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INDUSTRIAL ENGINEERING - OPERATIONS RESEARCH PROGRAM

Şimal Ekin DEMİRAL

OPPORTUNISTIC MAINTENANCE OF COMPLEX SYSTEMS USING DYNAMIC BAYESIAN NETWORKS

SUPERVISOR
Asst. Prof. Demet ÖZGÜR ÜNLÜAKIN

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ÖZET

KARMAŞIK SİSTEMLERİN DİNAMİK BAYESÇİ AĞLARI İLE FIRSATÇI BAKIMI

Endüstrinin gelişimiyle sistemlerin karmaşıklığı daha da çok artmıştır. Beklenmedik arıza süreleri şirketler için büyük maliyetler oluşturabilmektedir. Bu yüzden, uygun bakım stratejisini seçmek, kar kayıplarını önlemek için çok daha önemli hale gelmiştir. Sistemdeki bileşenler ve bağımlılıkları bu stratejileri değerlendirmede zorluk yaratabilir. Bu nedenle uygulanacak bakımın etkili olabilmesi için sistemin doğru modellenmesi çok önemlidir. Bayes ağları (BN'ler) karmaşık sistemlerin ve bileşenleri arasındaki bağımlılıkların modellenmesinde oldukça etkilidir. Dinamik Bayes Ağları (DBN'ler), işin dinamik doğasını temsil etmek için BN'lere zamansal bir boyut eklenerek BN'lerin genişletilmiş versiyonlarıdır.

Bu çalışmada, bir üretim tesisindeki CNC makineleri için DBN'leri kullanarak fırsatçı bir bakım çerçevesi sunduk. Bir CNC makinesi, birçok bileşenden oluşan ve bileşenleri arasında bağımlılıklar bulunan, kısmen gözlemlenebilir bir sistemdir. Farklı CNC makinelerini inceledik ve bakım problemini modellemek için en karmaşık olanı seçtik. Sistemi on alt sisteme ayırdık ve bakım problemini incelemek için bu alt sistemlerden işlevsel olarak en önemlisi olan eksen sistemini seçtik. HAZOP analizini kullanarak sistemdeki neden-sonuç ilişkilerini belirledik. Daha sonra sistemdeki bileşenlerin yaşlanmasını ve nedensel ilişkilerini modellemek ve olasılıksal çıkarımları hesaplamak için DBN'leri kullandık. Aralarında stokastik bağımlılıkların da bulunduğu on bir bileşenden oluşan bu karmaşık sistem için hem düzeltici hem de proaktif bakım stratejileri altında fırsatçı bir bakım yaklaşımı önerdik. Hem düzeltici hem de proaktif bakım koşullarında kullanılmak üzere iki fırsatçı bakım politikası geliştirdik. Bakım problemini iki farklı hedefle ele aldık. Biri toplam maliyeti en aza indirmek, diğeri ise toplam kesinti süresini en aza indirmektir.

Yöntemleri düzeltici ve proaktif bakım stratejilerinde farklı parametrelerle çalıştırdık. Bu iki yöntemi fırsatçı bir yaklaşım kullanmayan başka bir bakım metodolojisiyle karşılaştırdık. Son olarak önerilen fırsatçı bakım stratejilerinin daha iyi çalıştığı koşulları belirledik. Sonuçlar, fırsatçı yaklaşımların, planlı ya da plansız bir duruşun yüksek kesinti maliyetlerine yol açtığı durumlarda ümit verici performans gösterdiğini ortaya çıkardı. Dolayısıyla düzeltici bakımdaki duruş maliyeti proaktif bakıma göre daha yüksek olduğundan fırsatçı politikalar bu durumlarda daha iyi sonuçlar verdi. Proaktif bakımda duruş maliyeti arttırıldığında, fırsatçı politikaların proaktif bakımdaki performansı da iyileşti. Bu bulgular senaryo analizi sonuçlarıyla da desteklenmiştir.
Anahtar Kelimeler: Fırsatçı Bakım, Çok Bileşenli Sistemler, Stokastik Bağımlılık, Dinamik Bayesçi Ağı, CNC Makineleri

ABSTRACT

OPPORTUNISTIC MAINTENANCE OF COMPLEX SYSTEMS USING DYNAMIC BAYESIAN NETWORKS

With the development of industry, the complexity of systems has increased even more. Unexpected downtimes can create huge costs for companies. Therefore, choosing the appropriate maintenance strategy has become much more important to prevent profit losses. The components in the system and their dependencies can create difficulties in evaluating these strategies. Therefore, it is very important to model the system correctly for the maintenance to be applied to be effective. Bayesian networks (BNs) are highly effective in modeling complex systems and the dependencies between their components. Dynamic Bayesian Networks (DBNs) are the extended versions of BNs by adding a temporal dimension to BNs to represent the dynamic nature of the work.

In this study, we presented an opportunistic maintenance framework using DBNs for CNC machines in a production facility. A CNC machine is a partially observable system that consists of many components and has dependencies between its components. We examined different CNC machines and chose the most complex one to model the maintenance problem. We divided the system into ten subsystems, and we chose the Axis System, which was the most functionally important of these subsystems, to study the maintenance problem. We identified cause-and-effect relations in the system using HAZOP analysis. Then, we used DBNs to model the aging of components and the causal relations in the system, and to calculate the probabilistic inferences. We proposed an opportunistic maintenance approach under both corrective and proactive maintenance strategies for this complex system of eleven components with stochastic dependencies among them. We developed two opportunistic maintenance policies to be used in both corrective and proactive maintenance conditions. We tackled the maintenance problem with two different objectives.

One is to minimize the total cost while the other is to minimize the total downtime duration. We ran the methods with different parameters in the corrective and proactive maintenance strategies. We compared these two methods with another maintenance methodology that did not use an opportunistic approach. Finally, we determined the conditions where the proposed opportunistic maintenance strategies operated better. The results revealed that opportunistic approaches showed promising performance in situations where a planned or unplanned breakdown led to high downtime costs. Therefore, since the downtime cost in corrective maintenance was higher than that of proactive maintenance, opportunistic policies gave better results in these cases. When the downtime cost in proactive maintenance was increased, the performance of opportunistic policies in proactive maintenance also improved. These findings were also supported by the results of the scenario analysis.
Keywords: Opportunistic Maintenance, Multi-Component Systems, Stochastic Dependency, Dynamic Bayesian Network, CNC Machines

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ABBREVIATIONS LIST

BN: Bayesian Network

DBN: Dynamic Bayesian Network

CBM: Condition-based Maintenance

CM: Corrective Maintenance

PM: Proactive Maintenance

ThPM: Threshold-based Proactive Maintenance

DB: Downtime-based

CB: Cost-based

CNC: Computer Numerical Control

HAZOP: Hazard and Operability

$\boldsymbol{rt}$**:** Real time

$\boldsymbol{t}$**:** DBN time

$\boldsymbol{O_t}$**:** Observation status at time t

$\boldsymbol{Pdt}(\boldsymbol{i}^*)$**:** Proactive maintenance period of the selected component i

$\boldsymbol{Cdt}(\boldsymbol{i}^*)$**:** Corrective maintenance period of the selected component i

Obs: Observation list

OppM: Opportunistic Maintenance list

OppOM: Observation-based Opportunistic Maintenance list

Opp: Opportunistic maintenance policy

ObsOpp: Observation-based Opportunistic maintenance policy

NoOpp: No-Opportunistic maintenance policy

$\boldsymbol{Opp_{thr}}$**:** Opportunistic threshold

RB: Rotor Bearings

Enc: Encoder

RS: Rotor Shaft

Mot: Motor

Dri: Drivers

ODE: Oil Distributor Elements

ASB: Axis Shaft Bearings

Cou: Coupling

ASN: Axis Shaft and Nut

SS: Slide Surfaces

LS: Limit Switches

RSR: Rotor Shaft Rotation

ASR: Axis Shaft Rotation

AM: Axis Movement

RB M.: Rotor Bearings Maintenance

Enc M.: Encoder Maintenance

RS M.: Rotor Shaft Maintenance

Mot M.: Motor Maintenance

Dri M.: Drivers Maintenance

ODE M.: Oil Distributor Elements Maintenance

ASB M.: Axis Shaft Bearings Maintenance

Cou M.: Coupling Maintenance

ASN M.: Axis Shaft and Nut Maintenance

SS M.: Slide Surfaces Maintenance

LS M.: Limit Switches Maintenance

SOQ: Slide Oil Quality

RSV: Rotor Shaft Vibration

ASV: Axis Shaft Vibration

LM: Laser Measurement

$\boldsymbol{TC_i}$**:** Total Cost of component i

$\boldsymbol{MC_i}$**:** Maintenance Cost of component i

$\boldsymbol{MD_i}$**:** Maintenance Duration of component i

$\boldsymbol{DC_i}$**:** Downtime Cost per day for component i

CHAPTER 1

1. INTRODUCTION

In recent times, the rapid development of technology and the evolution of industry have led to systems acquiring a more complex structure. Industrial systems that were previously simple and composed of just a few components have now been replaced by complex structures with many components. These developments have made determining and implementing effective maintenance policies, particularly in multi-component systems, even more crucial.

Maintenance is an activity in which repairs are made at regular intervals to prolong the useful life of a machine or equipment. Maintenance is the set of operations necessary for production systems to continue to have their original production capacity (Sharma et al.,2011).

The smooth operation of numerous complex systems made up of various equipment that offers varied goods and services ensures the effective functioning of contemporary society. These include transportation systems, communication systems, utilities, manufacturing facilities, hospitals, and banks. With age and use, all equipment becomes fundamentally unreliable, which can lead to the failure of a complex system, causing serious financial losses, human suffering and environmental damage. A failed system can be brought back into working condition with appropriate corrective maintenance, such as repairing or replacing components that have failed and thus caused the system to malfunction. The probability of failure and its consequences can be reduced through effective preventive maintenance activities.

Over the past century, there has been a significant change in maintenance strategy. Previously, this approach was for corrective maintenance only. During the Second World War, the significance of preventative maintenance was understood. Preventive maintenance is more expensive and only useful when the profits outweigh the costs. Optimum maintenance decisions are made by developing appropriate models and using complex optimization techniques. These days, maintenance problems are beginning to be taken into account during the design stage. Thus, reliability and sustainability have become important concepts in system design and operation. As a result, maintenance is no longer only a technical issue; it is now a strategic management issue. (Kobbacy and Murthy, 2008, p. 13)

The choice of maintenance strategy is one of the most important elements of effective maintenance management. An appropriate maintenance strategy should be chosen for the company in order to achieve goals such as uninterrupted production, ensuring personnel and facility safety, and reducing maintenance costs.

1.1 MAINTENANCE STRATEGIES

The literature has a wide variety of maintenance strategies. Figure 1.1 shows the taxonomy of these (Geng et al., 2015). Information about corrective maintenance, time-based preventive maintenance, condition-based maintenance, and predictive maintenance will be provided in the subsequent subsections.

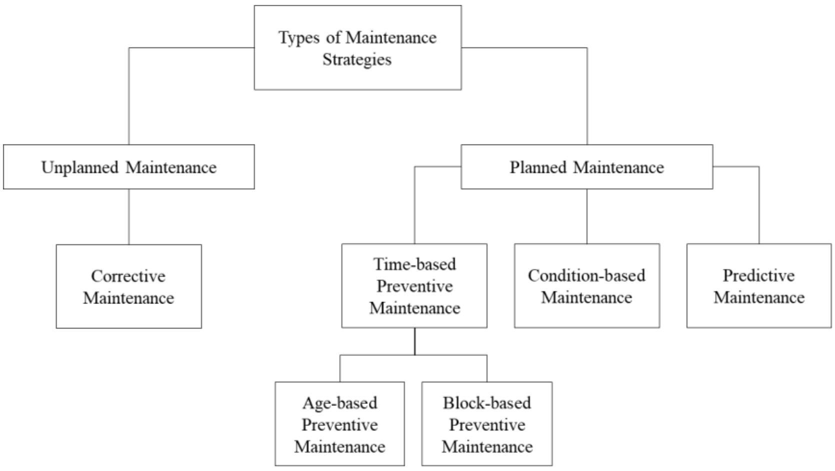

Figure 1.1 Types of Maintenance Strategies

1.1.1 Corrective Maintenance

Corrective maintenance is in the unplanned maintenance category. Its main feature is that maintenance is not performed until a malfunction occurs. It is considered a widely used strategy in industries with high-profit margins. However, this kind of maintenance frequently seriously harms the involved systems, employees, and environment. But besides that, low-profit margins and increased worldwide competition encourage maintenance managers to create more reliable and economical maintenance procedures. This method is a method that can be applied in enterprises that have not yet made a maintenance plan and in machinery or equipment that will not affect the production system in case of failure (Wang et al., 2007).

1.1.2 Time-based Preventive Maintenance

This is a planned maintenance type. To minimize frequent and unexpected breakdowns, maintenance is scheduled and carried out periodically based on the equipment or machine's reliability characteristics. That is why this maintenance type is also referred to as periodic maintenance. This maintenance type is a widely used strategy in the industry. A decision support system needs to be established to perform time-based preventive maintenance. However, finding the most efficient maintenance periods becomes challenging in the absence of sufficient historical data (Wang et al., 2007). Time-based preventive maintenance is divided into age-based and block-based. Block-based maintenance occurs at fixed and regular intervals, while age-based maintenance optimizes timing based on the equipment's age or usage duration.

1.1.3 Condition-based Maintenance

In this strategy, we make the maintenance decision based on measured data from sensor systems. With techniques such as vibration analysis, electrical analysis, ultrasonic testing, and lubrication analysis, conditions that cause poor performance or unexpected failure for the equipment can be monitored. Thus, it can be decided whether to perform maintenance or not by looking at the actual condition of the equipment. Using monitored condition data, engineers can determine whether a condition is normal and maintenance personnel can act before a fault occurs. This approach is used for reciprocating and rotary machines. However, limitations due to the lack of data or quality of data can reduce the effectiveness of this strategy (Wang et al., 2007).

1.1.4 Predictive Maintenance

This is a maintenance strategy that can predict temporary performance degradation trend and equipment failures by analyzing parameter data. Failure prediction enables maintenance planning. This maintenance strategy is aimed at achieving near-zero downtime performance of equipment (Wang et al., 2007).

1.2 DEPENDENCES IN MULTI-COMPONENT SYSTEMS

Since dependencies exist between components in a multi-component system, it is important to choose the appropriate maintenance strategy to achieve the optimal maintenance strategy. Multi-component systems are more difficult to maintain than single-component systems. Complex systems contain many components that are interdependent or not interdependent. Modeling and optimization of maintenance are made more difficult by interactions between components. On the other hand, it is crucial to identify the types of dependencies between components to minimize maintenance expense and duration.

There are three types of interactions between the components of a multicomponent system: economic dependency, structural dependency, and stochastic dependency (Nicolai & Dekker, 2008).

1.2.1 Economic Dependency

This dependency occurs when the total maintenance cost is reduced or raised by joint maintenance of multiple components. Reducing the maintenance cost is referred to as positive economic dependency whereas its increase is named as negative economic dependence (Dinh et al., 2022). When group maintenance is carried out on components, profit loss can be minimized owing to decreased downtime, or expenses may rise because of excessive replacement of parts in the group.

1.2.2 Structural Dependency

According to this dependency, two interdependent components cannot be replaced or repaired independently of each other; instead, maintenance and repair of these components must be done together. Thus, structural dependency means that other components must be disassembled to maintain a particular component. A system with strong structural dependencies among its components has higher maintenance costs and longer maintenance times.

1.2.3 Stochastic Dependency

This type of dependency occurs when the failure distribution of one component in the system is affected by the degradation of the other (Geng et al., 2015). It has two types which are Type I and Type II failure interactions. Type I occurs when failure in one component causes other components to fail. Conversely, Type II occurs when a component fails, and it affects the failure rate of one or more components or causes shock damage to the other components.

1.3 MOTIVATION AND CONTRIBUTION

Maintenance problems on a single component are extensively studied in the literature due to its relative simplicity compared to systems with multi-components. Maintenance on multi-components is studied mainly on two components or serial or parallel systems. Maintenance of the systems having several interacting components with stochastic and structural dependencies is generally difficult even to model. In this study, we aim to fill in this gap by handling the maintenance problem of a complex multi-component system on a CNC machine in a pump production facility.

We propose an opportunistic maintenance approach under both corrective and proactive maintenance strategies for this complex system of 11 components with stochastic dependencies among them. We develop two opportunistic policies to be used in both corrective and proactive maintenance conditions. We tackle the maintenance problem with two different objectives. One is to minimize the total cost and the other is to minimize the total downtime duration. We compare these two methods with another maintenance methodology that does not use an opportunistic approach. Finally, we try to determine the most appropriate maintenance policy by comparing these maintenance strategies among themselves.

The results show that opportunistic approaches show promising performance in systems when a breakdown leads to high downtime costs. Hence, in our study, they give better results under corrective maintenance when both downtime duration and cost are considered. However, under the proactive maintenance strategy, when the production loss cost is relatively low compared to the corrective case, the effect of opportunistic approaches on the total cost is not as significant as under the case of corrective maintenance, where the production loss cost is higher.

The organization of the thesis is as follows. The literature review of maintenance studies specifically in multicomponent systems is given in Chapter 2. The methodology and solution approach are given in Chapter 3. We use dynamic Bayesian networks to model the stochastic and structural maintenance dependencies of multi-component systems, and to infer the required probabilities. We identify cause-and-effect relations in the system using HAZOP analysis. We propose two opportunistic maintenance policies within the DBN framework under corrective and proactive maintenance strategies. We implement the proposed opportunistic maintenance policies on a CNC machine system in a pump production facility in Chapter 4 where the DBN modeling of the system is given in detail. Chapter 5 presents the detailed computational results. Lastly, Chapter 6 makes conclusions for the study and gives future possible work directions.

CHAPTER 2

2. LITERATURE

Nowadays, there is increasing interest in maintaining and troubleshooting multi-component systems. This situation is linked to the increasing interactivity and complexity of the components within these systems. In this chapter, we classify the literature related to the maintenance of multi-component systems. The first subsection presents studies related to opportunistic maintenance. Then, the taxonomy of the DBN applications in maintenance and related fields is given in the following section. Finally, the last section summarizes studies in opportunistic maintenance in CNC machines.

2.1 OPPORTUNISTIC MAINTENANCE

The opportunistic maintenance practice has two main purposes: First, to prolong the useful life of the equipment, or at least the mean time to failure (MTTF) until the next failure. This maintenance approach is expected to decrease the number of service interruptions and the negative effects of these interruptions. The second is to take advantage of the resources, effort, and time devoted to maintaining other components of the system to reduce the cost (Samhouri, 2009). Opportunistic maintenance includes a series of maintenance activities performed on a component when there is an opportunity while performing maintenance activities on other components in a multi-component system.

In terms of Opportunistic Maintenance, systems are divided into subgroups as two-component systems, serial systems, parallel systems, and complex systems, and then, examples of these systems are given from the studies in the literature. A summary of these selected applications is given in Table 2.1.

Table 2.1 Opportunistic Maintenance Applications

Article	Type of System	Methodology	Time Horizon	Cost Function	Strategy	System
Salari et al. (2017)	Two components system	Semi-Markov Decision Process	Finite	Average Cost	PM	Electric Power Distribution Systems
Van Do et al. (2019)	Two components system	Cost Model-Optimization	Finite	Total Cost	CBM	Gearbox System
Zhao et al. (2019)	Two components system	Reliability Model/Optimization Model	Finite	Average Cost	PM	Preset Self-repairing Mechanism
Ma et al. (2020)	Two components system	Multi-Stage Wiener Process	Infinite	Average Cost	CBM	Warm Standby Cooling System
Najafi et al. (2021)	Two components system	Proportional Hazards Model/Semi-Markov Decision Process	Infinite	Average Cost	CM/PM	Mechanical Systems
Uit Het Broek et al. (2021)	Two components system	Markov Decision Process	Infinite	Average Cost	CBM	Production Systems
Hou et al. (2013)	Serial Systems	Cost Model-Optimization	Finite	Total Cost	PM	Production System
Zhao et al. (2018)	Serial Systems	Weibull Proportional Hazards Model	Infinite	Average Cost	CBM	Wind Turbines
Keizer et al. (2018)	Parallel Systems	Markov Decision Process	Infinite	Average Cost	CBM	Numerical System Inspired by Gas Pump System
Keizer et al. (2016)	Parallel Systems	Dynamic Programming Model	Finite	Average Cost	CBM	Hot Standby System
Wang et al. (2022)	Parallel Systems	Monte Carlo Simulation Techniques / Particle Swarm Optimization-based Heuristic Algorithm	Infinite	Average Cost	CBM	Industrial System
Tian et al. (2011)	Two/Three Identical Components Systems	Proportional Hazards Model-Optimization	Finite	Average Cost	CBM	Shear Pump System
Hu vd. (2012)	Complex Systems	Dynamic Bayesian Network	Finite	Average Cost	PM	Gas Turbine Compressor System
Zhou et al. (2013)	Complex Systems	Universal Generating Function/Semi-regenerative Property/Ant Colony Optimisation	Finite	Average Cost	CBM	Production System
Xia et al. (2021)	Complex Systems	Capacity Balancing-Oriented Leasing Profit Optimization	Finite	Total Cost	PM	Manufacturing System
Martinod et al. (2018)	Complex Systems	Cost Model-Optimization/ Clustering Method	Finite	Total Cost	CM/PM	Passenger Urban Aerial Ropeway Transport System
Van Horenbeek et al. (2013)	Complex Systems	Cost Model-Optimization	Finite	Average Cost	CM/PM	Industrial Systems

2.1.1 Two-Component Systems

For a two-unit model with an economic dependency that might be used for electric power distribution systems. An improved opportunistic and preventative maintenance method is provided (Salari et al., 2017). In this two-unit system, unit one is monitored for condition, and age information is subject to unit two. A mathematical model is developed to determine the preventative and opportunistic maintenance decisions for both two units that reduce the long-term foreseen average cost per unit time. They solve this problem with a semi-Markov decision process (SMDP).

A condition-based maintenance policy model for a two-component system with stochastic and economic dependency is developed (Do et al., 2019). They suggest that the components to be applied for preventive maintenance should be determined by preventive replacement and opportunistic replacement policies. They aim to find the optimal values of the decision variables by developing a cost model. They apply this model to the gearbox system. Finally, they claim that when components have the propensity to degrade together than they do not, opportunistic maintenance is less advantageous.

