	1	1	0.99909	0
Burned	0	0	0.00091	1

Table A.3: Transition probabilities of Fan Belt

Action 3	**Replace**			**Do Nothing**		
(Self)[t-1]	**New**	**Corrosion**	**Failure**	**New**	**Corrosion**	**Failure**
New	1	1	1	0.99454	0	0
Corrosion	0	0	0	0.005	0.7	0
Failure	0	0	0	0.00046	0.3	1

Table A.4: Transition probabilities of LPG Filter

Action 4	Replace			Do Nothing		
(Self)[t-1]	Normal	Fouling	Blocked	Normal	Fouling	Blocked
Normal	1	1	1	0.99908	0	0
Fouling	0	0	0	0.00061	0.9	0
Blocked	0	0	0	0.0003	0.1	1

Table A.5: Transition probabilities of Resistance

Action 5	Replace					
(Self)[t-1]	Normal			Degraded		
Thermocouple	Normal	Fouling	Blocked	Normal	Fouling	Blocked
Normal	1	1	1	1	1	1
Degraded	0	0	0	0	0	0
Failure	0	0	0	0	0	0
Action 5	Do Nothing					
(Self)[t-1]	Normal			Degraded		
Thermocouple	Normal	Fouling	Blocked	Normal	Fouling	Blocked
Normal	0.997503	0.99726	0.99909	0.99	0.99	0.99
Degraded	0.00250	0.00264	0.00091	0.01	0.01	0.01
Failure	0	0.0001	0	0	0	0
Action 5	Replace			Do Nothing		
(Self)[t-1]	Failure			Failure		
Thermocouple	Normal	Fouling	Blocked	Normal	Fouling	Blocked
Normal	1	1	1	0.99	0.99	0.99
Degraded	0	0	0	0.01	0.01	0.01
Failure	0	0	0	0	0	0

Table A.6: Transition probabilities of Thermocouple

Action 6	Calibrate			Non Calibrate		
(Self)[t-1]	Normal	D. Low	D. High	Normal	D. Low	D. High
Normal	1	1	1	0.99863	0	0
Degraded Low	0	0	0	0.00068	1	0
Degraded High	0	0	0	0.00068	0	1

Table A.7: Transition probabilities of Endo Gas Retort Inlet

Action 7	**Replace**					
Heat	**Normal**			**Low Level**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	1	1	1	1	1	1
Fouling	0	0	0	0	0	0
Blocked	0	0	0	0	0	0
Action 7	**Do Nothing**					
Heat	**Normal**			**Low Level**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	0.983602	0	0	0.989	0	0
Fouling	0.009	0.99	0	0.01	0.999	0
Blocked	0.00740	0.01	1	0.001	0.001	1
Action 7	**Replace**			**Do Nothing**		
Heat	**High Level**			**High Level**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	1	1	1	0	0	0
Fouling	0	0	0	0.1	0.001	0
Blocked	0	0	0	0.9	0.999	0

Table A.8: Transition probabilities of Ceramic Catalyst

Action 8	**Replace**		
(Self)[t-1]	**Normal**	**L. Quantity**	**Finished**
Normal	1	1	1
L. Quantity	0	0	0
Finished	0	0	0
Action 8	**Do Nothing**		
(Self)[t-1]	**Normal**	**L. Quantity**	**Finished**
Normal	0.98361	0.01	0
L. Quantity	0.009	0.989	0.001
Finished	0.00740	0.001	0.999

Table A.9: Transition probabilities of Probe

Action 9	**Calibrate**			**Non Calibrate**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	1	1	1	0.99727	0	0
Fouling	0	0	0	0.0025	0.99	0
Blocked	0	0	0	0.00024	0.01	1

Appendix B

Conditional probabilities

Table B.1: Conditional probabilities of Fan Rotation

Motor Winding	**Normal**			**Burned**		
Fan Belt	**New**	**Corrosion**	**Failure**	**New**	**Corrosion**	**Failure**
Rotate	1	0.8	0	0	0	0
Not Rotate	0	0.2	1	1	1	1

Table B.2: Conditional probabilities of Air Pressure

Air Filter	**Normal**		**Fouling**		**Blocked**	
Fan Rotation	**New**	**Not Rotate**	**New**	**Not Rotate**	**New**	**Not Rotate**
Normal	1	0	0.001	0	0	0
Low	0	0	0.9989	0	0	0
Ultra Low	0	1	0.0001	1	1	1