An opportunistic maintenance model for the predetermined self-healing mechanism is constructed (Zhao et al., 2019). A two-unit serial system is created to illustrate the suggested model after the pre-set self-healing mechanism is initially discussed in the reliability model. An examination of the system's reliability is done to determine how the predetermined self-healing recovery method will affect it. Additionally, an opportunistic maintenance strategy that considers the expenses associated with downtime is suggested. They discover through numerical findings that the presence of downtime cost resulted in the taking of preventative measures at a higher level of disruption to avoid prolonged downtime. Finally, a comparison between the preventive maintenance program and the opportunistic maintenance policy is made.

Reliability analysis and maintenance optimization of a two-unit warm standby refrigeration equipment are worked on (Ma et al., 2020). They describe the degradation tendency of the system with a multi-step Wiener process. They formulate the reliability function of the system and accordingly develop a condition-based opportunistic maintenance policy based on temperature monitoring information.

An opportunistic maintenance strategy is suggested (Najafi et al., 2021) for the maintenance of mechanical systems that include two series of economically dependent units. There is condition monitoring for unit 1 and age information for unit 2. Unit 1's stochastic deterioration is described by a gamma process. Condition monitoring data is used to determine the hazard ratio using the proportional hazards model (PHM). The reliability of the two-unit serial system is determined using a matrix-based technique. Based on lifetime and PHM data, the policy suggests preventive actions at predetermined intervals to improve system reliability and decrease unexpected downtimes. Corrective measures fix the faulty unit while allowing for the opportunity to maintain the other unit. The problem is formulated as a semi-Markov decision process (SMDP) to minimize the long-run expected average cost over an infinite time horizon.

The impact of conditional load-sharing options for economically dependent two-unit systems is examined (Uit Het Broek et al., 2021). They formulate the system with the Markov decision process and provided optimal condition-based maintenance and production policies. With the numerical study, they find significant cost savings compared to the optimal condition-based maintenance policy under equal load sharing.

2.1.2 Serial Systems

An opportunistic maintenance policy for a multi-unit mass production system is proposed (Hou et al., 2013). This proposed maintenance policy is based on failure rate analysis. They incorporate three types of maintenance actions into the opportunistic maintenance model, including replacement, repair, and minimal repair, to align it more with real situations. They predict that in a limited time horizon, optimum preventive maintenance plans can be achieved by adjusting the preventive maintenance threshold and the opportunistic maintenance threshold. They support the proposed policy with a numerical example.

A condition-based opportunistic maintenance strategy for multi-component serial systems is presented (Zhao et al., 2018). The maintenance of more than one component under different conditions is combined with the definition of the opportunity concept and the maintenance of each component is coordinated. Wind turbines are taken as an example of a multi-component serial system and simulation analyzes are carried out to verify the feasibility of the condition-based opportunistic maintenance strategy.

2.1.3 Parallel Systems

A multi-component parallel condition-based maintenance system (CBM) with economic dependency due to maintenance setup costs and failure dependency due to load sharing is discussed (Keizer et al., 2018). They formulate this system with a Markov Decision Process. They arrive at the optimal maintenance policy structure with a numerical example and sensitivity analysis in which they change the degree of load sharing, maintenance installation cost, and deterioration process.

CBM tasks for a multi-component system with both economic dependencies and redundancy via a k-out-of-N structure are clustered and a dynamic programming model to determine the most effective maintenance plan is developed (Keizer et al., 2016). They carry out a cost analysis and discover that the optimal maintenance strategy outperforms all other plans that are taken into consideration.

A new condition-based opportunistic maintenance method applicable to multi-component systems with economic and stochastic dependency is developed (Wang et al., 2022). They monitor the effectiveness of group care with a dynamic care approach. They use the cost optimization model. Optimal maintenance decisions are made using Monte Carlo simulation methods and heuristic algorithm. They also analyze the effectiveness of maintenance decisions by comparing the proposed method with another method.

2.1.4 Other Systems

Because of the complexity of opportunistic maintenance optimization of multi-component systems with more than two components and not serial or parallel, it is rarely studied in the literature.

A case-based maintenance policy (CBM) based on a proportional hazard model, extending it from a single component to a multi-component system for systems with identical and independent multi-components with economic dependence is proposed (Tian et al., 2011). They develop a numerical algorithm for cost assessment of multi-component CBM policy based on the proportional hazards model (PHM). They give examples using real-world condition monitoring data to illustrate the proposed methods.

Hazard and operability (HAZOP) analysis and dynamic Bayesian networks (DBNs) to create an opportunistic predictive maintenance strategy in a gas turbine system are used (Hu et al., 2012). HAZOP is used to analyze and learn about the system, and utilizing the results, a DBN model is built. With the DBN-HAZOP model, they predict future deterioration trends and achieve optimum maintenance practice for each component. For a complex system, they realize that when one of the components stops performing the predictive maintenance (PdM) action, the entire complex system must be stopped, and they conclude that predictive maintenance opportunities emerge for the other degraded components in the system at a reduced overhead. Thus, they present an opportunistic PdM approach that makes all the costs in the system more economical.

A maintenance strategy for a serial and parallel system with multi-state components is developed (Zhou et al., 2013). This strategy uses both opportunistic maintenance and state-based inspection intervals. The suitability of the proposed maintenance policy and optimization techniques are tested by numerical simulation. They conclude that the applied maintenance approach is more economical considering the economic dependency and the inspection cost. They also present a novel stochastic method that can make the optimization more efficient.

An opportunistic maintenance policy integrating capacity balancing and rental profit is proposed (Xia et al., 2021). This policy analyzes the serial/parallel structures in the leased system and offers an outsourcing maintenance strategy by integrating capacity balancing into production processes. It is seen that the proposed policy increases the rental profit and affects the time and capacity lost during maintenance in a good way.

A stochastic optimization model to reduce the long-term total maintenance cost in multi-component systems is proposed (Martinod et al., 2018). They use a reliability analysis and clustering method with two different maintenance policies (periodic block type and age-based) for maintenance actions. This study assumes that a system is made up of several sets of components, each set of which can contain the same kind of components even though they are not identical. It is also demonstrated that the effects under more than one independent type of degradation process for each grouped component with a maintenance model. Finally, a passenger urban aerial ropeway transport system with a set of 426 components is subjected to the suggested optimization model.

A dynamic maintenance plan based on predictive information for a multi-component system with the combination of various dependencies is developed (Van Horenbeek et al., 2013). They also examine how partial dependencies affect the maintenance of multi-component systems. It is observed that this maintenance strategy reduces the long-term average maintenance cost per unit time when compared to other maintenance policies since it may dynamically address the dependencies of components in multi-component systems.

2.2 DBN APPLICATIONS IN MAINTENANCE FIELDS

In the literature, DBNs are studied in many areas. Table 2.2 provides a summary of some selected DBN applications.

Table 2.2 DBN Applications

Article	Application Area	System
Hu et al. (2017)	Prognosis	Flue Gas Energy System
Hu et al. (2011)	Prognosis	Gas Turbine Compressor System
Muller et al. (2008)	Prognosis	Industrial System
Hu et al. (2015)	Fault Detection	Petrochemical System
Codetta-Raiteri and Portinale (2014)	Fault Detection	Autonomous Spacecraft
Sandri et al. (2014)	Fault Detection	Healthcare
Cai et al. (2016)	Fault Detection	Electronic Systems
Chang et al. (2019)	Risk Analysis	Submarine System
Chen et al. (2019)	Risk Analysis	Reservoir System
Li et al. (2018)	Reliability	Control Unit
Liu et al. (2015)	Reliability	Submarine System
Hu vd. (2012)	Maintenance	Industrial System
Özgür-Ünlüakın ve Bilgiç (2014)	Maintenance	Infrastructure Systems
Özgür-Ünlüakın et al. (2019)	Maintenance	Thermal Power Plants
Özgür-Ünlüakın et al. (2021)	Maintenance	Thermal Power Plants
Özgür-Ünlüakın, D., & Türkali, B. (2021)	Maintenance	Thermal Power Plants

To give an example of studies in the field of prognosis, a DBN-based failure prognosis method for the complex system is proposed (Hu et al., 2017). While analyzing the dynamic fault scenarios, besides the interaction between the components, they also consider the effect of the protection layers in the system. The degradation mechanism, parameter deviation, reaction of the protection layers, as well as the external environment, are considered in the DBN modeling. The dynamic effect diagram of the component degradation tendencies can be generated using this model, and the various impacts of the protective layers can be assessed. An energy system is employed to test the suggested approach. This approach significantly improves the effectiveness of layers of protection and early warning in complex industrial systems.

A combined safety prognosis model with DBN and an ant colony algorithm is developed to foresee the performance and reliability of a complex system (Hu et al., 2011). The propagation paths of failures are shown in this model using a combination of the DBN and the ant colony algorithm. In addition, this model reveals the relationships between subsystems, components, and dependencies, with failure sources and consequences. This methodology is also suitable for predicting future deterioration trends and providing proactive maintenance plans. The ant colony algorithm is used to estimate the risk. Lastly, the case study is applied to a complex gas turbine compressor system.

A methodology that combines both a probabilistic approach to model the degradation mechanism and an event approach to monitor dynamic degradation is provided (Muller et al., 2008). This study is created with general modeling concepts for testing and applying the prognosis process. The applicability of this proposed method is tested on an industrial system.

If the studies in the field of fault detection in the literature are mentioned, the fault propagation behavior of the processing system is studied, and a DBN-based system to deal with the abnormal situation is proposed (Hu et al., 2015). They conduct a HAZOP study for the development of hazard scenarios in order to create a model that can systematically and accurately reflect the interdependence between the process parameters of the facilities. They analyze all possible deviations, and their possible failure causes and consequences. They then use the DBN to establish fault causal relationships.

A method for FDIR (fault detection, identification, and recovery) using DBN is presented (Codetta-Raiteri and Portinale, 2014). Discussion is made over the native handling of FDIR analysis-specific tasks in a DBN-based system, using the prediction capabilities of these models. They talk about how this method can be used in a real-world situation such as the analysis of spacecraft.

A DBN model using historical data to predict the process of organ failure in intensive care units is developed (Sandri et al., 2014). According to the findings, a series of organ failures can be reasonably predicted given the first organ failure at the time of ICU admission. They find that DBNs can be used to simulate temporal systems in the field of critical care. They predict that DBNs also can be used as a prognostic tool that can predict future sequences of organ failure, thereby helping doctors make patient-specific decisions.

A new perspective on the problem of fault diagnosis using DBNs for electronic systems with transient fault (TF) and intermittent fault (IF) states is presented (Cai et al., 2016). They model the process of the electronic system with DBNs and show the transition relationships of the 4 states of this system with Markov chains. They determine two rules to determine the fault diagnosis. They test the applicability of this methodology with four diagnostic states of a control system. They conclude that the diagnostic results obtained using the model proposed in this study agree with the actual results when the fault occurs.

Another area where the DBN method is involved is risk analysis applications. The fatigue probability of the wellhead by risk analysis is estimated, and DBNs for this analysis are used (Chang et al., 2019). They develop a model that can predict the potential risk of failure using the accumulated fatigue at the wellhead. They apply the model they used in this study to a real-life problem. In addition, they predict that the risk of failure of the wellhead can be considerably reduced with various safety control studies.

A DBN-based model for risk analysis of a multi-reservoir system is presented (Chen et al., 2019). They apply this methodology in a catchment area in China as an example of a real-life problem. They create a DBN with historical data obtained with Monte Carlo simulations. With this created DBN model, they obtain risk information about operation planning. The findings show that the proposed approach can be used as a decision-making tool in case of uncertainty when performing control processes of a multi-reservoir system.

Common Cause Failure (CCF) is an important issue in the reliability analysis of redundant systems. performed A reliability modeling of a control unit by considering various backup gates based on a dynamic fault tree and DBN is performed (Li et al., 2018). In addition, since the β factor model cannot be used for multi-component redundant systems, they propose the multiple error shock theory (MESH) to distinguish three or more faults.

In another study, a DBN for a parallel system has n components, accounting for common cause failure (CCF) and faulty coverage is proposed (Liu et al., 2015). They model the CCF with the multiple fault shock model. They develop DBNs of two types of BOP, traditional Blowout Preventer (BOP) and modern BOP. They compare the traditional BOP with the modern BOP in various situations.

DBNs are also applied in the maintenance problems of multi-component systems in recent years.

DBNs are used to replace the components of a multi-component system in a situation where not all components can be observed (Özgür-Ünlüakın and Bilgiç, 2014). In this study, they aim to replace components at an economical cost. They formulate the problem with a partially observable Markov decision process (POMDP). They integrate states and actions to provide an optimal policy.

The Luvo system, also called regenerative air heating system (RAH), in thermal power plants with many hidden components is discussed (Özgür-Ünlüakın et al., 2019). They model this system with DBN and proposed maintenance policies to minimize the number of maintenance under the reactive maintenance strategy in the finite planning horizon. They test the effectiveness of these policies with corrective maintenance. They find that the failure effect methods outperformed the other methods.

DBN-based methods to minimize the total maintenance cost of the reactive maintenance problem of the Luvo system is presented (Özgür-Ünlüakın et al., 2021). According to their predictions, the proposed techniques can be utilized in corrective maintenance plans of systems with stochastic and structural dependency hidden components. They reach the lowest cost with the error effect method. With other analyses, they also find that the proposed methodology provides an improvement in terms of costs.

Different proactive maintenance methods for unseen multi-component systems with random dependency are proposed, and the authors compare them using DBNs (Özgür-Ünlüakın, D., & Türkali, B., 2021). They present a proactive maintenance algorithm that works with the tabu procedure to minimize the maintenance cost. The effectiveness of these methods is compared under various scenarios on a system used in a thermal power plant environment. They observe that in practically all cases, threshold-based maintenance, a predictive technique, provides the lowest cost and number of maintenance.

2.3 OPPORTUNISTIC MAINTENANCE IN CNC MACHINES

Opportunistic maintenance is a commonly used strategy in maintaining multi-unit systems. The inconsistency of the maintenance strategies at the unit level is tackled, and an optimization model for scheduled maintenance (SM) and condition-based maintenance (CBM) is developed (Li et al., 2023). They then build an optimization model for preventive opportunistic maintenance methods under hybrid unit-level maintenance strategies that account for imperfect preventive maintenance. In this model, they use Monte Carlo simulation to optimize maintenance intervals and costs. Finally, an opportunistic maintenance strategy is developed for the CNC gear grinding machine and they conclude that this strategy significantly reduces maintenance costs compared to other maintenance approaches.

Opportunistic preventive maintenance strategies for CNC lathe systems are optimized (Wu et al., 2022). Since independent maintenance applications of units in multi-unit systems are time-consuming and costly, this work incorporates opportunistic maintenance into preventive maintenance. With the proposed strategy, even if the components are not restored to new condition, their reliability can be brought to a satisfactory level. In the decision-making process, the failure rates of components are determined using the service age regression factor and the failure rate growth factor. Additionally, the study optimizes the maintenance approach by converting individual imperfect PM operations into a coordinated group activity based on a reliability threshold. The advantage of their approach is confirmed through a case study on 18 CNC lathes.

CHAPTER 3

3. METHODOLOGY AND SOLUTION APPROACH

In this study, we examine the maintenance processes of a complex multi-component system. We utilize DBNs to model the aging of components and their interdependencies within this system. We conduct HAZOP analysis to identify cause-and-effect relationships between components. We develop two opportunistic maintenance policies to be used in both corrective and proactive maintenance conditions. In this chapter, the Bayesian network, dynamic Bayesian network, HAZOP methodology, and proposed solution are provided in Section 3.1, Section 3.2, Section 3.3, and Section 3.4, respectively.

3.1 BAYESIAN NETWORK

Bayesian network is a graphical method used to show probabilistic dependencies between random variables. Bayesian networks are used in reasoning under uncertainty with the relationships it establishes between variables.

Bayesian networks consist of two main parts, the graphical part and the numerical part. The graphical part is represented by a directional acyclic graph showing the dependency/independence relationships between the variables and forms the structure of the network. A directional acyclic graph has nodes and arrows. The nodes show the random variables in the model, and the arrows show the dependency relationships between the nodes. When two nodes in the network are connected with an arrow, the node at the start of the arrow is referred to as the parent node, and the node at the end of the arrow is referred to as the child node. In the example in Figure 3.1, variables A and B are associated with probability. Variable A is the parent node of B and variable B is the child node of A.

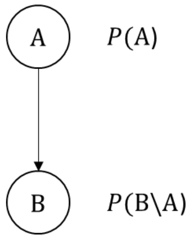

Figure 3.1 A Simple Bayesian Network

Every node in a Bayesian network has a probability distribution. If a node has no parent, it has a marginal probability distribution, if it has a parent, it has a conditional probability distribution. Conditional probabilities express the strength of the relationship between nodes and are shown through conditional probability tables. Conditional probability tables represent the numerical part of the Bayesian network. Conditional dependency relationships in the network are represented by arrows between nodes.

A Bayesian network structure with three component nodes, two process nodes, one observation node, and their respective probability distributions are depicted in Figure 3.2. The system components are represented by C_1, C_2 and C_3 in the BN network, while the process nodes P_1 and P_2 demonstrate how the variables influencing the system interact, and O stands for the observation node reflecting information obtained from the main process node. Component nodes and the process nodes have two states, observation node have three states. In the model, W represents "Working", F represents "Failure", H represents "High", M represents "Medium" and L represents "Low".

The C_1 variable is associated as the parent node of P_1 and C_3 variables, while the C_2 variable is associated as the parent node of P_1, so P_1 and C_3 variables are child nodes of the C_1 variable and P_1 is also the child node of the C_2 variable. In this network, P_1 and C_3 are also associated as parent nodes of P_2, so in this condition, P_2 is a child node. The P_1 variable is associated with the parent node of P_2, while P_2 is also associated with the parent node of the O variable.

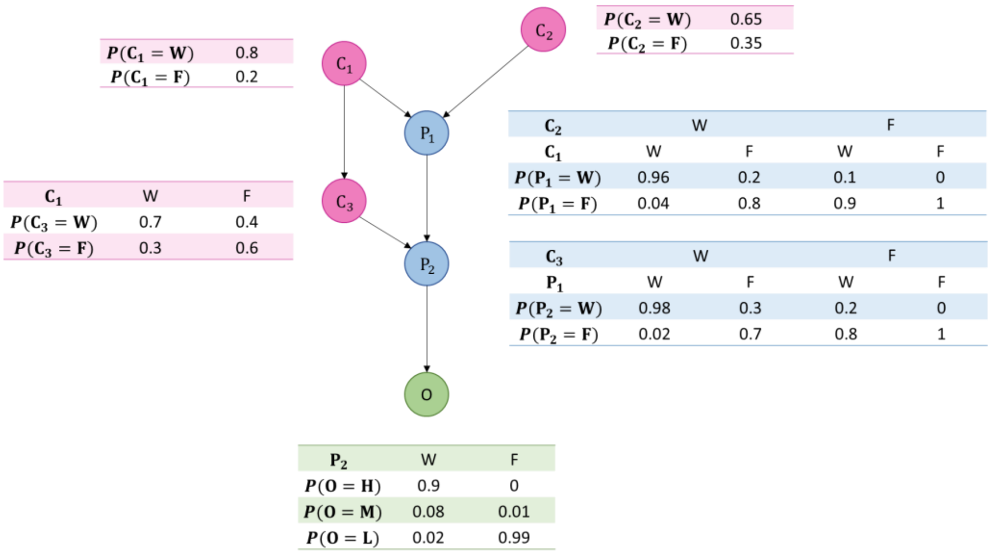

Figure 3.2 A Structure of Bayesian Network

Conditional probabilities obtained from a Bayesian network allow us to predict the state that the child node will take, given information about the parent node. For example, as illustrated in Figure 3.2, if it is known that the C_1 node is in the W state, it can be estimated that the C_3 variable will be in the F state with a 30% probability, however; when the C_1 node is in the F state, it can be estimated that the C_3 variable will be in the F state with 60% probability.

In any Bayesian network model, it is important to define the parameters of the dependencies between the variables. To illustrate the conditional probabilities of each node, a conditional probability table (CPT) is created. These tables, as shown in Figure 3.2, present the probability of the states of the variables based on combinations of the parent nodes' states. In examining the columns in the tables, it is seen that under a certain state of each node's parents, the sum of the probabilities of that node's states must be 1.

In a decision problem, where X = $\{X_1, X_2, \dots, X_N\}$ is a set of a finite number of variables; the Bayesian network has a combined probability distribution calculated over X according to Equation 3.1 where $Pa(X_i)$ is the parents of the variable X_i. The joint probability of the network is equal to the product of the conditional probabilities of the variables in the network.

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

The close expression in Equation 3.1 is written explicitly as in Equation 3.2 for the BN model in Figure 3.2.

$$P(C_1, C_2, C_3, P_1, P_2, O) = P(C_1) * P(C_2) * P(C_3|C_1) * P(P_1|C_1, C_2) * P(P_2|C_3, P_1) * P(O|P_2) \tag{3.2}$$

Since most nodes often have few parents relative to the whole size of the network, this feature enables us to significantly minimize the amount of processing needed for joint probability calculation in bigger networks.

3.2 DYNAMIC BAYESIAN NETWORK

Dynamic Bayesian Network (DBN) is a type of Bayesian Network (BN). It emerges from the addition of the time dimension to explain the dynamic behavior of random variables (Murphy, 2002). When the system is in a static condition, BNs are utilized. The great majority of engineering systems are dynamic and contain causal relationships between the state at time t and the state at time t-1. Such a temporal dimension is not taken into consideration by the Bayesian network. Therefore, the temporal dimension is handled using the DBN. The DBN can be used to see the system's performance based on the value recorded in the previous time step (Kammouh et al., 2020).

In Figure 3.3, components can be degraded over time with constant transition probabilities. They are modeled with the dash lines. The transition probabilities of the C_3 at time t are given in Table 3.1. While C_3 is in an F state at time t-1, even though C_1 is in a W state at time t, the probability of remaining in state F will be 1 since no maintenance is applied to component C_3. Conversely, if C_3 is in a W state at t-1, then its states at t are dependent upon C_1's state at t. If C_1 fails at t, the working probability of C_3 at t decreases from 0.95 to 0.55.

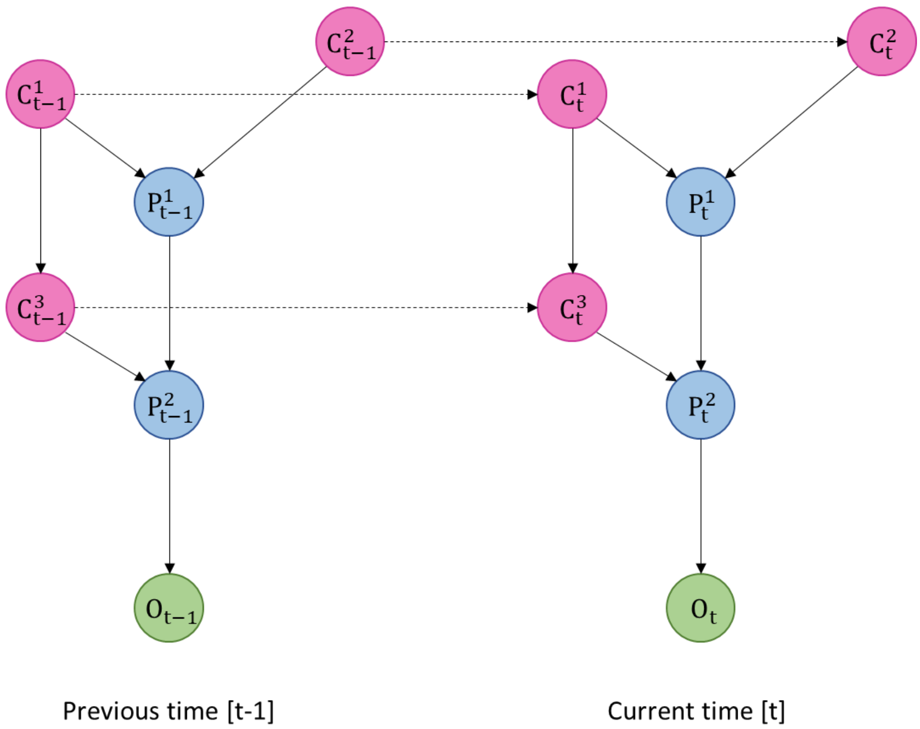

Figure 3.3 A Structure of Dynamic Bayesian Network

Table 3.1 Transition Probabilities of Third Component

$\mathbf{C^1_t}$	W		F	
$\mathbf{C^3_{t-1}}$	W	F	W	F
$\mathbf{P(C^3_t = W)}$	0.95	0	0.55	0
$\mathbf{P(C^3_t = F)}$	0.05	1	0.45	1

In Figure 3.4, action nodes are also added to the previously created DBN model. An action node is defined for each component to show the effect of maintenance. Action nodes allow timely and efficient maintenance of parts in the system to be planned. Table 3.2 shows the transition probabilities of the C_3 component under the influence of the action node at time t. In the table, when the action node of the C_3 component is in the “Replace” state, the probability of the C_3 component being in the W state is observed to be 1, regardless of the state of the components that affect it. If the action node of component C_3 is "Do nothing", the possibilities in Table 3.1 will be valid since no maintenance occurs.

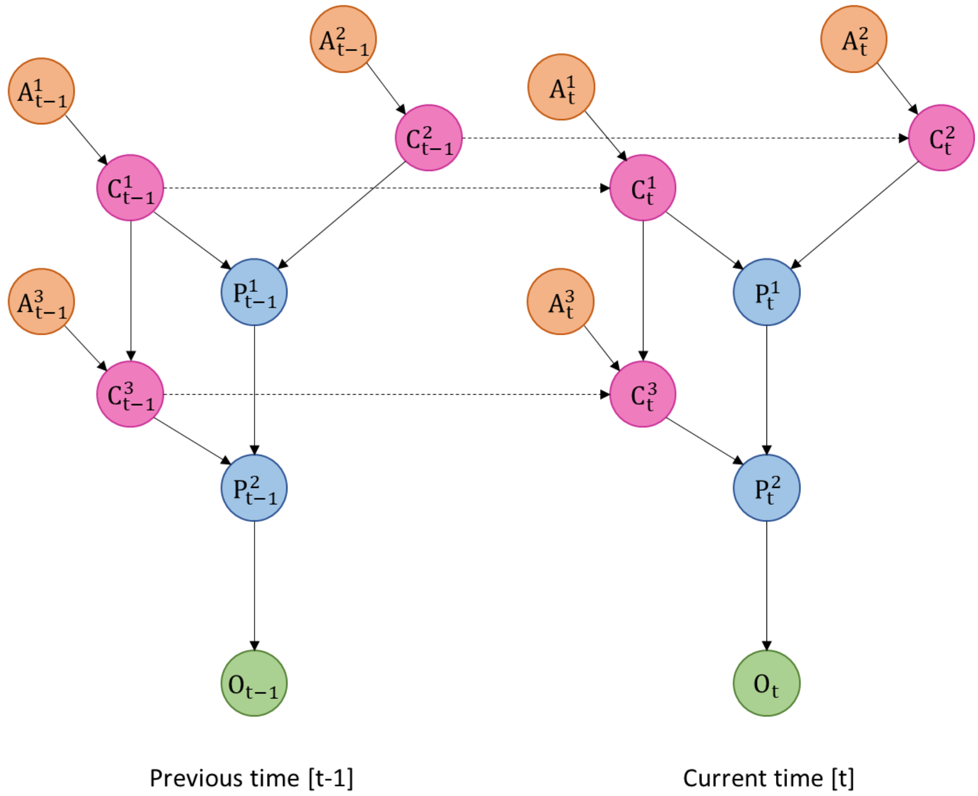

Figure 3.4 A Structure of Dynamic Bayesian Network with Action Nodes

Table 3.2 Transition Probabilities of Third Component with Action Node

$\mathbf{A_t^3}$	Replace				Do Nothing			
$\mathbf{C_t^1}$	W		F		W		F	
$\mathbf{C_{t-1}^3}$	W	F	W	F	W	F	W	F
$\mathbf{P(C_t^3 = W)}$	1	1	1	1	0.95	0	0.55	0
$\mathbf{P(C_t^3 = F)}$	0	0	0	0	0.05	1	0.45	1

The joint probabilities for the DBN can be formulated as in Equation 3.3.

$$P(X_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P\left(X_t^i | Pa\left(X_t^i\right)\right) \tag{3.3}$$

where T denotes the number of time slices, N denotes the number of random variables in a time slice, X_t^i represents the i^{th} node in time-slice t, $Pa(X_t^i)$ represents all the parents of X_t^i in the current or previous time slices and $X_{1:T}$ = $\{X_1, X_2, \dots, X_T\}$ is a set of finite number of variables in the network.

To give an example of one of the variables in the model in Figure 3.3, the conditional probability of component 3 at time t can be written explicitly as in Equation 3.4.

$$P\left(C_t^3 \middle| Pa(C_t^3)\right) = P(C_t^3 | C_{t-1}^3, C_t^1) \tag{3.4}$$

To give an example of one of the variables in the model in Figure 3.4, the conditional probability of component 3 at time t can be written explicitly as in Equation 3.5.

$$P\left(C_t^3 \middle| Pa(C_t^3)\right) = P(C_t^3 | C_{t-1}^3, C_t^1, A_t^3) \tag{3.5}$$

3.3 HAZOP METHODOLOGY

The word HAZOP comes from the abbreviation of the words “Hazard and Operability”. HAZOP is a method used to identify potential hazards in a system. It is widely applied in complex industrial systems to prevent accidents caused by hazards and system failures. The process flow chart for applying HAZOP is given in Figure 3.5.

First, information about the system and its components is collected by expert teams. This expert team usually consists of engineers from different disciplines. The system is subdivided and analyzed in detail to identify potential hazards to the components and the system. Next, the parameters that are important for each subsystem are selected. These parameters can be many variables such as flow, heat, temperature, and density.

Guide words are then created to identify possible hazards, malfunctions or deviations in the system. These words can be words such as “More”, “Less”, “No” and “Other Than”. Sample guide words and their meanings are given in

Table 3.3. With the guide words used for process parameters, possible situations that may cause hazards are determined more clearly. Then, the causes and consequences of the hazards are examined. Finally, experts present the precautions to be taken against the identified dangers and risks.

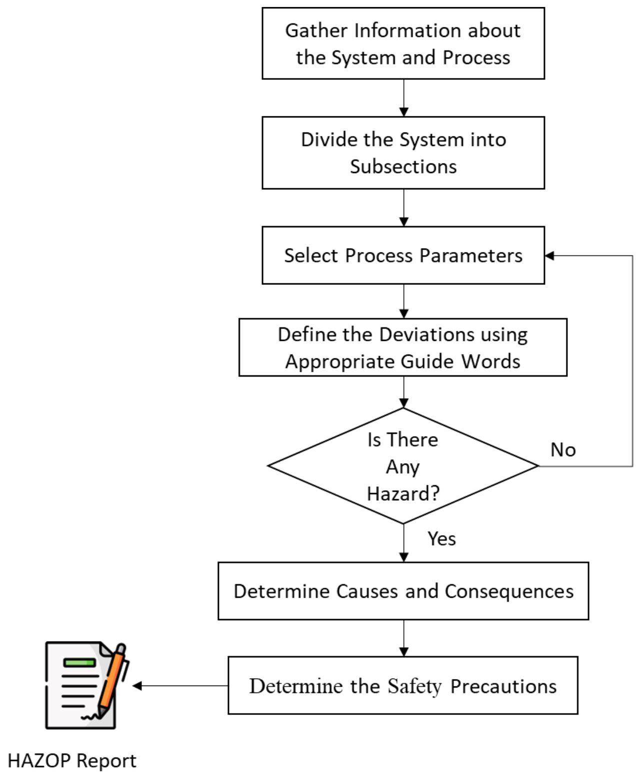

Figure 3.5 HAZOP Flow Chart

Table 3.3 Sample HAZOP Guide Words

Guide Word	Meaning
More	Increase in Process Parameter
Less	Reduction in Process Parameter
No	Absence of Process Parameter
Other Than	Presence of Unexpected Process Parameter

3.4 PROPOSED SOLUTION

We propose an opportunistic maintenance approach under both corrective and proactive maintenance strategies for a complex system with multi-component and we develop two opportunistic maintenance policies for determining maintenance activities. We address the maintenance issue with two distinct objectives. One is to minimize the total cost and the other is to minimize the total downtime duration. We use the cost-effective component selection method, FEL_{fp} (Özgür-Ünlüakın et al., 2021) to determine which component should be replaced at the time of maintenance to minimize the total cost. We also propose an adapted version of this measure to minimize the total downtime duration.

In this section, we briefly give the considerations of maintenance time and maintenance objectives in Section 3.4.1 and Section 3.4.2, respectively. Then, we talk about the maintenance strategies in Section 3.4.3. Lastly, we present proposed opportunistic maintenance policies in Section 3.4.4.

3.4.1 Considerations of Maintenance Time

In this section, it will be explained why there is a need to use DBN and real-time. It is the DBN time that keeps the time of the model whereas it is real time that monitors real time and keeps time in real life. When the system is stopped for maintenance, activities such as setting up the team, making necessary purchases, and performing maintenance activities will incur a downtime duration. This affects the real time; however, it does not affect the DBN time under the assumption that the system components age due to use. When the maintenance duration is one day or exceeds one day, a separate parameter is necessary to ensure real-time tracking. The flow chart showing how DBN time and real-time progress in the proposed methodologies is given in Figure 3.6. In this figure, "t" represents the DBN time, "rt" represents the real-time, "dt" represents the maintenance time of the selected component, and "T" shows the maintenance planning horizon.

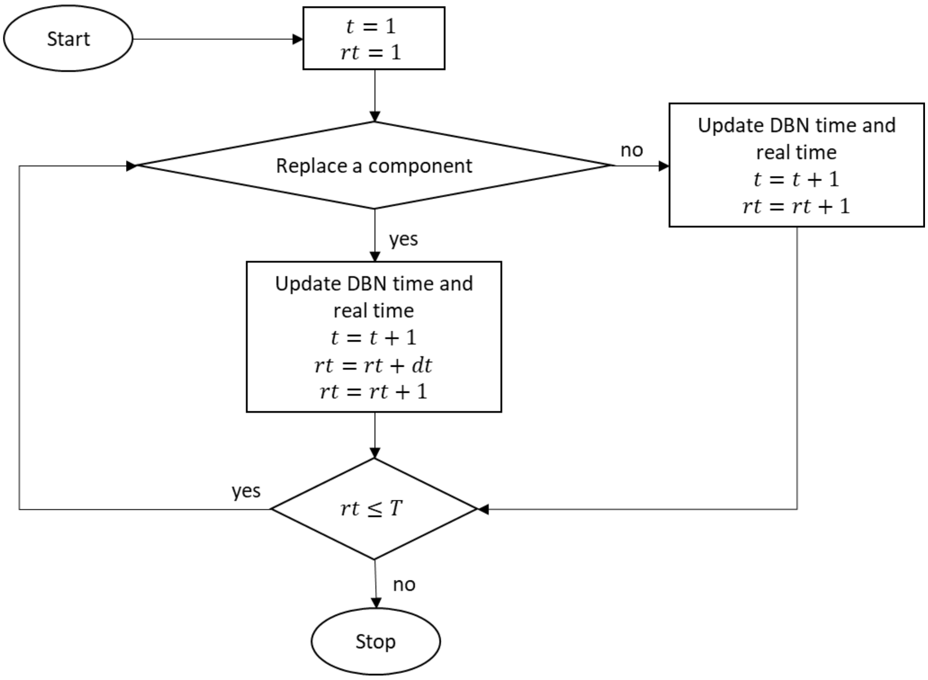

Figure 3.6 DBN Time and Real Time

3.4.2 Considerations of Maintenance Objectives

The main strategies are designed under two different objectives. The first is to minimize downtime duration and the other is to minimize cost. To select the component to be maintained, the $\mathrm{FEL_{fp}}$ method which is proposed (Özgür-Ünlüakın et al., 2019) is used to look at the posterior probability of the components in the “next” period rather than the period in which the observation shows the failure. With this forward-looking approach, the effect of the transition probabilities of the components is also included. The efficiency measure, ${ef_{it}}^{FEL_{fp}}$, in Equation 3.6 is designed to make calculations by looking only at probabilities without considering neither cost nor duration. $C_{i,t+1}$ shows the state of component i at time t+1, F represents failure (the worst case) of all components, ε indicates collected evidence list and “$\{O_t \neq "Accurate"\}$” indicates that the observed node (O_t) is not observed as “$Accurate$”. This calculation in Equation 3.6 varies depending on which objective is used.

$$ef_{it}^{FEL_{fp}} = P(C_{i,t+1} = \text{"F"} \setminus \varepsilon \cup \{O_t \neq \text{"}Accurate\text{"}\}) \tag{3.6}$$

When cost-based maintenance is applied, Equation 3.6 becomes as in Equation 3.7 dividing it by $Cost_{it}^{N}$, which expresses the normalized cost of performing maintenance on component i at time t. (Özgür-Ünlüakın et al., 2021).

$$ef_{it}^{FEL_{fp}} = P(C_{i,t+1} = \text{"F"} \setminus \varepsilon \cup \{O_t \neq \text{"}Accurate\text{"}\})/Cost_{it}^{N} \tag{3.7}$$

When duration-based maintenance is applied, Equation 3.6 becomes as in Equation 3.8 dividing it by $Duration_{it}^{N}$, which denotes the normalized duration of maintenance on component i at time t.

$$ef_{it}^{FEL_{fp}} = P(C_{i,t+1} = \text{"F"} \setminus \varepsilon \cup \{O_t \neq \text{"}Accurate\text{"}\})/Duration_{it}^{N} \tag{3.8}$$

3.4.3 Maintenance Strategies

Corrective maintenance is the activities carried out to repair the faulty part after an error in a way that meets certain conditions. Proactive maintenance is a maintenance method used to predict and prevent possible malfunctions. Proactive maintenance, unlike corrective maintenance, focuses on preventing malfunctions from occurring rather than intervening after they occur. In the Axis System considered within the scope of the study, if the axis movement, which is the final observation node, is not "$Accurate$", it indicates a failure in the system, and corrective maintenance is initiated to eliminate it. In each period, an observation value of the observed axis movement is sampled based on posterior probabilities under the condition of the evidence accumulated up to that period. If this sampled observation value indicates that the system is in a faulty state (i.e., $O_t \neq$ "$Accurate$"), corrective maintenance is performed. If the observation value does not indicate a malfunction, it is then checked whether the proactive maintenance condition is met. If system reliability is not greater than a given threshold reliability, proactive maintenance is started. Corrective or proactive maintenance is then performed using the $\mathrm{FEL_{fp}}$ method described in Equation

3.7 or Equation 3.8, depending on the objective considered is cost or downtime duration, to determine the component to be maintained. Then, it is evaluated whether opportunistic maintenance should be performed. Opportunistic maintenance is the maintenance activity that is used to replace other components even if they are not in a state of failure when the system is stopped to service the maintenance of a component. Components to be maintained under opportunistic maintenance are selected according to the proposed opportunistic maintenance methods given in the following subsection. After the selected components are maintained, the observation node is checked again and if the observation node is still in fault condition, another component is selected for maintenance from the remaining components using the same procedure. An evidence list is maintained throughout the implementation of the maintenance strategy and is updated each time a maintenance activity is performed. The process continues until the end of the planning horizon is reached. This maintenance strategy is applied to optimize the maintenance activities over a planning horizon.

Figure 3.7 gives the flow chart of the maintenance strategies used in this study for both corrective and proactive maintenance. Here, rt, t ve O_t represent real time, DBN time, and observation status at time t, respectively. The "$O_t \neq$ Accurate" state indicates that the observed movement is not accurate. $Pdt(i^*)$ indicates the proactive maintenance period of the selected component, while $Cdt(i^*)$ indicates the corrective maintenance period of the selected component.

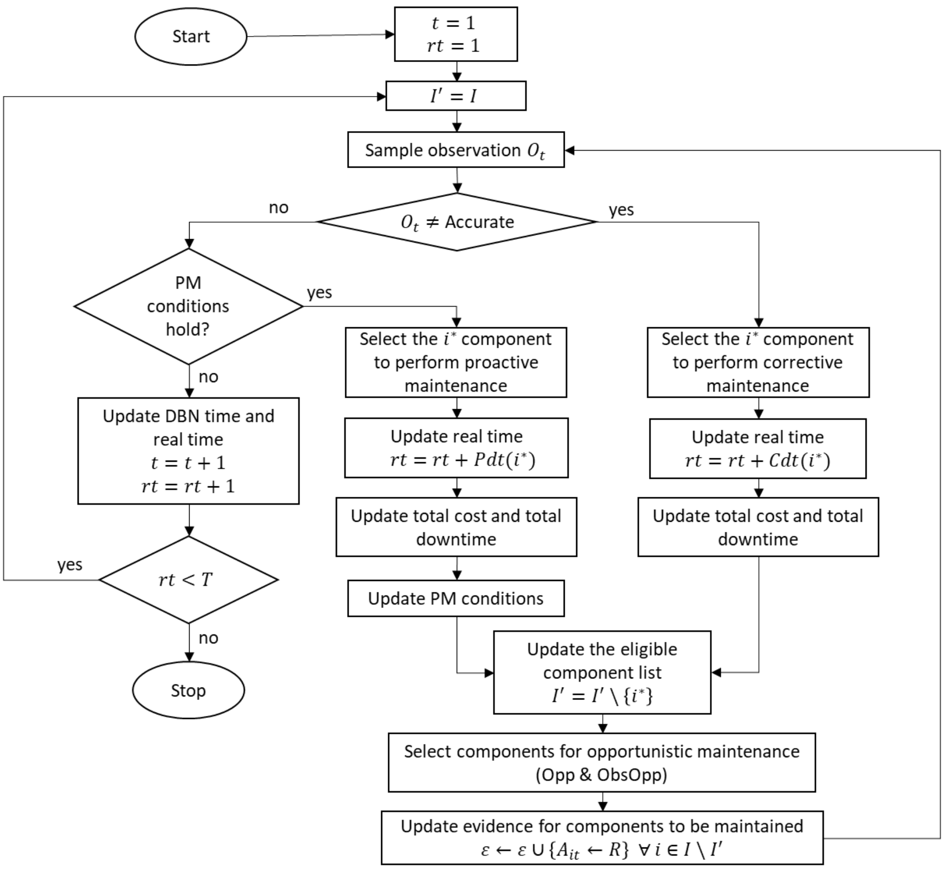

Figure 3.7 Flow Charts of Corrective and Proactive Maintenance Strategies

3.4.4 Opportunistic Maintenance Policies

To perform opportunistic maintenance, two different methods based on reliability and observation are developed within the corrective and proactive maintenance strategies of which the flow chart is given in Section 3.4.3. These policies are Opp and ObsOpp.

3.4.4.1 Opp Maintenance Policy

Opp maintenance policy considers the reliability of the components during the system shutdown to make the decision of which components are to be maintained within the opportunistic perspective. Figure 3.8 gives the flow chart of Opp policy. An opportunistic maintenance list is created with OppM in this reliability-based maintenance policy. I' represents the list of components that are eligible to be maintained. When the system encounters a malfunction or suitable conditions for proactive maintenance occur, the component to be maintained is selected as given in Figure 3.7. During each fault period, the most likely faulty component having also cost or downtime duration advantage is selected for replacement. At the same time, opportunistic maintenance is performed on the other components if their reliability is below or equal to a certain threshold, Opp_{thr}, and their maintenance durations are less than or equal to the duration of the selected component. With this opportunistic maintenance, it is aimed to provide maintenance to the required components as much as possible when the system is already stopped, without incurring extra downtime costs. Components that need maintenance are selected considering their reliabilities. If the component is eligible for opportunistic maintenance, OppM list is updated by appending the index i' of this component, and the cost of the component placed in opportunistic maintenance is calculated and total maintenance cost is updated. This process continues until all components are examined.