Table B.3: Conditional probabilities of LPG Pressure

Air Filter	**Normal**	**Fouling**	**Blocked**
Normal	1	0.0001	0
Low	0	0.9899	0
Not Available	0	0.01	1

Table B.4: Conditional probabilities of Heat

Resistance	**Normal**		
Thermocouple	**Normal**	**D. Low**	**D. High**
Normal	1	1	1
L. Level	0	0	0
H. Level	0	0	0
Resistance	**Degraded**		
Thermocouple	**Normal**	**D. Low**	**D. High**
Normal	0	0	0
L. Level	1	1	1
H. Level	0	0	0
Resistance	**Failure**		
Thermocouple	**Normal**	**D. Low**	**D. High**
Normal	0	0	0
L. Level	0	0	0
H. Level	1	1	1

Table B.5: Conditional probabilities of Endo Gas Formation

Ceramic Catalyst	**Normal**								
LPG Pressure	**Normal**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	1	0	0	0	0	0	0	0	0
Low	0	0.8	0	0.8	0.3	0.8	0	0	0
Super Low	0	0.2	0	0.2	0.7	0.2	1	1	1
Ceramic Catalyst	**Normal**								
LPG Pressure	**Low**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0.8	0.3	0.8	0.3	0	0.3	0	0	0
Super Low	0.2	0.7	0.2	0.7	1	0.7	1	1	1
Ceramic Catalyst	**Normal**								
LPG Pressure	**Not Available**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0	0	0	0	0	0	0	0	0
Super Low	1	1	1	1	1	1	1	1	1

Table B.6: Conditional probabilities of Endo Gas Formation (Con'd)

Ceramic Catalyst	**Low Quantity**								
LPG Pressure	**Normal**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0.8	0.3	0.8	0.3	0	0.3	0	0	0
Super Low	0.2	0.7	0.2	0.7	1	0.7	1	1	1
Ceramic Catalyst	**Low Quantity**								
LPG Pressure	**Low**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0	0.3	0	0.3	0	0	0	0	0
Super Low	1	0.7	1	0.7	1	1	1	1	1
Ceramic Catalyst	**Low Quantity**								
LPG Pressure	**Not Avaible**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0	0	0	0	0	0	0	0	0
Super Low	1	1	1	1	1	1	1	1	1

Table B.7: Conditional probabilities of Endo Gas Formation (Con'd)

Ceramic Catalyst	**Finished**								
LPG Pressure	**Normal**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0	0	0	0	0	0	0	0	0
Super Low	1	1	1	1	1	1	1	1	1
Ceramic Catalyst	**Finished**								
LPG Pressure	**Low**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0	0	0	0	0	0	0	0	0
Super Low	1	1	1	1	1	1	1	1	1
Ceramic Catalyst	**Finished**								
LPG Pressure	**Not Avaible**								
Air Pressure	**Normal**			**Low**			**Ulra Low**		
Heat	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**	**Normal**	**L. Level**	**H. Level**
Normal	0	0	0	0	0	0	0	0	0
Low	0	0	0	0	0	0	0	0	0
Super Low	1	1	1	1	1	1	1	1	1

Table B.8: Conditional probabilities of Endo Gas CO_2 Measure

Probe	**Normal**								
Endo Gas Formation	**Normal**			**Low**			**Super Low**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	1	0.3	0	0	0	0	0	0	0
Low	0	0.7	0	1	0.6	0	0	0	0
Super Low	0	0	1	0.4	1	1	1	1	1
Probe	**Fouling**								
Endo Gas Formation	**Normal**			**Low**			**Super Low**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	0.8	0	0	0	0	0	0	0	0
Low	0.2	0.8	0	0.6	0.3	0	0	0	0
Super Low	0	0.2	1	0.4	0.3	1	1	1	1
Probe	Blocked								
Endo Gas Formation	**Normal**			**Low**			**Super Low**		
(Self)[t-1]	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**	**Normal**	**Fouling**	**Blocked**
Normal	0	0	0	0	0	0	0	0	0
Low	0	0	0	0	0	0	0	0	0
Super Low	1	1	1	1	1	1	1	1	1

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