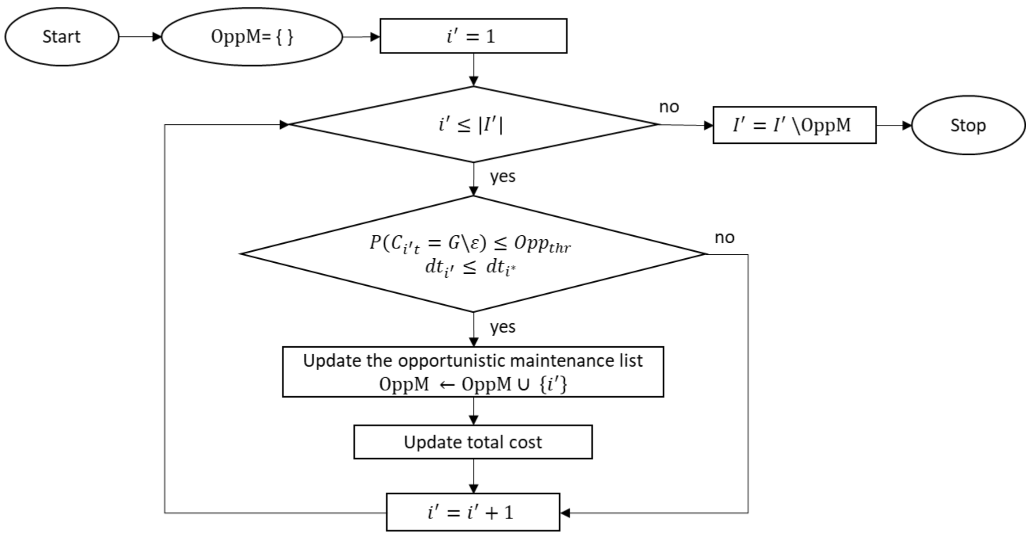

Figure 3.8 Reliability-based Opportunistic Maintenance Policy (Opp)

3.4.4.2 ObsOpp Maintenance Policy

In addition to the main observation, some components in the system can be observed. Information about the system is obtained from these auxiliary observations that we add to the system to perform opportunistic maintenance. In this ObsOpp policy, priority is given to the maintenance of the components that affect these observations. Afterward, if the conditions in the previous Opp policy are met for the remaining components, Opp maintenance is applied.

The flow chart of the algorithm of the Observation-based opportunistic maintenance policy is given in Figure 3.9. An observation-based opportunistic maintenance list is created with OppOM in this policy. An observation is sampled for each auxiliary observation node which is kept in a list of Obs. If it is in the undesirable state, “Vibration”, the responsible components which are also in the eligible component list I' are maintained if their maintenance durations are less than or equal to the duration of the main selected component. If the component is eligible for opportunistic maintenance, OppOM list is updated by appending the index i' of this component, the cost of the component placed in opportunistic maintenance is calculated and total maintenance cost is updated. This process continues until all components of each auxiliary observation are examined sequentially and all auxiliary observations are checked. This algorithm continues with the previous Opp opportunistic policy to consider the remaining components for further opportunistic maintenance.

The Observation-based maintenance algorithm is also tested by removing the "Go to Opp" step, shown in yellow in Figure 3.9; however, it is observed that the algorithm gives better results when there is this step.

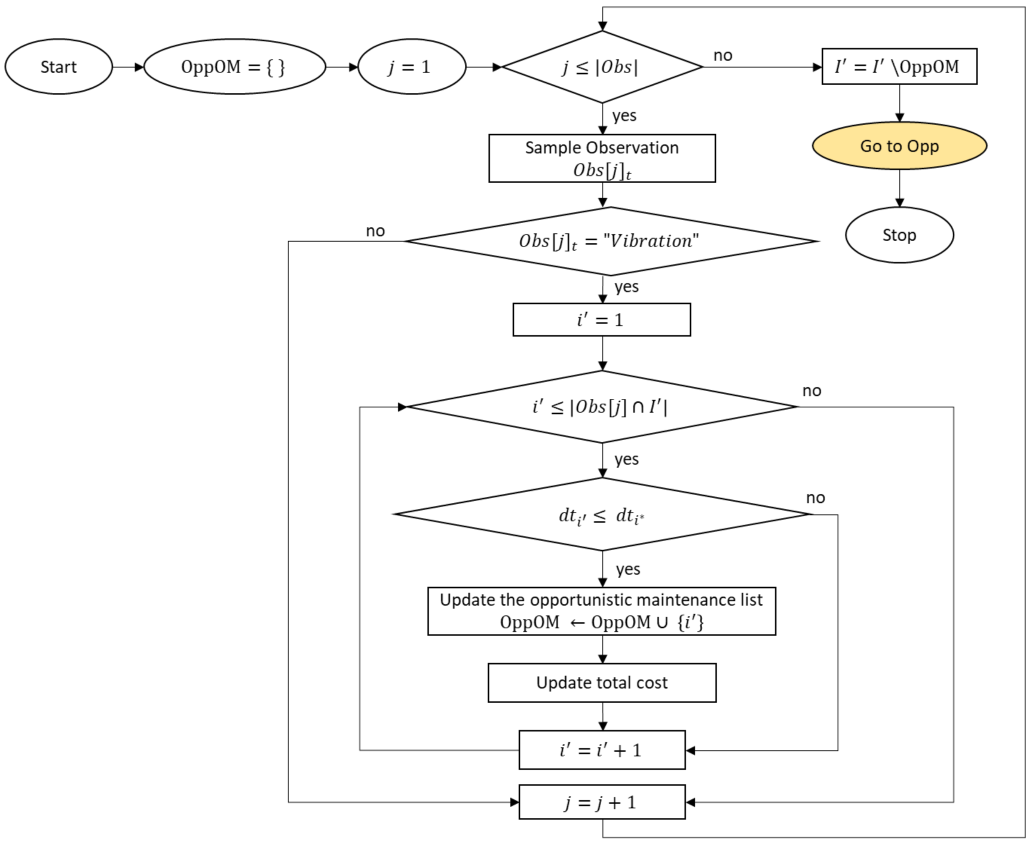

Figure 3.9 Observation-based Opportunistic Maintenance Policy (ObsOpp)

CHAPTER 4

4. A CASE STUDY: THE CNC MACHINE SYSTEM

Production systems are complex systems with multiple components and dependencies between them. It is very crucial to choose the most appropriate maintenance for such systems as unforeseen malfunctions can lead to significant profit losses. We offer a maintenance approach using DBN for a CNC machine in a pump production facility. There are limited studies on the maintenance of CNC machines. In this section, we will provide an overview of the production facility's operations, followed by information about CNC machines and their subsystems. Lastly, we will present the Axis System, which we consider most critical for the CNC system's operation, and the modeling of this system with DBN.

4.1 PUMP PRODUCTION FACILITY

Pumps are elements used to transmit liquids in a pipeline. The liquid pumping process is the supply of additional energy required to transfer the liquid from one environment to another. In short, pumps are machines that absorb or convert mechanical energy into hydraulic energy. Pumps have a wide variety of uses. For instance, they are integral to building infrastructure, used in heating and booster systems. In the industrial sector, they are essential in transferring sulfuric acid. Their application in deep wells is crucial for the supply of water, and they play a key role in fire suppression systems, guaranteeing effectiveness and safety.

Considering the different needs, various basic pump types are developed since one type of pump is not the solution for all needs. The factory produces a wide range of pumps, including those for general industrial applications, wastewater management, and specialized needs like chemical processing and fire safety.

The production flow chart shown in Figure 4.1 illustrates the production processes of pumps in the pump production facility. Pump production is carried out as redesigned according to the customer's request or according to mass production. If the customer wants a specific pump, the pump is designed first. If the customer wants a standard pump, available ready-made designs are used. Afterward, casting pattern modeling is made by these designs. Castings made according to this casting modeling are taken from sub-industry organizations affiliated with the company. These unprocessed/raw products go through quality control. If there is a problem, these parts are returned and the missing parts are recast.

Once raw materials pass the first quality check, then they are delivered to the machining shop to be processed on CNC machines according to the predetermined dimensions and tolerances. After machining, products undergo a second quality assessment and, if approved, proceed to the assembly unit. Here, assembly workers assemble the products according to order specifications. Completed assemblies are sent to the accouplement unit if required, or it is sent directly to the testing unit. The pump arriving at the accouplement unit is mounted onto a suitable chassis with the motor specified in the order (an electric or diesel motor) and prepared for testing. In the test section, pumps are evaluated for flow rate, pressure, electrical draw, sealing, and efficiency. Those that pass are moved to the painting unit, while those that do not are returned to assembly for correction. Finally, the pumps are painted, labeled, and prepared for shipment according to customer requests.

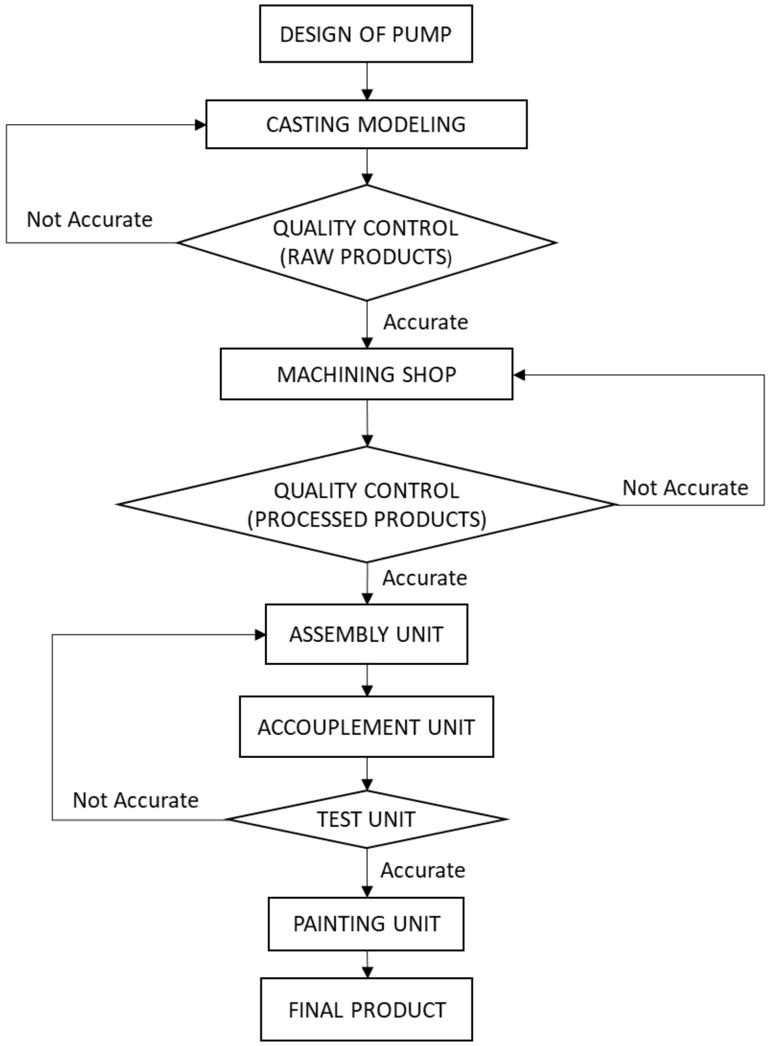

Figure 4.1 Stages of Pump Production

4.2 CNC SYSTEM

CNC (Computer Numerical Control) systems form the basis of modern manufacturing processes and enable complex parts to be produced with higher speed and precision. These systems work by transforming various raw materials such as metal, plastic, and wood into specific shapes and forms under the guidance of numerical command sequences stored in computer programs known as NC (Numerical Control) programs. This automation significantly increases mass production capabilities.

A typical CNC machine consists of various axes that move according to the parts' dimensions and design. The most common axes are X and Z; however, more complex models may include additional axes such as Y, A, or B. Each axis allows a part of the machine to move differently, allowing the material being processed to achieve the desired final shape and size. This is particularly important in cases where complex geometries and precise tolerances are required. These machines are equipped to perform a variety of operations like cutting, drilling, and shaping, all conducted automatically without the need for re-clamping or manual adjustment.

All CNC machines have their own capacity and operational capabilities. Today, CNC machine tools are used in almost every field where manufacturing takes place. From automotive to aerospace, from furniture to defense, they play a critical role. Some of the CNC machine tools available in the facility are CNC lathes, CNC milling machines, and CNC vertical and horizontal machining centers.

4.2.1 CNC Machining Centers

CNC machining centers are machines designed to process various work pieces. In fact, the machining process performed on these machines is the same as on milling machines. The reason why these machines are called machining centers is that, in addition to milling, operations such as drilling, hole enlargement, tapping and reaming, threading and even turning can be performed. In other words, all kinds of operations on the workpiece connected to these types of CNC machines can be performed in a single clamping. The main types are CNC Vertical Machining Center, CNC Horizontal Machining Center and CNC Bridge Type Machining Center. Because it is a complex system within the scope of the study and when a breakdown occurs in this complex system, it causes more costs than other machining centers, CNC Vertical Machining Center is chosen among the CNC machining centers in the facility to plan maintenance applications.

4.2.2 CNC Vertical Machining Center

In the CNC Vertical Machining center, the part is attached to the workbench table with the help of a vise or apparatus. While the workpiece remains stationary, the cutting tool rotates. Movements are applied to the workpiece in the X, Y, and Z axes as desired for cutting. A visual diagram is available in Figure 4.2. The cutting tool's up-and-down motion is controlled by the Z-axis. For the cutting process to occur, the cutting tool (spindle) must rotate; if it doesn't rotate, cutting cannot take place. Additionally, the workpiece moves in the X and Y axes relative to the machining mechanism. The functionality of the control panel needs to be maintained while cutting the workpiece. These are the primary elements observed during the operation of a vertical machining center.

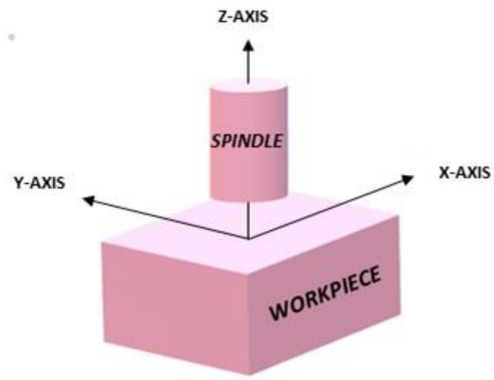

Figure 4.2 CNC Vertical Machine Center Diagram

4.2.3 CNC Vertical Machining Center Parts

Subsystems in the CNC Vertical Machining Center system are determined together with the maintenance engineer in Figure 4.3. In this section, the functions of the subsystems and their integrity in the system are explained. CNC Vertical Machining Center System consists of these subsystems; Spindle, Tool Magazine, Axis, Auxiliary Axis (Diffuser), Hydraulic, Boron Oil, Lubrication, Chip Conveyor, Panel, and Control Systems.

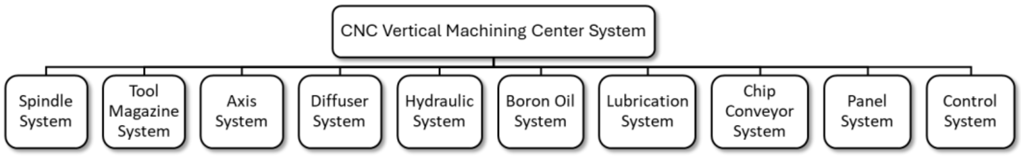

Figure 4.3 CNC Vertical Machining Center System

Spindle System

The part that provides the rotational motion of the cutter in CNC machining centers is called the spindle. The spindle system consists of the part where the spindle motor, spindle bearing, and cutting tool are connected. The spindle transmits the rotational motion it receives from the motor to the cutting tool attached to it and located at its end.

Tool Magazine System

In CNC machining centers, the mechanisms on which the cutting tools are placed and which allow the tool to be changed when necessary are called magazines. In this vertical machining center, 24 cutting tools can be connected to the magazines.

Axis System

In CNC machines, the movements of the workpiece or cutting tool are made according to the Cartesian coordinate system. In this coordinate system, there are 3 basic axes: X, Y and Z, which intersect each other perpendicularly. CNC programs are written according to this coordinate system.

Diffuser System

In addition to the basic axes, there is also an auxiliary rotary axis in the CNC vertical machining center. This axis is called the 4th axis or diffuser. The diffuser allows the workpiece to rotate 360 degrees in place.

Hydraulic System

The hydraulic system consists of an engine, pump, and various connecting elements. The hydraulic unit enables the operation of the opposing center of the diffuser. The tailstock center ensures that the workpiece remains stationary during machining.

Boron Oil System

The boron oil system consists of a pump and tank. Boron oil is also called cutting oil. This oil provides both cooling of the tool and better-quality processing of the work surface.

Lubrication System

The lubrication unit consists of a motor, oil distribution elements, and a pump. The lubrication unit creates an oil film on the frictional surfaces of the slides. This allows the slides to operate with reduced friction.

Chip Conveyor System

It carries the chips accumulated inside the machine to the chip box. It consists of an engine and a conveyor.

Panel System

The panel includes the battery, contactors, and drivers. The battery powers the memory of the machine. The drivers issue the necessary commands for the motors to rotate.

Control System

It is the panel used in CNC machining centers to enter data and programs into the machine, to record cutting tool information and system information of the machine, and to carry out workpiece manufacturing.

When any subsystem of these parts fails, the computer system gives an alarm and stops working. The subsystems and tasks of the CNC Vertical Machining Center are examined in the interviews held with the maintenance engineer at the production facility. The Axis sub-system is selected for the study due to its critical importance in ensuring the workpiece is machined to the desired dimensions and specifications. This selection is also based on several factors: if it is not functioning, the cutting of parts cannot be performed, and the system will halt; it is part of the machine that most frequently encounters errors; the relationships between its components are complex; and there is a high number of components involved.

4.2.4 Axis System

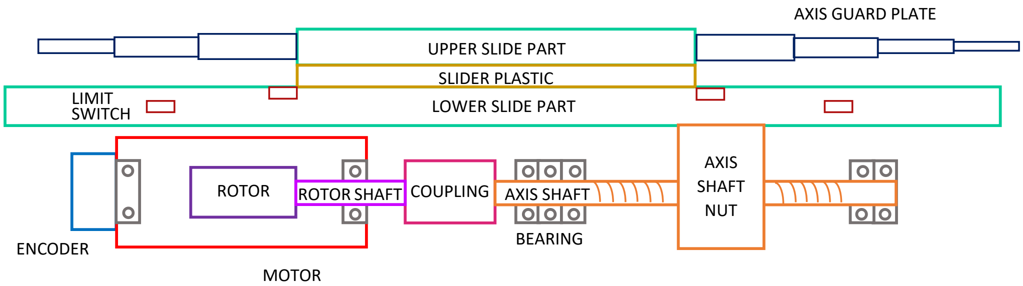

Figure 4.4 Axis System

The Axis System includes 3 axes: X, Y, and Z. Since all three of these systems work in the same way, only the X system is considered as representative. The diagram of the Axis System is shown in Figure 4.4. The Axis System mainly consists of the motor, coupling, axis shaft and nut and slide surfaces. The motor part consists of the encoder, rotor (rotating part), rotor shaft, and bearings.

The events occur in the following order within the Axis System:

- Drivers issue the necessary commands for the motor to rotate.
- The motor converts electrical energy into mechanical energy, transferring this energy to the rotor shaft, and during this process, the encoder (counter) counts the number of rotations made by the rotor shaft.
- The coupling acts as a connecting element. The mechanical energy in the rotor shaft is transferred to the axis shaft through the coupling. Bearings are used to ensure the smooth transfer of this energy and minimize friction.
- The axis shaft nut is also used as a connecting element. The axis shaft moves the slide surface using the axis shaft nut. Again, the bearings ensure the correct transmission of this movement.
- Finally, the workpiece moves towards the tip of the cutting tool and the piece is processed.

In this system, the slider plastic prevents the slide surfaces from rubbing against each other. An axis guard plate is used to prevent material and chips from damaging the axes during processing. Limit switches determine the limits of axis movement.

4.3 HAZOP ANALYSIS OF THE AXIS SYSTEM

HAZOP methodology is explained in Chapter 3 (See: Section 3.3). As an example, the HAZOP analysis of the Rotor Bearing in the Axis System is given in Table 4.1. System process parameters/deviations are selected with the information obtained from the maintenance engineer during field visits. For the rotor bearing, deviations are identified as “Bearing Vibration”, “Load on Bearing”, “Creepage” and “Corrosion”. Each deviation is defined with “MORE” as the guide word, indicating that it can be observed if the deviation exceeds normal levels. We determine the possible causes and consequences of these deviations, as well as possible precautions, based on the information provided by the engineer. For example, the possible cause for bearing vibration is determined as “There is friction, heat, and wear in bearing housings’’. When looking at the first consequence, the components that may be affected by this deviation results are determined as the Encoder, Rotor Shaft, and Motor. Through the HAZOP study, it is determined that there is a stochastic dependency between the rotor bearing and these components. When looking at the second consequence, it is determined that in the case of rotor bearing wear, the rotor shaft rotation process is restricted or hindered. The causes and effect relationships determined for the variables with this analysis are treated and modeled as stochastic dependencies in the DBN model given in the next section. Furthermore, while determining the state space of the components and the conditional aging probabilities of components, arising from stochastic dependencies, we also benefit from the HAZOP study.

Table 4.1 HAZOP Analysis of Rotor Bearing

Element	Deviation	Possible Causes	Consequences	Safety Precautions
Rotor Bearing	Bearing vibration+*"MORE"*	1. There is friction, heat, and wear in bearing housings.	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform regular maintenance on the rotor bearings. 2. Check the lubrication of the rotor bearings.
	Load on bearing+*"MORE"*	1. There is wrong bearing selection and wrong alignment (assembling).	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. It shortens the operating life of the bearing and causes wear on the bearing. For this reason, the rotation of the rotor shaft is restricted or hindered.	1. Ensure that the correct bearing is selected for the rotor shaft. 2. Ensure proper alignment during the assembly process.
	Creepage+*"MORE"*	1. There is high heat generated due to rotation and an excessive number of revolutions.	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. As the bearing heats up, it becomes deformed and unable to function properly, restricts or hinders rotor shaft rotation.	1. Make sure that the bearing housing has high durability. 2. Avoid overloading and high-speed operation.
	Corrosion+*"MORE"*	1. There are worn or damaged seals. 2. Bearings have come into contact with water. 3. Bearings have been exposed to electric current. 4. There is a wrong grease oil selection.	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. The rotation of the rotor shaft is restricted or hindered.	1. Check seals regularly. 2. Avoid contact of the bearings with water. 3. Prevent electric current from passing through the bearings. 4. Make sure to choose the correct type of grease oil.

4.4 DBN MODELING OF THE AXIS SYSTEM

While creating the DBN modeling of the Axis System, the information obtained during the field visits is used. Information is obtained from the maintenance engineer about the components of the Axis System, the dependencies between the components, the interaction of the components and the Axis System, and which components the failure of a component affects.

4.4.1 Model Variables and States

While determining the DBN model, the equipment in the system and how it works are examined. The Axis System consists of 11 components which are rotor bearing, encoder, rotor shaft, motor, drivers, oil distributor elements, axis shaft bearings, coupling, axis shaft and nut, slide surfaces, and limit switches. The DBN model is given in Figure 4.5. The model has 4 different node types: Dynamic nodes are shown in pink, process nodes are shown in blue, exogenous nodes are shown in yellow, and observation nodes are shown in green.

Dynamic nodes illustrate how components change over time due to aging, i.e. the temporal behavior. All components are modeled as dynamic nodes having such temporal properties. Process nodes depict the output of the interactions that occur between components at a time. For example, rotor shaft rotation is a process node affected by the following components: rotor bearing, encoder, motor, rotor shaft, and drivers. Exogenous nodes show external factors that facility employees cannot fully control. Slide oil quality is considered an exogenous variable within this context. The observation node indicates the current state of the system. The circular arrows denoted with "1" are used to model temporal relations. Other arrows show the causal relations among the nodes which are identified as stochastic dependencies with the help of HAZOP study. For instance, there exists a stochastic dependency between axis shaft and nut, and the following two components: oil distributor elements and axis shaft bearings.

Axis movement can be measured and observed with lasers. Therefore, "Laser measurement" is considered as the main observation node in the model. In the current system, it is assumed that there exists only this observation which is systematically measured. However, while modeling the system under opportunistic maintenance, we will add auxiliary observations in order to provide observation-based opportunistic maintenance. The states that the components and all nodes in the model can take are determined together with the maintenance engineer in the facility.

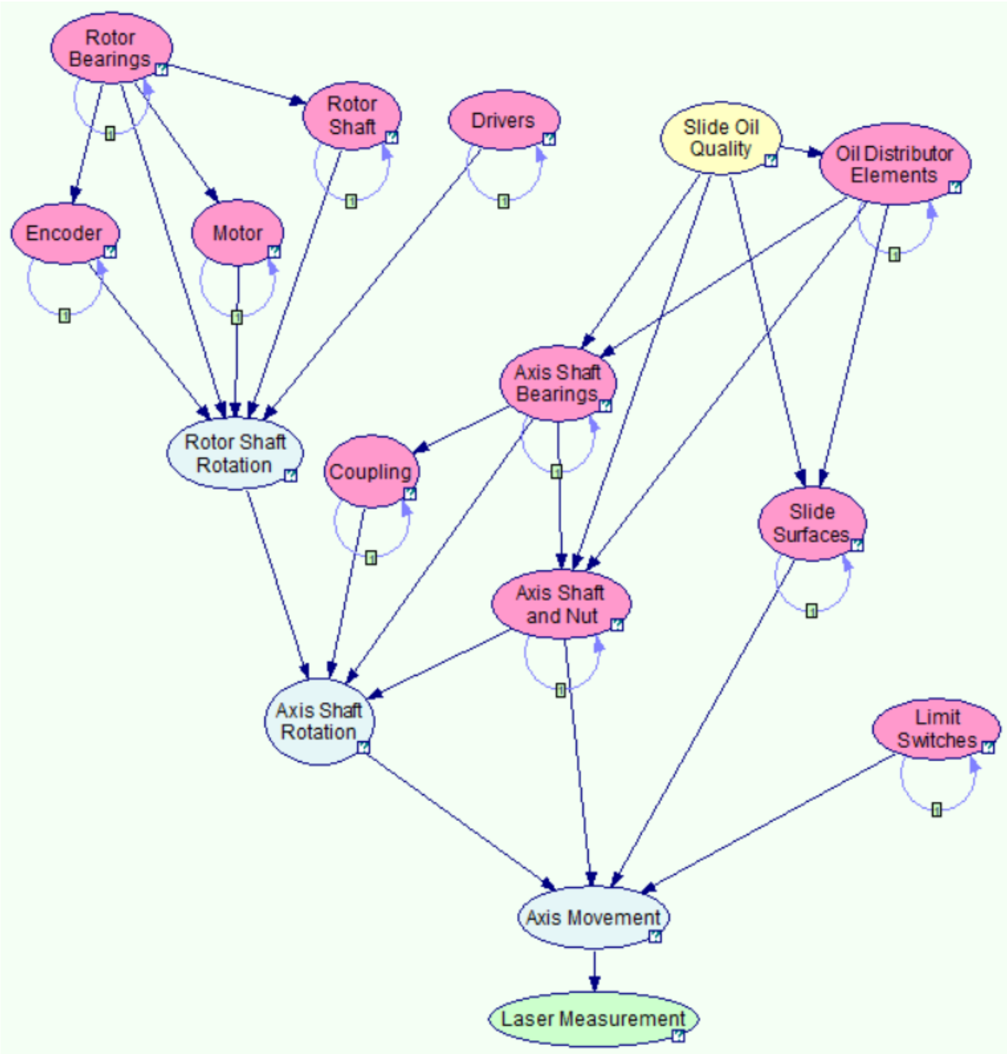

Figure 4.5 DBN Model of Axis System

The DBN model with action and auxiliary observation nodes is given in Figure 4.6. To benefit from the observations, auxiliary "vibration" related observations can be included in the system. Action nodes are in orange and auxiliary nodes in green, as in the main observation. Action nodes indicate whether components are currently undergoing maintenance or not.

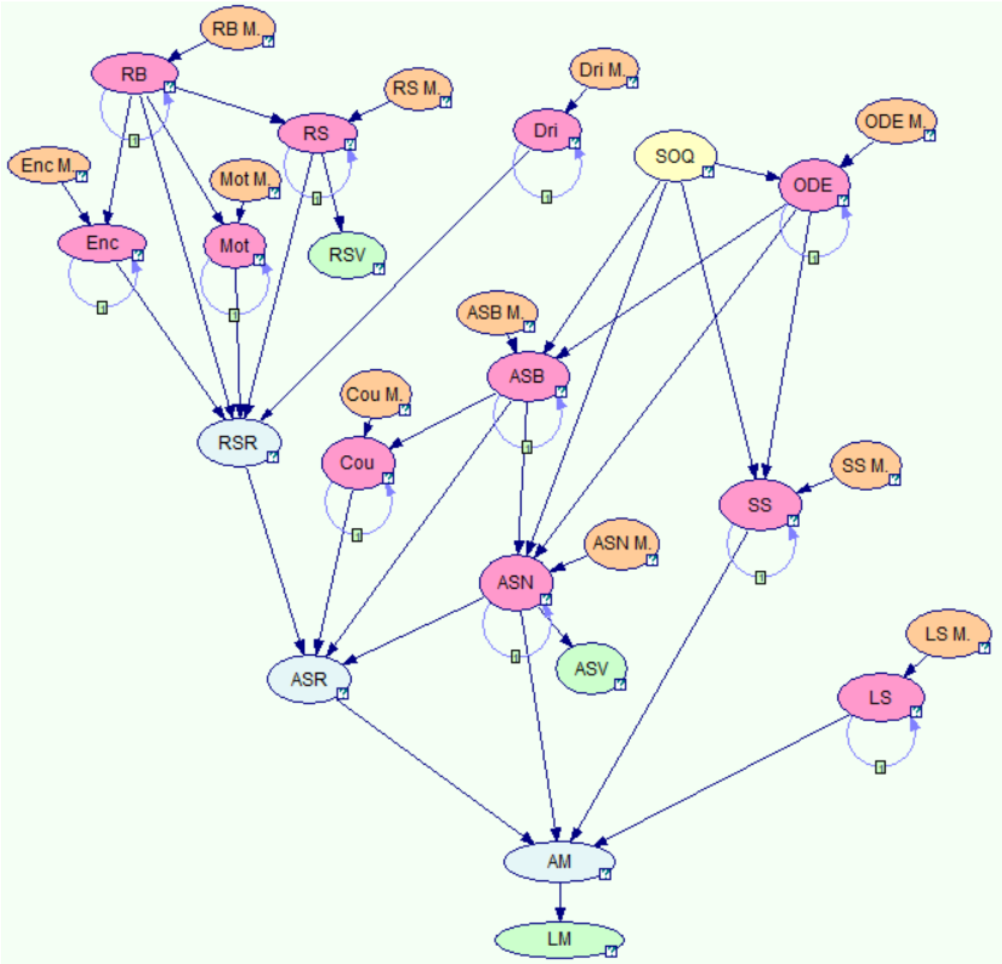

Figure 4.6 DBN Model of Axis System with Action and Auxiliary Observation Nodes

The nodes, node types, and state spaces of the DBN model are given in Table 4.2. Auxiliary observations in ObsOpp policy (See: Section 3.4.4.2) are RSV and ASV nodes in this model. “Vibration” information is obtained from both observations. Each vibration-related observation node is tackled with its responsible components. While the responsible components connected to RSV are RB and RS, the other responsible components connected to ASV are ODE, ASB, and ASN. The "Replace" state in action nodes indicates replacing the components with a new one, whereas the "Do Nothing" action indicates that the components remain without any maintenance in that period.

Table 4.2 DBN Nodes and Their State Spaces

Symbol	Nodes	Node Type	State Space
RB	Rotor Bearings	Dynamic	{Good, Worn}
Enc	Encoder	Dynamic	{Good, Worn}
RS	Rotor Shaft	Dynamic	{Good, Worn}
Mot	Motor	Dynamic	{Good, Burn}
Dri	Drivers	Dynamic	{Good, Burn}
ODE	Oil Distributor Elements	Dynamic	{Good, Clogged}
ASB	Axis Shaft Bearings	Dynamic	{Good, Worn}
Cou	Coupling	Dynamic	{Good, Loose}
ASN	Axis Shaft and Nut	Dynamic	{Good, Worn}
SS	Slide Surfaces	Dynamic	{Good, Worn}
LS	Limit Switches	Dynamic	{Good, Cracked}
RSR	Rotor Shaft Rotation	Process	{Rotate, Not Rotate}
ASR	Axis Shaft Rotation	Process	{Rotate, Not Rotate}
AM	Axis Movement	Process	{Accurate, Inaccurate, No Movement}
RB M.	Rotor Bearings Maintenance	Action	{Replace, Do Nothing}
Enc M.	Encoder Maintenance	Action	{Replace, Do Nothing}
RS M.	Rotor Shaft Maintenance	Action	{Replace, Do Nothing}
Mot M.	Motor Maintenance	Action	{Replace, Do Nothing}
Dri M.	Drivers Maintenance	Action	{Replace, Do Nothing}
ODE M.	Oil Distributor Elements	Action	{Replace, Do Nothing}
ASB M.	Axis Shaft Bearings Maintenance	Action	{Replace, Do Nothing}
Cou M.	Coupling Maintenance	Action	{Replace, Do Nothing}
ASN M.	Axis Shaft and Nut Maintenance	Action	{Replace, Do Nothing}
SS M.	Slide Surfaces Maintenance	Action	{Replace, Do Nothing}
LS M.	Limit Switches Maintenance	Action	{Replace, Do Nothing}
SOQ	Slide Oil Quality	Exogenous	{Good, Bad}
RSV	Rotor Shaft Vibration	Observation	{Vibration, No Vibration}
ASV	Axis Shaft Vibration	Observation	{Vibration, No Vibration}
LM	Laser Measurement	Observation	{Accurate, Inaccurate, No Movement}

4.4.2 System Interactions and Dependencies

While constructing the DBN model of the Axis System we consider the following interactions and dependencies among the system variables.

- For the axis movement, the rotation of the rotor shaft must first be ensured, and then the rotation of the axis shaft must be achieved.
- Rotor bearing affects encoder, motor, and rotor shaft. In the case of rotor bearing wear, the motor can overheat and burn.
- Rotor bearing wear also causes the motor to rotate with pulsation, which can accelerate the aging of both the rotor shaft and the encoder, a sensitive part.

- The encoder, rotor bearing, motor, rotor shaft, and drivers are the components that ensure the rotor shaft to rotate.
- If the slide oil quality is poor, the oil distributor elements, axis shaft bearings, axis shaft and nut, and slide surfaces may wear more over time.
- If the oil distributor elements are clogged, it may result in the wear of the axis shaft bearings, axis shaft and nut, and slide surfaces due to a lack of oil transmission.
- Wear of the axis shaft bearings may cause the shaft to rotate with pulsation, which may cause the coupling to loosen and the axis shaft and nut to wear.
- Coupling, axis shaft bearings, axis shaft and nut enable the axis shaft to rotate.
- Limit switches determine the boundaries of the axis movement; if they are broken, the cutting tool edge may hit violently and damage the workpiece.
- If the sliding surfaces are worn, the axis movement may not be achieved to the desired extent, potentially leading to inappropriate movement.
- Axis shaft rotation, axis shaft and nut, slide surfaces, and limit switches ensure accurate axis movement. In this way, workpieces can be processed to the desired size.
- When the axis movement ends and the workpiece is produced, laser measuring instruments are used to check whether the part has the desired dimensions and tolerances.

Stochastic dependencies are observed among the components in the Axis System. There is a stochastic dependence between the rotor bearing and the motor, as rotor bearing wear can cause motor burn. In addition, since the wear of the rotor bearing may cause the wear of the rotor shaft and a decrease in the rotation ability of the rotor shaft, there is a stochastic dependence between the rotor bearing and the rotor shaft. Likewise, since the wear of the rotor bearing may cause the wear of the encoder, there is a stochastic dependence between the rotor bearing and the encoder.

Since clogged oil distributor elements may cause wear on the axis shaft bearings, axis shaft and nut, and slide surfaces, there is a stochastic dependence between these components and the oil distributor elements.

There exists a stochastic dependence between the axis shaft bearing and the coupling, as wear of the axis shaft bearing can cause the coupling to loosen. There is also a stochastic dependence between the axis shaft bearing and the axis shaft and nut, as the wear of the axis shaft bearing may cause the axis shaft and nut to wear and the rotation ability of the axis shaft to decrease.

4.4.3 Assumptions of the Model

The following assumptions are considered when establishing the DBN model

- The axis shaft and the axis shaft nut are considered as a single component because they must be replaced at the same time when one of these components fails.
- Since the pipes of the oil distributor elements can be replaced immediately in case of failure, they are not included in the Axis System model.
- Since the connection cables can be replaced instantly when broken, they are not included in the model as it is thought that they would not have much effect on the model.
- Since the axis guard plate protects the parts in the axis movement system, it is decided to age the components assuming that the parts are under the protection of the axis guard plate.
- There are balls between the axis shaft and the axis shaft nut to transmit movement to the slide surfaces. The balls are not included in the system as a separate component, as they can only be changed once and the effect would not be long-lasting.
- The slide plastic is not shown as a separate component in the model, as it can be changed while performing maintenance on the slide surfaces during revision.

4.4.4 Probability Structure

In the DBN model, the aging of the components and their conditional and transition probabilities are determined based on information provided by the maintenance engineer in the facility. Table 4.3 gives the probabilities of the components remaining in their best state according to the expected time until they reach their best state.

Table 4.3 The Probabilities of the Components Staying in the Best State

Components|Parents $X\|\mathrm{Pa}(X)$	Expected time until leaving the best state (yr)	Expected time until leaving the best state (day)	λ	$P(X_t = "Good"\| X_{t-1} = "Good", \mathrm{Pa}(X_t))$
RB	5	1500	0.00067	0.99933
Enc|RB="Good"	10	3000	0.00033	0.99967
Enc|RB="Worn"	5	1500	0.00067	0.99933
RS|RB="Good"	10	3000	0.00033	0.99967
RS|RB="Worn"	5	1500	0.00067	0.99933
Mot|RB="Good"	15	4500	0.00022	0.99978
Mot|RB="Worn"	7	2100	0.00048	0.99952
Dri	15	4500	0.00022	0.99978
ODE|SOQ="Good"	5	1500	0.00067	0.99933
ODE|SOQ="Bad"	3	900	0.00111	0.99889
ASB |(ODE="Good", SOQ="Good")	5	1500	0.00067	0.99933
ASB |(ODE="Good", SOQ="Bad")	4	1200	0.00083	0.99917
ASB|(ODE="Clogged", SOQ="Good")	3	900	0.00111	0.99889
ASB|(ODE="Clogged", SOQ="Bad")	2	600	0.00167	0.99833
Cou|ASB="Good"	10	3000	0.00033	0.99967
Cou|ASB="Worn"	4	1200	0.00083	0.99917
ASN|(ASB="Good", ODE="Good", SOQ="Good")	8	2400	0.00042	0.99958
ASN|(ASB="Good", ODE="Good", SOQ="Bad")	7	2100	0.00048	0.99952
ASN|(ASB="Good", ODE="Clogged", SOQ="Good")	5	1500	0.00067	0.99933
ASN|(ASB="Good", ODE="Clogged", SOQ="Bad")	3	900	0.00111	0.99889
ASN|(ASB="Worn", ODE="Good", SOQ="Good")	5	1500	0.00067	0.99933
ASN|(ASB="Worn", ODE="Good", SOQ="Bad")	3	900	0.00111	0.99889
ASN|(ASB="Worn", ODE="Clogged", SOQ="Good")	2	600	0.00167	0.99833
ASN|(ASB="Worn", ODE="Clogged", SOQ="Bad")	1	300	0.00333	0.99667
SS|(ODE="Good", SOQ="Good")	20	6000	0.00017	0.99983
SS|(ODE="Good", SOQ="Bad")	15	4500	0.00022	0.99978
SS|(ODE="Clogged", SOQ="Good")	12	3600	0.00028	0.99972
SS|(ODE="Clogged", SOQ="Bad")	10	3000	0.00033	0.99967
LS	5	1500	0.00067	0.99933

We assume that all components are exponentially distributed under the assumption of regular revision maintenance of components every 300 working days. Under exponential distribution of the aging of components, the following transition probability calculation holds.

$$P(X_t = "Good" \backslash X_{t-1} = "Good") = e^{-\lambda t} \quad (4.1)$$

In Equation 4.1, t indicates the time period and λ denotes the failure rate of the component. In this way, the possibility of the component remaining in its best condition is achieved. The probability of X_t being in the “Good” state is calculated with this formulation in the last column of Table 4.3. The possibility of it not being “Good” is its complementary probability. When calculating, t is taken as 1 since it indicates the transition probability in one day.

The conditional probabilities of all components are calculated with the information obtained from the maintenance engineer. Initially, all components are assumed to be in good condition, and during maintenance, the components are renewed with the "Replace" status.

To provide an example, the conditional probabilities of the rotor bearing, which is a temporal node, are given in Table 4.4. The probability of transition from “Good” to “Good” is formulated based on the average number of days until it leaves the “Good” state. This value is provided by the maintenance engineer at the production facility as approximately 300x5=1500 days, and the P(G|G) transition probability results in 0.99933. The remaining probability is 0.00067.

Table 4.4 Conditional Probabilities of the Rotor Bearing

RB M.	**Replace**		**Do Nothing**	
(Self) [t-1]	**Good**	**Worn**	**Good**	**Worn**
Good	1	1	0.99933	0
Worn	0	0	0.00067	1

To give another example, the conditional probabilities of the axis shaft and nut, which is a temporal node, are given in Table 4.5. When the ASB, ODE, and SOQ variables are in the “Good” state, the probability of transition from “Good” to “Good” is formulated based on the average number of days until it leaves the

"Good" state. This value is provided by the engineer at the production facility as approximately 300x8=2400 days, and the P(G|G) transition probability results in 0.99958. The remaining probability is 0.00042. With the same calculation, the probability of transition from "Good" to a "Good" state in cases where ASB is "Worn", ODE is "Clogged" and SOQ is "Bad" is calculated as 0.99667 over 300 days.

Table 4.5 Conditional Probabilities of the Axis Shaft and Nut

ASB	**Good**							
ODE	**Good**							
SOQ	**Good**				**Bad**			
ASN M.	**Replace**		**Do Nothing**		**Replace**		**Do Nothing**	
(Self) [t-1]	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Good	1	1	0.99958	0	1	1	0.99952	0
Worn	0	0	0.00042	1	0	0	0.00048	1
ASB	**Good**							
ODE	**Clogged**							
SOQ	**Good**				**Bad**			
ASN M.	**Replace**		**Do Nothing**		**Replace**		**Do Nothing**	
(Self) [t-1]	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Good	1	1	0.99933	0	1	1	0.99889	0
Worn	0	0	0.00067	1	0	0	0.00111	1
ASB	**Worn**							
ODE	**Good**							
SOQ	**Good**				**Bad**			
ASN M.	**Replace**		**Do Nothing**		**Replace**		**Do Nothing**	
(Self) [t-1]	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Good	1	1	0.99933	0	1	1	0.99889	0
Worn	0	0	0.00067	1	0	0	0.00111	1
ASB	**Worn**							
ODE	**Clogged**							
SOQ	**Good**				**Bad**			
ASN M.	**Replace**		**Do Nothing**		**Replace**		**Do Nothing**	
(Self) [t-1]	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Good	1	1	0.99833	0	1	1	0.99667	0
Worn	0	0	0.00167	1	0	0	0.00333	1

4.4.5 Cost Structure

Each component in the system has two types of maintenance cost components. The first one is the direct maintenance cost which is related with the maintenance action. The other is the cost of the production loss due to a system halt. This latter cost is proportional to the maintenance duration of the component. Table 4.6 gives the parts of the maintenance cost for each component under corrective maintenance and proactive maintenance respectively. MC_i indicates the maintenance cost of component i. MD_i stands for the maintenance duration of component i. This maintenance time covers the duration from the start of the maintenance to the end of the maintenance. DC_i stands for the downtime cost per day. This cost includes the cost of lost production when the system stops, the cost of overtime, and the cost of reputational damage because of not satisfying the promised order on time. Equation 4.2 calculates the total cost of maintenance for each component i considering the above parts of the cost where TC_i stands for the total cost of component i in the model.

$$TC_i = MC_i + MD_i * DC_i \tag{4.2}$$

Table 4.6 Maintenance Cost and Durations

Component	Corrective Maintenance			Proactive Maintenance		
	$\boldsymbol{MC_i}$(€)	$\boldsymbol{MD_i(day)}$	$\boldsymbol{DC_i}$(€)	$\boldsymbol{MC_i}$(€)	$\boldsymbol{MD_i(day)}$	$\boldsymbol{DC_i}$(€)
RB	600	4	4,800	400	2	2,400
Enc	1,500	2	4,800	1,000	1	2,400
RS	900	4	4,800	600	2	2,400
Mot	3,750	4	4,800	2,500	2	2,400
Dri	3,750	4	4,800	2,500	2	2,400
ODE	150	2	4,800	100	1	2,400
ASB	1,200	2	4,800	800	1	2,400
Cou	750	2	4,800	500	1	2,400
ASN	900	4	4,800	600	2	2,400
SS	9,000	60	4,800	6,000	30	2,400
LS	225	2	4,800	150	1	2,400

All corrective and proactive maintenance costs and durations given in Table 4.6 are determined according to the information provided by the maintenance engineer at the production facility. While calculating the downtime cost per day of proactive maintenance, the cost of lost productivity, lost revenue, overtime, and reasonable reputational damage are considered. So, the cost of downtime for proactive maintenance is computed to be approximately €2,400 per day. On the other hand, the cost of corrective maintenance action is taken as twice as much as the cost of proactive maintenance. This increase in cost is primarily due to the stress that can be experienced during maintenance organization at the time of a breakdown such that there may not be enough employees available to address the need for corrective maintenance and replacement parts are often purchased at the last minute, leading to higher maintenance related costs. Furthermore, in corrective maintenance, significant reputational damage cost is also incurred.

CHAPTER 5

5. COMPUTATIONAL RESULTS

Simulations of the methods proposed in Chapter 3 within the scope of corrective maintenance and preventive maintenance strategies are carried out based on the total number of maintenance, downtime duration, opportunistic maintenance, corrective maintenance, and proactive maintenance on the Axis System. In this section, the maintenance problem is handled under two objectives, reducing the total downtime duration and the total cost. The cost-effective component selection method, FEL_{fp}, presented in (Özgür-Ünlüakın, D et al., 2021) is used in this study to determine the component to replace at a maintenance time to minimize total cost. This measure is also adapted in this thesis to consider minimizing the total downtime duration as given in Equation 3.8. Corrective maintenance policy (CM) developed in (Özgür-Ünlüakın, D et al., 2021) and proactive maintenance policy (ThPM) proposed in (Özgür-Ünlüakın, D & Bilgiç, T,2014) are used in this study to compare the performances of the opportunistic maintenance methodologies developed in Chapter 3 (See: Section 3.4.4).

Downtime-based (DB) maintenance results are given in Section 5.1, and cost-based (CB) maintenance results are given in Section 5.2. First, a general comparison of the results in downtime-based and cost-based maintenance is given in Sections 5.1.1 and 5.2.1. Then, in Sections 5.1.2 and 5.2.2, component-level comparison results are given for each strategy to understand their effects on the components when strategies change. Lastly, in Sections 5.1.3 and 5.2.3, strategies are subjected to post-ANOVA to see which are significantly different.

To test the proposed methods, three scenarios are designed by referencing the base scenario: increasing corrective downtime cost, then increasing both corrective downtime cost and corrective maintenance duration, and finally increasing proactive downtime cost. Their results are given one after another in

Section 5.3. The maintenance results for DB and CB are given in separate subsections for each scenario. In addition, a summarization of the scenario results is given in Section 5.4. Lastly, proactive threshold sensitivity analysis for proactive maintenance is given in Section 5.5 to compare the performance of the proposed opportunistic strategies under various threshold reliability values.

Each method is run using MATLAB over a 300-day planning horizon with 50 replications. For comparisons, ANOVA with a 0.05 significance level is applied. Then, the adequacy of the model is checked, and it is concluded that all models meet the normality and constant variance assumptions. Finally, the Tukey test is used for pairwise comparisons. A single CM replication lasts 13.7 min, while one ThPM(0.95) replication lasts 14.4 min on average.

5.1 DOWNTIME-BASED MAINTENANCE RESULTS

5.1.1 General Comparison Results

Three methods under corrective and proactive maintenance strategies are compared based on the downtime duration on the Axis System. The reliability-based maintenance policy is also applied within the observation-based opportunistic maintenance policy at each maintenance time.

Observation-based opportunistic maintenance, reliability-based opportunistic maintenance, and no opportunistic maintenance are denoted by ObsOpp, Opp, and NoOpp, respectively. As in the expression “ThPM(0.95)-ObsOpp”, the threshold value used in a ThPM strategy is written in parentheses. On the other side, the opportunistic maintenance threshold value is determined as 0.97 after many trials. For example, a threshold value of 0.97 indicates that maintenance should be applied when the reliability of the inquired component falls below 0.97. When the threshold value is taken as 0.95, there is rarely opportunistic maintenance. When it is taken as 0.99, a lot of opportunistic maintenance is involved. As a result, we determine that the 0.97 threshold is the best-balanced option.

Firstly, CM and ThPM strategies are replicated to minimize downtime duration. The results of DB maintenance are given in Table 5.1 where SD shows the standard deviation of 50 replications. Dt, Opp, Cor and Pro stand for downtime, opportunistic, corrective and proactive respectively. According to the table, it is observed that ObsOpp and Opp policies give lower downtime duration compared to NoOpp policy in all CM, ThPM(0.95) and ThPM(0.90) strategy groups.

Table 5.1 DB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	33.26	1.51	16.24	2.78	51.76	7.51	17.02	1.65	33.26	1.51	0	0
CM-Opp	31.92	1.41	15.16	2.71	48.56	7.96	16.76	1.59	31.92	1.41	0	0
CM-NoOpp	18.40	1.18	18.40	2.27	58.48	7.03	0	0	18.40	1.18	0	0
ThPM(0.95)-ObsOpp	40.42	1.61	28.70	1.18	64.38	5.34	11.72	1.84	16.28	1.24	24.14	1.38
ThPM(0.95)-Opp	39.06	1.52	29.28	0.99	65.26	5.84	9.78	1.80	15.30	1.19	23.76	1.35
ThPM(0.95)-NoOpp	31.20	1.92	31.20	0.95	69.78	4.78	0	0	12.74	1.20	18.46	1.51
ThPM(0.90)-ObsOpp	34.22	1.52	15.78	2.38	49.76	7.24	18.44	1.72	31.58	1.45	2.64	0.22
ThPM(0.90)-Opp	32.66	1.45	16.32	2.47	50.60	7.62	16.34	1.61	29.72	1.39	2.94	0.27
ThPM(0.90)-NoOpp	19.88	1.26	19.88	1.97	60.30	7.65	0	0	18.52	1.23	1.36	0.25

The cost results of DB maintenance are given in Table 5.2 where total cost is initially broken down into replacement cost and production loss cost components and then CM cost and PM cost components with the respective standard deviations. In addition, CM and PM cost components are further broken down into replacement cost and production loss cost subcomponents. In the second column of the table, ObsOpp and Opp policies give the lower total cost compared to NoOpp policy in all strategy groups. The production loss cost component dominates the total cost in all strategies. This domination is more densely observed in CM cost component compared to PM cost component. In CM strategies, the proactive maintenance column results are all zero since there is no proactive maintenance.

Table 5.2 DB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	288893	24651	40445	3609	248448	21770	288893	24651	40445	3609	248448	21770	0	0	0	0	0	0
CM-Opp	272048	24165	38960	3515	233088	21332	272048	24165	38960	3515	233088	21332	0	0	0	0	0	0
CM-NoOpp	310163	21848	29459	3094	280704	19735	310163	21848	29459	3094	280704	19735	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	284536	20586	42184	3940	242352	17925	196109	18027	20429	2236	175680	16215	88427	8418	21755	2586	66672	6359
ThPM(0.95)-Opp	283582	20068	40942	3866	242640	17621	191010	17634	18978	2096	172032	15946	92572	8842	21964	2675	70608	6778
ThPM(0.95)-NoOpp	297178	21556	41098	4285	256080	18667	196464	18129	19248	2277	177216	16287	100714	9421	21850	2767	78864	7326
ThPM(0.90)-ObsOpp	277183	24657	40639	3645	236544	21687	273071	24423	38831	3561	234240	21516	4112	793	1808	244	2304	594
ThPM(0.90)-Opp	278813	23389	38621	3484	240192	20578	273908	23147	36404	3368	237504	20428	4905	1060	2217	329	2688	779
ThPM(0.90)-NoOpp	314232	21855	30888	3218	283344	19623	306524	21651	29276	3085	277248	19466	7708	1479	1612	351	6096	1165

5.1.2 Component Level Comparison Results

The numbers of opportunistic maintenance performed on each component in DB maintenance are given in Figure 5.1, using different colors to represent the maintenance distribution. The purple, orange, and gray boxes represent the maintenance of ObsOpp, Opp, and NoOpp policies under CM. The yellow, dark blue, and pink ones show their maintenance within ThPM(0.95), and the green, brown, and light blue indicate their maintenance within ThPM(0.90). Opportunistic maintenance is performed if the maintenance duration of the component is less than or equal to the duration of the selected component and its reliability is less than or equal to the opportunistic threshold. The maintenance duration of Mot is 4 (See: Section 4.4.5), and it is among the components with a relatively long maintenance duration. For example, RB, RS, and ASN have the same duration as Mot; however, according to Figure 5.1, opportunistic maintenance is applied to them whereas opportunistic maintenance is not applied to Mot. This situation shows that RB, RS, and ASN require opportunistic maintenance since their reliability is lower than the threshold reliability. Since Mot's reliability does not fall below the opportunistic threshold, it is not considered in opportunistic maintenance. However, it is regarded as part of non-opportunistic maintenance during the component selection process with FEL_{fp} due to its significance in the system.

Dri and Mot have the same maintenance duration; however, Dri undergoes a very low level of opportunistic maintenance level, 0.04. No opportunistic maintenance is applied to the SS like the Mot; however, the underlying reasons for not maintaining SS and Mot are different. The maintenance duration of SS is very long. From the opportunistic maintenance perspective, since the duration of the component to be maintained should be less than or equal to the duration of the main maintenance component, SS does not have the chance to undergo opportunistic maintenance anyway. It is also not considered within the scope of non-opportunistic maintenance since its total maintenance cost is very high.

Instead of the other components, ODE and LS components stand out in the choice of opportunistic maintenance with their reliabilities and shorter maintenance durations. ASB, ASN, RB, Enc, RS, and Cou components are also subject to a certain amount of opportunistic maintenance.

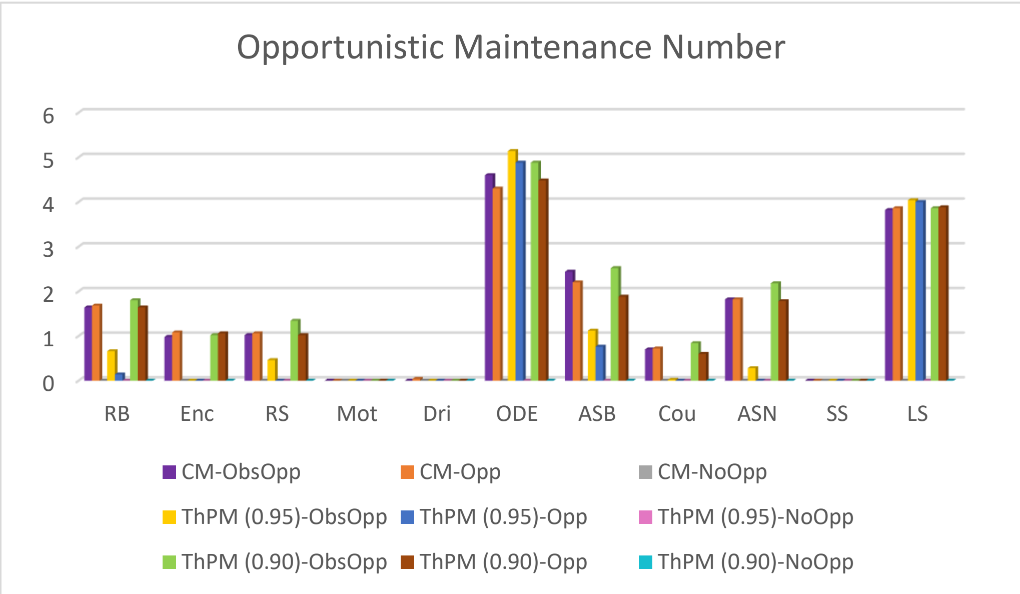

Figure 5.1 Distribution of Opportunistic Maintenance Number

The numbers of non-opportunistic maintenance performed on each component in DB maintenance are given in Figure 5.2. Contrary to the other graph, it is possible to say that the non-opportunistic maintenance numbers are more evenly distributed since the maintenance duration constraint required in opportunistic maintenance is not considered here.

As seen in Figure 5.1, all strategies apply a significant amount of opportunistic maintenance to ODE and LS components, while in Figure 5.2 less non-opportunistic maintenance is applied to them. They are not very critical components for the operation of the system. FEL_{fp} method (See: Section 3.4.2) looks at the effect of this on the reliability of the system if a component fails. FEL_{fp} method does not consider LS and ODE very critical during component selection when applying corrective and proactive maintenance. That's why not much non-opportunistic maintenance is applied to these components. Although these parts are not critical in opportunistic maintenance, they are considered for replacement as their reliability falls below a certain threshold. Therefore, since opportunistic maintenance is applied to these components, they are under control, and there is no need for non-opportunistic maintenance of these parts.

Figure 5.2 also shows that non-opportunistic maintenance is little applied in NoOpp policy for LS and ODE components. The reason for this is that in NoOpp policies opportunistic maintenance is not allowed. Therefore, even if slightly, these strategies need to replace LS and ODE components within the scope of non-opportunistic maintenance. However, in scenarios other than NoOpp, this need does not arise at all because other strategies have already considered LS and ODE within the scope of opportunistic maintenance. In addition, while in Figure 5.1 it is seen that no maintenance is applied to the Mot and almost no maintenance is applied to Dri, in Figure 5.2 it is seen that a lot of non-opportunistic maintenance is applied to these components with the FEL_{fp} selection method.

In ThPM(0.95) strategy, due to its proactive structure, a lot of maintenance is applied on almost all components except ODE, LS, and SS of which the first two are considered mainly in opportunistic maintenance, and SS does not go any type of maintenance due to its very high maintenance duration and cost.

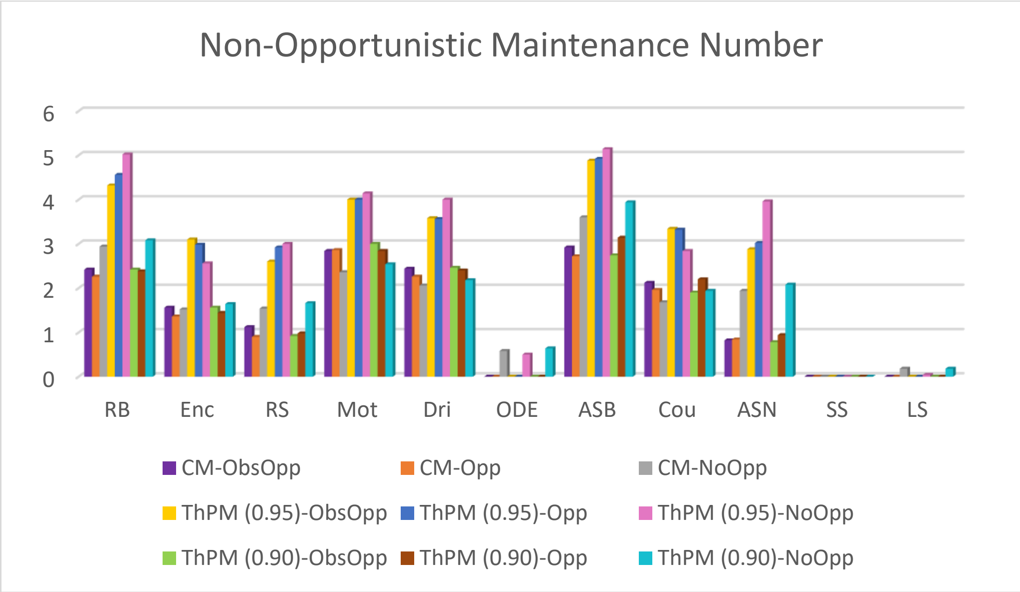

Figure 5.2 Distribution of Non-Opportunistic Maintenance Number

5.1.3 Post-ANOVA Results

Each strategy CM, ThPM(0.95), and ThPM(0.90) are examined among themselves, with the effect variable being "downtime duration". A post-ANOVA test is conducted. The results interpreted using the Tukey pairwise comparison test for a significance level of 0.05 are shown in Tables 5.3 and 5.4.

If the policies have the same group names in the test results, this indicates that there is no statistically significant difference between the approaches. Table 5.3 gives DB post-ANOVA duration results. According to the table, NoOpp policy has the highest duration compared to all strategies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.3 DB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	51.76	7.51	(49.66, 53.86)	B
CM-Opp	48.56	7.96	(46.46, 50.66)	B
CM-NoOpp	58.48	7.03	(56.38, 60.58)	A
ThPM(0.95)-ObsOpp	64.38	5.34	(62.89, 65.87)	B
ThPM(0.95)-Opp	65.26	5.84	(63.77, 66.75)	B
ThPM(0.95)-NoOpp	69.78	4.78	(68.29, 71.27)	A
ThPM(0.90)-ObsOpp	49.76	7.24	(47.66, 51.86)	B
ThPM(0.90)-Opp	50.60	7.62	(48.50, 52.70)	B
ThPM(0.90)-NoOpp	60.30	7.65	(58.20, 62.40)	A

Table 5.4 gives DB post-ANOVA cost results. According to the table, NoOpp policy has the highest cost compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in CM and ThPM(0.90) strategies. In addition, there is no significant difference between ObsOpp and Opp policies. When ThPM(0.95) strategies are examined, the result shows that ObsOpp, Opp, and NoOpp policies are not significantly different from each other.

Table 5.4 DB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	288,893	38,904	(278,002, 299,783)	B
CM-Opp	272,048	40,729	(261,157, 282,938)	B
CM-NoOpp	310,163	37,182	(299,272, 321,053)	A
ThPM(0.95)-ObsOpp	284,536	39,329	(273,449, 295,622)	A
ThPM(0.95)-Opp	283,582	43,614	(272,496, 294,668)	A
ThPM(0.95)-NoOpp	297,178	35,659	(286,092, 308,264)	A
ThPM(0.90)-ObsOpp	277,183	38,680	(265,501, 288,864)	B
ThPM(0.90)-Opp	278,813	40,486	(267,131, 290,494)	B
ThPM(0.90)-NoOpp	314,232	45,888	(302,550, 325,913)	A

5.2 COST-BASED MAINTENANCE RESULTS

5.2.1 General Comparison Results

Three methods under corrective and proactive maintenance strategies are compared based on the cost. The results of the CB maintenance are given in Table 5.5. The downtime duration column shows that ObsOpp and Opp policies have lower downtime compared to NoOpp policy in all strategy groups.

Table 5.5 CB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	32.52	1.47	16.46	2.89	53.32	8.37	16.06	1.63	32.52	1.47	0	0
CM-Opp	31.66	1.43	16.04	2.51	52.36	7.67	15.62	1.58	31.66	1.43	0	0
CM-NoOpp	18.78	1.13	18.78	1.96	59.12	7.07	0	0	18.78	1.13	0	0
ThPM(0.95)-ObsOpp	40.08	1.62	28.80	1.25	64.72	4.99	11.28	1.85	15.40	1.16	24.68	1.46
ThPM(0.95)-Opp	38.86	1.51	28.72	1.13	65.20	5.90	10.14	1.82	15.22	1.15	23.64	1.41
ThPM(0.95)-NoOpp	31.58	1.86	31.58	0.99	69.74	4.18	0	0	12.78	1.18	18.80	1.50
ThPM(0.90)-ObsOpp	32.82	1.50	16.42	2.51	52.60	7.95	16.40	1.65	30.58	1.46	2.24	0.21
ThPM(0.90)-Opp	31.88	1.43	16.04	2.87	51.68	9.24	15.84	1.62	29.52	1.37	2.36	0.22
ThPM(0.90)-NoOpp	19.46	1.20	19.46	1.69	59.10	6.28	0	0	18.04	1.15	1.42	0.28

All the costs are examined under the CB maintenance as given in Table 5.6. The total cost column indicates that ObsOpp and Opp policies give lower costs compared to NoOpp policy in all strategy groups.

Table 5.6 CB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	293412	23141	37476	3082	255936	21007	293412	23141	37476	3082	255936	21007	0	0	0	0	0	0
CM-Opp	287895	23522	36567	3034	251328	21469	287895	23522	36567	3034	251328	21469	0	0	0	0	0	0
CM-NoOpp	311648	21106	27872	2753	283776	19413	311648	21106	27872	2753	283776	19413	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	280391	20011	38951	3255	241440	17899	192462	17738	20238	2230	172224	15914	87929	8007	18713	1867	69216	6787
ThPM(0.95)-Opp	281202	19986	38226	3263	242976	17911	192920	17773	19928	2186	172992	16023	88282	8168	18298	1847	69984	7014
ThPM(0.95)-NoOpp	293916	20451	38508	3734	255408	18073	194400	17646	18336	2179	176064	15910	99516	8911	20172	2380	79344	7259
ThPM(0.90)-ObsOpp	287268	22993	36996	3053	250272	20896	283581	22935	35517	3021	248064	20836	3687	741	1479	202	2208	590
ThPM(0.90)-Opp	281397	22860	35925	2973	245472	20840	277295	22697	34415	2947	242880	20666	4102	833	1510	211	2592	681
ThPM(0.90)-NoOpp	305375	20719	28175	2710	277200	19065	297405	20478	26685	2606	270720	18837	7970	1578	1490	323	6480	1299

5.2.2 Component Level Comparison Results

The numbers of opportunistic maintenance performed on each component in CB maintenance are given in Figure 5.3, using different colors to represent the maintenance distribution. The purple, orange, and gray boxes represent the maintenance of ObsOpp, Opp, and NoOpp policies under CM. The yellow, dark blue, and pink ones show their maintenance within ThPM(0.95), and the green, brown, and light blue indicate their maintenance within ThPM(0.90). The findings regarding the distribution of opportunistic maintenance numbers presented in Section 5.1.2 are also valid in this section. When the maintenance distributions of the components are examined, it is observed that the general structure of the cost-based and duration-based objectives gives the same patterns.

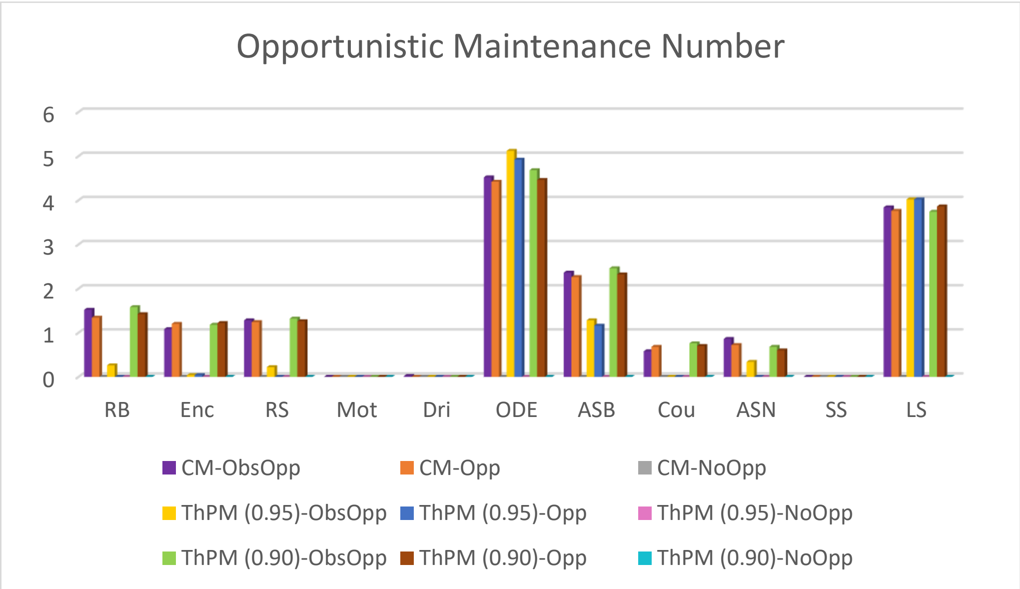

Figure 5.3 Distribution of Opportunistic Maintenance Number

The numbers of non-opportunistic maintenance performed on each component in CB maintenance are given in Figure 5.4. The findings regarding the distribution of non-opportunistic maintenance numbers presented in Section 5.1.2 are also valid in this section. When the maintenance distributions of the components are examined, it is observed that the general structure of the cost-based and duration-based objectives gives the same patterns.

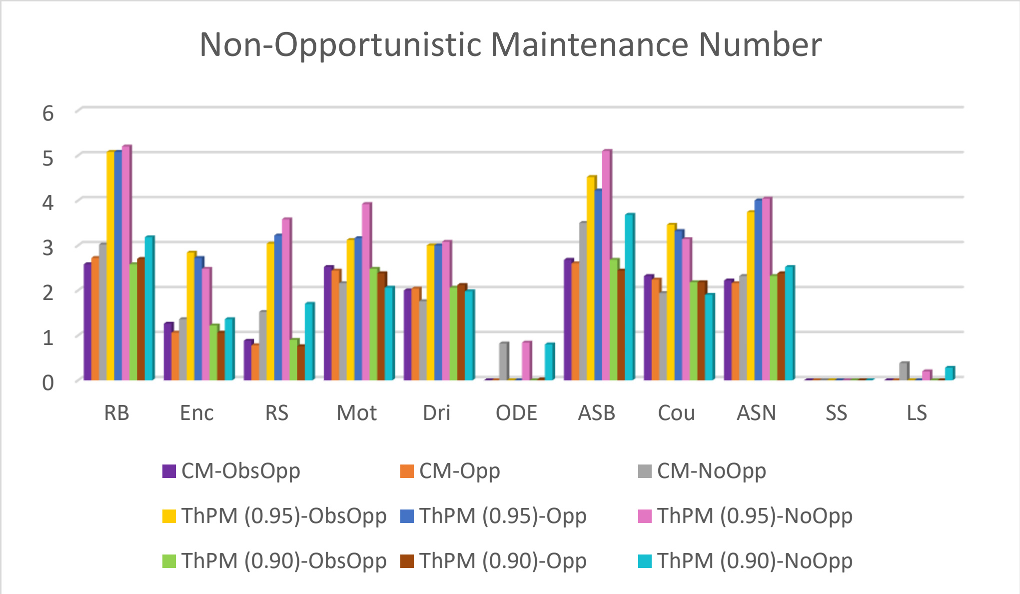

Figure 5.4 Distribution of Non-Opportunistic Maintenance Number

5.2.3 Post-ANOVA Results

Each strategy CM, ThPM(0.95), and ThPM(0.90) are examined among themselves, with the effect variable being “total cost”. Table 5.7 gives CB post-ANOVA duration results. According to the table, NoOpp policy has the highest duration compared to all strategies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.7 CB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	53.32	8.37	(51.16, 55.48)	B
CM-Opp	52.36	7.67	(50.20, 54.52)	B
CM-NoOpp	59.12	7.07	(56.96, 61.28)	A
ThPM(0.95)-ObsOpp	64.72	4.99	(63.30, 66.14)	B
ThPM(0.95)-Opp	65.20	5.90	(63.79, 66.62)	B
ThPM(0.95)-NoOpp	69.74	4.18	(68.32, 71.16)	A
ThPM(0.90)-ObsOpp	52.60	7.95	(50.39, 54.81)	B
ThPM(0.90)-Opp	51.68	9.24	(49.47, 53.89)	B
ThPM(0.90)-NoOpp	59.10	6.28	(56.89, 61.31)	A

In Table 5.8, CB post-ANOVA cost results are given. According to the CM and ThPM(0.90) results, Opp policy is significantly better than NoOpp policy; however, there is no significant difference between ObsOpp and NoOpp policies. When ThPM(0.95) strategies are examined, the result shows that ObsOpp, Opp, and NoOpp policies are not significantly different from each other.

Table 5.8 CB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	293,412	42,324	(282,263, 304,561)	A,B
CM-Opp	287,895	39,618	(276,746, 299,044)	B
CM-NoOpp	311,648	37,594	(300,498, 322,797)	A
ThPM(0.95)-ObsOpp	280,391	34,152	(270,146, 290,636)	A
ThPM(0.95)-Opp	281,202	42,180	(270,956, 291,447)	A
ThPM(0.95)-NoOpp	293,916	32,956	(283,671, 304,161)	A
ThPM(0.90)-ObsOpp	287,268	42,636	(275,162, 299,374)	A,B
ThPM(0.90)-Opp	281,397	49,269	(269,291, 293,502)	B
ThPM(0.90)-NoOpp	305,375	37,196	(293,269, 317,481)	A

When the downtime-based results are examined, ObsOpp and Opp policies demonstrate a better performance regarding downtime duration compared to NoOpp policy in all strategies. Also, in this condition, when the costs are examined, ObsOpp and Opp policies are significantly different from the other maintenance policy under the CM and ThPM(0.90) strategies; however, there are no significant differences among the policies under the ThPM(0.95) strategy.

In terms of cost-based results, ObsOpp and Opp policies are better again than NoOpp policy regarding downtime duration under all strategies. Furthermore, when examining costs in this context, Opp policy is significantly different from NoOpp policy under the CM and ThPM(0.90) strategies. Conversely, ObsOpp and Opp are not significantly different from each other. Under the ThPM(0.95) strategy, all policies are not significantly different from each other.

5.3 SCENARIO ANALYSIS

Three scenarios are developed to determine the conditions where the proposed opportunistic maintenance strategies operate better. The first scenario is created by taking 1.5 times the corrective downtime cost given in Section 4.4.5, the second scenario is created by taking 1.5 times the corrective maintenance duration of the base scenario and keeping the costs as in the first scenario, and the third scenario is created by taking 1.5 times the proactive downtime cost of the base scenario. The scenarios are given one after another in Sections 5.3.1- 5.3.3. Proposed opportunistic policies and the non-opportunistic policy under corrective and proactive maintenance strategies are compared for each scenario based on the downtime in Sections 5.3.1.1, 5.3.2.1, and 5.3.3.1 and the cost in Sections 5.3.1.2, 5.3.2.2, and 5.3.3.2.

5.3.1 Scenario 1.5*CDC

5.3.1.1 Downtime-based Maintenance Results

Firstly, replications are taken under corrective and proactive maintenance based on downtime (Dt). The results of DB maintenance are given in Table 5.9. The downtime duration column shows that ObsOpp and Opp policies have lower downtime duration compared to NoOpp policy in all CM, ThPM(0.95), and ThPM(0.90) strategy groups.

Table 5.9 Scenario 1.5*CDC DB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	33.10	1.48	16.66	2.88	52.80	8.38	16.44	1.61	33.10	1.48	0	0
CM-Opp	32.36	1.43	15.74	2.75	50.28	7.49	16.62	1.61	32.36	1.43	0	0
CM-NoOpp	18.86	1.20	18.86	2.74	59.60	8.36	0	0	18.86	1.20	0	0
ThPM(0.95)-ObsOpp	40.14	1.57	28.70	1.30	64.12	5.24	11.44	1.86	15.88	1.21	24.26	1.37
ThPM(0.95)-Opp	39.20	1.50	29.08	1.16	64.60	5.18	10.12	1.84	14.62	1.12	24.58	1.34
ThPM(0.95)-NoOpp	30.86	1.95	30.86	0.97	68.56	4.97	0	0	12.18	1.17	18.68	1.54
ThPM(0.90)-ObsOpp	32.84	1.46	16.02	2.74	50.44	8.10	16.82	1.61	30.50	1.40	2.34	0.20
ThPM(0.90)-Opp	32.78	1.44	16.76	2.40	52.52	7.50	16.02	1.62	31.04	1.42	1.74	0.16
ThPM(0.90)-NoOpp	19.60	1.24	19.60	1.51	59.38	5.71	0	0	18.14	1.19	1.46	0.29

The cost results of DB maintenance are given in Table 5.10. The total cost column indicates that ObsOpp and Opp policies give lower costs compared to NoOpp policy, in all strategy groups.

Table 5.10 Scenario 1.5*CDC DB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	420513	35007	40353	3582	380160	32163	420513	35007	40353	3582	380160	32163	0	0	0	0	0	0
CM-Opp	400923	35217	38907	3423	362016	32611	400923	35217	38907	3423	362016	32611	0	0	0	0	0	0
CM-NoOpp	459053	31741	29933	3093	429120	29686	459053	31741	29933	3093	429120	29686	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	367432	27543	41704	3880	325728	25192	277457	25663	19697	2207	257760	23909	89975	8540	22007	2618	67968	6454
ThPM(0.95)-Opp	363751	27038	40903	3875	322848	24624	270758	24569	19046	2087	251712	22916	92993	8483	21857	2539	71136	6582
ThPM(0.95)-NoOpp	374822	28513	40550	4246	334272	25878	272819	25514	18227	2146	254592	23781	102003	9551	22323	2837	79680	7362
ThPM(0.90)-ObsOpp	398345	34734	39401	3551	358944	31932	394728	34611	37896	3502	356832	31827	3617	757	1505	202	2112	612
ThPM(0.90)-Opp	414066	34935	39378	3540	374688	32161	411216	34852	38256	3515	372960	32086	2850	588	1122	151	1728	477
ThPM(0.90)-NoOpp	445163	30806	30587	3201	414576	28674	436625	30533	28529	2967	408096	28500	8538	1726	2058	456	6480	1306

Each strategy CM, ThPM(0.95), and ThPM(0.90) are examined among themselves, with the effect variable being "downtime duration". A post-ANOVA test is conducted. The results are interpreted using the Tukey pairwise comparison test for a significance level of 0.05 are shown in Tables 5.11 and 5.12. Table 5.11 gives DB post-ANOVA duration results. According to the results, NoOpp policy has the highest duration compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.11 Scenario 1.5*CDC DB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	52.80	8.38	(50.54, 55.06)	B
CM-Opp	50.28	7.49	(48.02, 52.54)	B
CM-NoOpp	59.60	8.36	(57.34, 61.86)	A
ThPM(0.95)-ObsOpp	64.12	5.24	(62.69, 65.55)	B
ThPM(0.95)-Opp	64.60	5.18	(63.17, 66.03)	B
ThPM(0.95)-NoOpp	68.56	4.97	(67.18, 69.99)	A
ThPM(0.90)-ObsOpp	50.44	8.10	(48.43, 52.45)	B
ThPM(0.90)-Opp	52.52	7.50	(50.51, 54.53)	B
ThPM(0.90)-NoOpp	59.38	5.71	(57.37, 61.39)	A

Table 5.12 gives DB Post-ANOVA cost results. NoOpp policy has the highest cost compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in CM and ThPM(0.90) strategies. In addition, there is no significant difference between ObsOpp and Opp policies. When ThPM(0.95) strategies are examined, the result shows that ObsOpp, Opp, and NoOpp policies are not significantly different from each other.

Table 5.12 Scenario 1.5*CDC DB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	420,513	63,833	(403,264, 437,762)	B
CM-Opp	400,923	56,247	(383,674, 418,172)	B
CM-NoOpp	459,053	64,724	(441,803, 476,302)	A
ThPM(0.95)-ObsOpp	367,432	61,311	(350,452, 384,411)	A
ThPM(0.95)-Opp	363,751	61,023	(346,771, 380,730)	A
ThPM(0.95)-NoOpp	374,822	59,913	(357,842, 391,801)	A
ThPM(0.90)-ObsOpp	398,345	65,529	(381,764, 414,926)	B
ThPM(0.90)-Opp	414,066	58,920	(397,485, 430,647)	B
ThPM(0.90)-NoOpp	445,163	52,861	(428,581, 461,744)	A

5.3.1.2 Cost-based Maintenance Results

Three methods under corrective and proactive maintenance strategies are compared based on the cost. The results of the CB maintenance are given in Table 5.13. The downtime duration column shows that ObsOpp and Opp policies have lower downtime compared to NoOpp policy in all strategy groups.

Table 5.13 Scenario 1.5*CDC CB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	33.10	1.48	16.34	2.94	52.56	8.24	16.76	1.67	33.10	1.48	0	0
CM-Opp	31.34	1.40	15.64	2.43	51.28	6.69	15.70	1.59	31.34	1.40	0	0
CM-NoOpp	19.24	1.19	19.24	2.03	60.88	6.26	0	0	19.24	1.19	0	0
ThPM(0.95)-ObsOpp	40.54	1.64	28.62	1.37	64.06	5.04	11.92	1.89	15.98	1.23	24.56	1.49
ThPM(0.95)-Opp	39.26	1.54	29.08	1.07	66.24	4.73	10.18	1.82	15.98	1.21	23.28	1.41
ThPM(0.95)-NoOpp	31.50	1.86	31.50	0.86	70.46	4.87	0	0	13.28	1.21	18.22	1.44
ThPM(0.90)-ObsOpp	33.12	1.45	17.12	3.05	54.72	8.98	16.00	1.68	31.94	1.41	1.18	0.13
ThPM(0.90)-Opp	32.16	1.40	16.58	2.60	53.14	8.07	15.58	1.62	29.92	1.34	2.24	0.23
ThPM(0.90)-NoOpp	20.12	1.22	20.12	1.55	61.20	5.82	0	0	18.86	1.19	1.26	0.28

All the costs are examined under the CB maintenance as given in Table 5.14. In the total cost column, it is seen that ObsOpp and Opp policies give lower costs compared to NoOpp policy in all strategy groups.

Table 5.14 Scenario 1.5*CDC CB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	417227	34429	38795	3270	378432	32071	417227	34429	38795	3270	378432	32071	0	0	0	0	0	0
CM-Opp	406037	34151	36821	3142	369216	31958	406037	34151	36821	3142	369216	31958	0	0	0	0	0	0
CM-NoOpp	467964	32032	29628	2972	438336	30162	467964	32032	29628	2972	438336	30162	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	362474	27001	40154	3453	322320	24453	275084	25601	22220	2520	252864	23419	87390	8104	17934	1697	69456	7029
ThPM(0.95)-Opp	378676	28657	39220	3400	339456	26369	292461	27053	21741	2423	270720	25088	86215	8039	17479	1740	68736	6942
ThPM(0.95)-NoOpp	392634	28755	39402	3890	353232	26099	296978	26176	20786	2466	276192	24171	95656	8495	18616	2120	77040	7056
ThPM(0.90)-ObsOpp	430083	34091	38787	3332	391296	31685	428045	34044	38093	3327	389952	31629	2038	452	694	104	1344	386
ThPM(0.90)-Opp	415419	34454	37515	3270	377904	32086	411828	34346	36276	3264	375552	31958	3591	801	1239	174	2352	697
ThPM(0.90)-NoOpp	459018	31299	29322	2830	429696	29600	452307	31262	28083	2772	424224	29548	6711	1542	1239	313	5472	1245

Each strategy CM, ThPM(0.95), and ThPM(0.90) are examined among themselves, with the effect variable being “total cost”. Table 5.15 gives CB post-ANOVA duration results. The results show that NoOpp policy has the highest duration compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.15 Scenario 1.5*CDC CB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	52.56	8.24	(50.57, 54.55)	B
CM-Opp	51.28	6.69	(49.29, 53.27)	B
CM-NoOpp	60.88	6.26	(58.89, 62.87)	A
ThPM(0.95)-ObsOpp	64.06	5.04	(62.70, 65.42)	B
ThPM(0.95)-Opp	66.24	4.73	(64.88, 67.60)	B
ThPM(0.95)-NoOpp	70.46	4.87	(69.10, 71.82)	A
ThPM(0.90)-ObsOpp	54.72	8.98	(52.56, 56.88)	B
ThPM(0.90)-Opp	53.14	8.07	(50.98, 55.30)	B
ThPM(0.90)-NoOpp	61.20	5.82	(59.04, 63.36)	A

In Table 5.16, CB post-ANOVA cost results are given. According to the results, NoOpp policy has the highest cost compared to all policies. When looking at the CM results, the results of CM-ObsOpp and CM-Opp are significantly better than CM-NoOpp. When ThPM(0.95) results are examined, Opp policy gives better results than NoOpp policy; however, it is not statistically significant; On the other hand, ObsOpp policy is significantly better than NoOpp policy. According to the ThPM(0.90) results, Opp policy is significantly better than NoOpp policy; however, there is no significant difference between ObsOpp and NoOpp policies.

Table 5.16 Scenario 1.5*CDC CB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	417,227	61,970	(402,140, 432,313)	B
CM-Opp	406,037	50,695	(390,950, 421,123)	B
CM-NoOpp	467,964	48,282	(452,878, 483,050)	A
ThPM(0.95)-ObsOpp	362,474	54,239	(346,519, 378,428)	B
ThPM(0.95)-Opp	378,676	56,523	(362,721, 394,631)	A,B
ThPM(0.95)-NoOpp	392,634	60,332	(376,679, 408,588)	A
ThPM(0.90)-ObsOpp	430,083	69,980	(412,803, 447,362)	A,B
ThPM(0.90)-Opp	415,419	63,747	(398,140, 432,698)	B
ThPM(0.90)-NoOpp	459,018	50,066	(441,739, 476,297)	A

5.3.2 Scenario 1.5*CDC–1.5*CDT

5.3.2.1 Downtime-based Maintenance Results

Firstly, replications are taken under corrective and proactive maintenance based on downtime (Dt). The results of DB maintenance are given in Table 5.17. The downtime duration column shows that ObsOpp and Opp policies have lower downtime compared to NoOpp policy in all strategy groups.

Table 5.17 Scenario 1.5*CDC–1.5*CDT DB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	29.90	1.35	14.52	2.38	73.02	10.72	15.38	1.51	29.90	1.35	0	0
CM-Opp	29.72	1.30	14.60	2.46	73.26	11.63	15.12	1.48	29.72	1.30	0	0
CM-NoOpp	16.58	1.15	16.58	1.57	81.00	8.06	0	0	16.58	1.15	0	0
ThPM(0.95)-ObsOpp	37.40	1.49	26.24	1.20	78.20	10.12	11.16	1.77	14.62	1.05	22.78	1.29
ThPM(0.95)-Opp	36.20	1.41	26.96	1.05	80.72	7.43	9.24	1.69	14.62	1.06	21.58	1.19
ThPM(0.95)-NoOpp	28.20	1.82	28.20	0.86	86.26	7.13	0	0	12.36	1.07	15.84	1.32
ThPM(0.90)-ObsOpp	30.00	1.34	14.50	2.33	71.14	11.70	15.50	1.49	28.20	1.31	1.80	0.16
ThPM(0.90)-Opp	29.40	1.29	14.76	2.10	72.54	9.95	14.64	1.47	27.80	1.26	1.60	0.14
ThPM(0.90)-NoOpp	17.36	1.17	17.36	1.59	81.16	9.23	0	0	16.24	1.13	1.12	0.24

The costs of DB maintenance are given in Table 5.18. According to the table, it is observed that ObsOpp and Opp policies give lower total costs compared to NoOpp policy, in all of the strategy groups.

Table 5.18 Scenario 1.5*CDC–1.5*CDT DB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	563036	51606	37292	3508	525744	48970	563036	51606	37292	3508	525744	48970	0	0	0	0	0	0
CM-Opp	564650	51926	37178	3477	527472	49329	564650	51926	37178	3477	527472	49329	0	0	0	0	0	0
CM-NoOpp	610568	46240	27368	2964	583200	44276	610568	46240	27368	2964	583200	44276	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	480785	39891	39089	3754	441696	37821	400032	38234	19008	2167	381024	36585	80753	7651	20081	2368	60672	5739
ThPM(0.95)-Opp	496505	40292	38393	3750	458112	38158	415794	38047	19218	2138	396576	36468	80711	7311	19175	2232	61536	5573
ThPM(0.95)-NoOpp	527786	43813	39386	4381	488400	40929	442944	40802	20880	2590	422064	38782	84842	7989	18506	2322	66336	6228
ThPM(0.90)-ObsOpp	545582	49779	36446	3384	509136	47240	542828	49662	35228	3350	507600	47136	2754	592	1218	173	1536	463
ThPM(0.90)-Opp	555377	49265	35969	3381	519408	46747	552879	49213	34911	3358	517968	46694	2498	523	1058	145	1440	415
ThPM(0.90)-NoOpp	602551	45675	27607	2955	574944	43808	596285	45587	26045	2826	570240	43732	6266	1375	1562	372	4704	1023

Table 5.19 gives DB post-ANOVA duration results. According to the table, NoOpp policy has the highest duration compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.19 Scenario 1.5*CDC–1.5*CDT DB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	73.02	10.72	(70.16, 75.88)	B
CM-Opp	73.26	11.63	(70.40, 76.12)	B
CM-NoOpp	81.00	8.06	(78.14, 83.86)	A
ThPM(0.95)-ObsOpp	78.20	10.12	(75.87, 80.53)	B
ThPM(0.95)-Opp	80.72	7.43	(78.39, 83.05)	B
ThPM(0.95)-NoOpp	86.26	7.13	(83.93, 88.59)	A
ThPM(0.90)-ObsOpp	71.14	11.7	(68.25, 74.03)	B
ThPM(0.90)-Opp	72.54	9.95	(69.65, 75.43)	B
ThPM(0.90)-NoOpp	81.16	9.23	(78.27, 84.05)	A

Table 5.20 gives DB post-ANOVA cost results. NoOpp policy has the highest cost compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in CM and ThPM(0.90) strategies. In addition, there is no significant difference between ObsOpp and Opp policies. When ThPM(0.95) results are examined, Opp policy gives better results than

NoOpp policy; however, there is no significant difference; On the other hand, ObsOpp policy is significantly better than NoOpp policy.

Table 5.20 Scenario 1.5*CDC–1.5*CDT DB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	563,036	79,026	(541,816, 584,255)	B
CM-Opp	564,650	85,711	(543,430, 585,869)	B
CM-NoOpp	610,568	60,839	(589,348, 631,787)	A
ThPM(0.95)-ObsOpp	480,785	101,862	(456,978, 504,592)	B
ThPM(0.95)-Opp	496,505	75,287	(472,698, 520,312)	A,B
ThPM(0.95)-NoOpp	527,786	75,653	(503,979, 551,593)	A
ThPM(0.90)-ObsOpp	545,582	88,458	(523,050, 568,113)	B
ThPM(0.90)-Opp	555,377	75,872	(532,845, 577,909)	B
ThPM(0.90)-NoOpp	602,551	76,924	(580,019, 625,082)	A

5.3.2.2 Cost-based Maintenance Results

Three methods under corrective and proactive maintenance strategies are compared based on the cost. The results of the CB maintenance are given in Table 5.21. The downtime duration column shows that ObsOpp and Opp policies have lower downtime duration compared to NoOpp policy in all strategy groups.

Table 5.21 Scenario 1.5*CDC–1.5*CDT CB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	29.94	1.34	14.36	2.33	72.72	10.54	15.58	1.49	29.94	1.34	0	0
CM-Opp	29.04	1.28	14.52	2.26	73.02	10.17	14.52	1.42	29.04	1.28	0	0
CM-NoOpp	16.90	1.15	16.90	1.92	82.80	9.03	0	0	16.90	1.15	0	0
ThPM(0.95)-ObsOpp	37.42	1.53	26.32	1.28	77.82	9.59	11.10	1.77	15.38	1.08	22.04	1.31
ThPM(0.95)-Opp	36.22	1.44	26.32	1.20	78.16	8.30	9.9	1.73	14.16	1.07	22.06	1.32
ThPM(0.95)-NoOpp	28.72	1.81	28.72	1.81	83.76	8.46	0	0	11.50	1.07	17.22	1.36
ThPM(0.90)-ObsOpp	30.36	1.36	14.32	2.06	71.14	9.94	16.04	1.53	29.08	1.32	1.28	0.12
ThPM(0.90)-Opp	29.36	1.30	15.60	2.45	76.16	12.32	13.76	1.44	27.80	1.26	1.56	0.16
ThPM(0.90)-NoOpp	17.84	1.21	17.84	1.50	83.40	9.66	0	0	16.80	1.17	1.04	0.22

All the costs are examined under the CB maintenance as given in Table 5.22. The total cost column indicates that ObsOpp and Opp policies give lower costs compared to NoOpp policy in all strategy groups.

Table 5.22 Scenario 1.5*CDC–1.5*CDT CB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	560508	51901	36924	3400	523584	49459	560508	51901	36924	3400	523584	49459	0	0	0	0	0	0
CM-Opp	561761	50743	36017	3341	525744	48306	561761	50743	36017	3341	525744	48306	0	0	0	0	0	0
CM-NoOpp	623997	46783	27837	3016	596160	44784	623997	46783	27837	3016	596160	44784	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	473385	39370	37785	3416	435600	36955	394667	37638	21419	2445	373248	35673	78718	7114	16366	1569	62352	6113
ThPM(0.95)-Opp	472471	41289	37207	3515	435264	38715	392850	39992	21330	2682	371520	37739	79621	7422	15877	1528	63744	6475
ThPM(0.95)-NoOpp	497787	42875	37563	4032	460224	39840	409481	40361	20681	2801	388800	38006	88306	7777	16882	1805	71424	6605
ThPM(0.90)-ObsOpp	546466	50026	36754	3386	509712	47466	544554	50000	36090	3390	508464	47431	1912	377	664	81	1248	338
ThPM(0.90)-Opp	581134	50714	36046	3371	545088	48223	578739	50705	35283	3387	543456	48196	2395	498	763	96	1632	454
ThPM(0.90)-NoOpp	620200	47257	28648	3148	591552	45072	615020	47211	27932	3148	587088	45015	5180	1105	716	158	4464	962

Each strategy CM, ThPM(0.95), and ThPM(0.90) are examined among themselves, with the effect variable being "total cost". In Table 5.23, CB post-ANOVA duration results are given. According to the table, NoOpp policy has the highest duration compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.23 Scenario 1.5*CDC–1.5*CDT CB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	72.72	10.54	(69.94, 75.50)	B
CM-Opp	73.02	10.17	(70.24, 75.80)	B
CM-NoOpp	82.8	9.03	(80.02, 85.58)	A
ThPM(0.95)-ObsOpp	77.82	9.59	(75.36, 80.28)	B
ThPM(0.95)-Opp	78.16	8.30	(75.70, 80.62)	B
ThPM(0.95)-NoOpp	83.76	8.46	(81.30, 86.22)	A
ThPM(0.90)-ObsOpp	71.14	9.94	(68.15, 74.13)	B
ThPM(0.90)-Opp	76.16	12.32	(73.17, 79.15)	B
ThPM(0.90)-NoOpp	83.40	9.66	(80.41, 86.39)	A

In Table 5.24, CB post-ANOVA cost results are given. According to the results, NoOpp policy has the highest cost compared to all policies. When looking at the CM results, the results of CM-ObsOpp and CM-Opp are significantly better than CM-NoOpp. When ThPM(0.95) strategies are examined, the result shows that ObsOpp, Opp, and NoOpp policies are not significantly different from each other. When ThPM(0.90) results are examined, Opp policy gives better results than NoOpp policy; however, this is not significantly justified; On the other hand, ObsOpp policy is significantly better than NoOpp policy.

Table 5.24 Scenario 1.5*CDC–1.5*CDT CB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	560,508	77,095	(539,974, 581,042)	B
CM-Opp	561,761	74,897	(541,227, 582,294)	B
CM-NoOpp	623,997	68,120	(603,463, 644,531)	A
ThPM(0.95)-ObsOpp	473,385	93,354	(448,749, 498,020)	A
ThPM(0.95)-Opp	472,471	82,898	(447,836, 497,106)	A
ThPM(0.95)-NoOpp	497,787	87,875	(473,151, 522,422)	A
ThPM(0.90)-ObsOpp	546,466	75,659	(523,008, 569,924)	B
ThPM(0.90)-Opp	581,134	95,265	(557,676, 604,592)	A,B
ThPM(0.90)-NoOpp	620,200	79,589	(596,742, 643,657)	A

5.3.3 Scenario 1.5*PDC

5.3.3.1 Downtime-based Maintenance Results

Firstly, replications are taken under corrective and proactive maintenance based on downtime (Dt). The results of DB maintenance are given in Table 5.25. The downtime duration column shows that ObsOpp and Opp policies have lower downtime than NoOpp policy in all strategy groups.

Table 5.25 Scenario 1.5*PDC DB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	32.90	1.43	15.86	2.65	53.20	8.07	17.04	1.64	32.90	1.43	0	0
CM-Opp	31.70	1.38	15.30	2.31	52.36	7.36	16.40	1.56	31.70	1.38	0	0
CM-NoOpp	19.04	1.27	19.04	2.42	62.08	7.75	0	0	19.04	1.27	0	0
ThPM(0.95)-ObsOpp	39.58	1.56	27.86	1.13	64.16	5.10	11.72	1.86	15.40	1.07	24.18	1.28
ThPM(0.95)-Opp	38.42	1.47	28.36	0.80	65.04	5.30	10.06	1.80	14.46	1.02	23.96	1.29
ThPM(0.95)-NoOpp	30.50	1.99	30.50	1.04	72.06	4.69	0	0	13.38	1.17	17.12	1.39
ThPM(0.90)-ObsOpp	32.70	1.45	14.94	2.37	49.90	7.49	17.76	1.64	29.84	1.37	2.86	0.23
ThPM(0.90)-Opp	32.20	1.36	15.70	2.12	51.64	6.92	16.50	1.58	30.56	1.32	1.64	0.15
ThPM(0.90)-NoOpp	19.30	1.26	19.30	1.75	60.70	6.16	0	0	18.14	1.24	1.16	0.26

The cost results of DB maintenance are given in Table 5.26. When looking at the total cost column, it is observed that ObsOpp and Opp policies give lower cost compared to NoOpp policy, in all strategy groups.

Table 5.26 Scenario 1.5*PDC DB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	296366	26283	41006	3808	255360	23322	296366	26283	41006	3808	255360	23322	0	0	0	0	0	0
CM-Opp	291177	26933	39849	3779	251328	24075	291177	26933	39849	3779	251328	24075	0	0	0	0	0	0
CM-NoOpp	329666	24846	31682	3528	297984	22373	329666	24846	31682	3528	297984	22373	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	317072	23247	41696	4058	275376	20453	198077	17938	20477	2316	177600	16166	118995	10719	21219	2375	97776	8944
ThPM(0.95)-Opp	318749	23577	40589	3985	278160	20998	195482	18309	19418	2167	176064	16725	123267	10931	21171	2386	102096	9184
ThPM(0.95)-NoOpp	352142	26632	41750	4505	310392	23516	225762	20680	21858	2611	203904	18659	126380	11592	19892	2435	106488	9792
ThPM(0.90)-ObsOpp	277793	25825	39545	3732	238248	22898	272108	25490	37676	3679	234432	22566	5685	1163	1869	230	3816	1008
ThPM(0.90)-Opp	286602	24710	39594	3662	247008	21862	282794	24414	38378	3586	244416	21625	3808	819	1216	169	2592	686
ThPM(0.90)-NoOpp	319918	23781	31222	3437	288696	21371	310269	23557	29565	3304	280704	21194	9649	2200	1657	425	7992	1805

Table 5.27 gives DB post-ANOVA duration results. According to the table, NoOpp policy has the highest duration compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.27 Scenario 1.5*PDC DB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	53.20	8.07	(51.04, 55.36)	B
CM-Opp	52.36	7.36	(50.20, 54.52)	B
CM-NoOpp	62.08	7.75	(59.92, 64.24)	A
ThPM(0.95)-ObsOpp	64.16	5.10	(62.75, 65.57)	B
ThPM(0.95)-Opp	65.04	5.30	(63.63, 66.45)	B
ThPM(0.95)-NoOpp	72.06	4.69	(70.65, 73.47)	A
ThPM(0.90)-ObsOpp	49.90	7.49	(47.98, 51.82)	B
ThPM(0.90)-Opp	51.64	6.93	(49.72, 53.56)	B
ThPM(0.90)-NoOpp	60.70	6.16	(58.78, 62.62)	A

Table 5.28 gives DB post-ANOVA cost results. NoOpp policy has the highest cost compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.28 Scenario 1.5*PDC DB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	296,366	40,706	(285,206, 307,525)	B
CM-Opp	291,177	37,462	(280,018, 302,336)	B
CM-NoOpp	329,666	41,502	(318,506, 340,825)	A
ThPM(0.95)-ObsOpp	317,072	30,460	(308,433, 325,710)	B
ThPM(0.95)-Opp	318,749	32,938	(310,110, 327,387)	B
ThPM(0.95)-NoOpp	352,142	29,213	(343,503, 360,781)	A
ThPM(0.90)-ObsOpp	277,793	39,261	(267,586, 287,999)	B
ThPM(0.90)-Opp	286,602	35,553	(276,395, 296,808)	B
ThPM(0.90)-NoOpp	319,918	34,576	(309,712, 330,124)	A

5.3.3.2 Cost-based Maintenance Results

Three methods under corrective and preventive maintenance strategies are compared based on the cost. The results of the CB maintenance are given in Table 5.29. The downtime duration column shows that ObsOpp and Opp policies have lower downtime than NoOpp policy in all strategy groups.

Table 5.29 Scenario 1.5*PDC CB Results

Strategy-Policy	Total Number	SD	Dt. Number	SD	Dt. Duration	SD	Opp. Number	SD	Cor. Number	SD	Pro. Number	SD
CM-ObsOpp	32.16	1.44	15.78	2.74	53.04	8.16	16.38	1.61	32.16	1.44	0	0
CM-Opp	31.48	1.37	15.92	2.75	53.60	8.35	15.56	1.56	31.48	1.37	0	0
CM-NoOpp	19.38	1.24	19.38	2.03	62.60	6.79	0	0	19.38	1.24	0	0
ThPM(0.95)-ObsOpp	40.02	1.63	27.82	1.40	64.14	5.17	12.20	1.89	15.74	1.08	24.28	1.35
ThPM(0.95)-Opp	39.10	1.49	28.38	1.37	66.38	5.73	10.72	1.84	15.24	1.06	23.86	1.35
ThPM(0.95)-NoOpp	30.86	1.93	30.86	1.03	71.84	5.22	0	0	13.56	1.15	17.30	1.42
ThPM(0.90)-ObsOpp	32.34	1.45	15.66	2.68	52.54	8.69	16.68	1.62	30.18	1.37	2.16	0.19
ThPM(0.90)-Opp	31.90	1.40	16.26	2.50	53.58	8.05	15.64	1.61	29.80	1.33	2.10	0.23
ThPM(0.90)-NoOpp	19.44	1.28	19.44	1.91	61.92	6.45	0	0	18.46	1.24	0.98	0.21

All the costs are examined under the CB maintenance as given in Table 5.30. The total cost column indicates that ObsOpp and Opp policies have lower costs compared to NoOpp policy in all strategy groups.

Table 5.30 Scenario 1.5*PDC CB Cost Results

Strategy-Policy	Total Cost	SD	Total Rep. Cost	SD	Total Prod. Loss Cost	SD	CM Cost	SD	CM Rep. Cost	SD	CM Prod. Loss Cost	SD	PM Cost	SD	PM Rep. Cost	SD	PM Prod. Loss Cost	SD
CM-ObsOpp	292515	24734	37923	3253	254592	22495	292515	24734	37923	3253	254592	22495	0	0	0	0	0	0
CM-Opp	294809	25171	37529	3263	257280	22960	294809	25171	37529	3263	257280	22960	0	0	0	0	0	0
CM-NoOpp	330174	23715	29694	2997	300480	21863	330174	23715	29694	2997	300480	21863	0	0	0	0	0	0
ThPM(0.95)-ObsOpp	314554	23026	39490	3471	275064	20887	196545	18502	19905	2176	176640	16860	118009	10557	19585	2028	98424	9173
ThPM(0.95)-Opp	325192	23236	39472	3523	285720	21108	207692	18771	20684	2279	187008	17089	117500	10683	18788	1909	98712	9499
ThPM(0.95)-NoOpp	349231	25444	40687	4308	308544	22495	220836	19745	21156	2532	199680	17711	128395	11884	19531	2386	108864	10156
ThPM(0.90)-ObsOpp	288761	24684	37553	3250	251208	22460	284490	24509	36234	3212	248256	22290	4271	908	1319	171	2952	786
ThPM(0.90)-Opp	293202	24263	37194	3242	256008	22014	288441	24047	35961	3215	252480	21796	4761	1105	1233	181	3528	986
ThPM(0.90)-NoOpp	324266	24020	29114	2912	295152	22269	317028	23817	28068	2851	288960	22063	7238	1600	1046	246	6192	1374

Each strategy CM, ThPM(0.95), and ThPM(0.90) are examined among themselves, with the effect variable being “total cost”. Table 5.31 presents the CB post-ANOVA duration results. According to the table, NoOpp policy has the highest duration compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.31 Scenario 1.5*PDC CB Post-ANOVA Duration Results

Strategy-Policy	Dt. Duration	SD	95% CI	Group
CM-ObsOpp	53.04	8.16	(50.86, 55.22)	B
CM-Opp	53.60	8.35	(51.42, 55.78)	B
CM-NoOpp	62.60	6.79	(60.42, 64.78)	A
ThPM(0.95)-ObsOpp	64.14	5.17	(62.64, 65.64)	B
ThPM(0.95)-Opp	66.38	5.73	(64.88, 67.88)	B
ThPM(0.95)-NoOpp	71.84	5.22	(70.34, 73.34)	A
ThPM(0.90)-ObsOpp	52.54	8.69	(50.36, 54.72)	B
ThPM(0.90)-Opp	53.58	8.05	(51.40, 55.76)	B
ThPM(0.90)-NoOpp	61.92	6.46	(59.74, 64.10)	A

In Table 5.32, CB post-ANOVA cost results are given. According to the results, NoOpp policy has the highest cost compared to all policies. The results of ObsOpp and Opp policies are significantly better than NoOpp policy in all strategy groups. In addition, there is no significant difference between ObsOpp and Opp policies.

Table 5.32 Scenario 1.5*PDC CB Post-ANOVA Cost Results

Strategy-Policy	Total Cost	SD	95% CI	Group
CM-ObsOpp	292,515	41,595	(281,270, 303,760)	B
CM-Opp	294,809	42,793	(283,564, 306,053)	B
CM-NoOpp	330,174	35,984	(318,929, 341,419)	A
ThPM(0.95)-ObsOpp	314,554	29,915	(305,472, 323,636)	B
ThPM(0.95)-Opp	325,192	34,584	(316,110, 334,273)	B
ThPM(0.95)-NoOpp	349,231	32,814	(340,149, 358,313)	A
ThPM(0.90)-ObsOpp	288,761	45,538	(277,243, 300,279)	B
ThPM(0.90)-Opp	293,202	42,222	(281,684, 304,720)	B
ThPM(0.90)-NoOpp	324,266	35,192	(312,748, 335,784)	A

5.4 SUMMARIZATION OF SCENARIOS

We organize the results in this section to present the studies from Sections 5.1, 5.2, and 5.3 more clearly. First, we summarize the base scenario results given in Sections 5.1 and 5.2 where the corrective and proactive maintenance durations and costs of the components are taken as in Section 4.4.5. Post-ANOVA results for the base scenario are given in Table 5.33. The averages of replications for both DB and CB are given in the “Dt. Duration” and “Total Cost” columns. Tukey test results are also given in the “Group” column.

Dt. Duration test results for DB and CB indicate that ObsOpp and Opp policies yield significantly better results than NoOpp policy in all strategy groups. Total Cost test results for DB show that ObsOpp and Opp policies yield significantly better results than NoOpp policy in CM and ThPM(0.90) strategies whereas they are in the same group in ThPM(0.95) strategy. Total Cost test results for CB show that Opp policy is significantly better than NoOpp policy; however, there is no significant difference between ObsOpp and NoOpp policies in CM and ThPM(0.90) results. When ThPM(0.95) strategies are examined, the result shows that all strategies are in the same group.

Table 5.33 Base Scenario Post-ANOVA Results

Strategy-Policy	DB				CB			
	Dt. Duration	Group	Total Cost	Group	Dt. Duration	Group	Total Cost	Group
CM-ObsOpp	51.76	B	288,893	B	53.32	B	293,412	A,B
CM-Opp	48.56	B	272,048	B	52.36	B	287,895	B
CM-NoOpp	58.48	A	310,163	A	59.12	A	311,648	A
ThPM(0.95)-ObsOpp	64.38	B	284,536	A	64.72	B	280,391	A
ThPM(0.95)-Opp	65.26	B	283,582	A	65.20	B	281,202	A
ThPM(0.95)-NoOpp	69.78	A	297,178	A	69.74	A	293,916	A
ThPM(0.90)-ObsOpp	49.76	B	277,183	B	52.60	B	287,268	A,B
ThPM(0.90)-Opp	50.60	B	278,813	B	51.68	B	281,397	B
ThPM(0.90)-NoOpp	60.30	A	314,232	A	59.10	A	305,375	A

For Scenario 1.5*CDC, the unit downtime cost of corrective maintenance is multiplied by 1.5. According to Table 5.34, unlike the base scenario, there is an improvement in the Total Cost test results in CM and ThPM(0.95) strategies for CB. It should be noted that when the opportunistic policies diverge significantly from the NoOpp strategy, this is considered an improvement. Here, both ObsOpp and Opp policies are significantly better than NoOpp policy in CM. In addition, ObsOpp policy is significantly better than NoOpp policy in ThPM(0.95); however, there is still no significant difference between Opp and NoOpp policies.

Table 5.34 Scenario 1.5*CDC Post-ANOVA Results

Strategy-Policy	DB				CB			
	Dt. Duration	Group	Total Cost	Group	Dt. Duration	Group	Total Cost	Group
CM-ObsOpp	52.80	B	420,513	B	52.56	B	417,227	B
CM-Opp	50.28	B	400,923	B	51.28	B	406,037	B
CM-NoOpp	59.60	A	459,053	A	60.88	A	467,964	A
ThPM(0.95)-ObsOpp	64.12	B	367,432	A	64.06	B	362,474	B
ThPM(0.95)-Opp	64.60	B	363,751	A	66.24	B	378,676	A,B
ThPM(0.95)-NoOpp	68.56	A	374,822	A	70.46	A	392,634	A
ThPM(0.90)-ObsOpp	50.44	B	398,345	B	54.72	B	430,083	A,B
ThPM(0.90)-Opp	52.52	B	414,066	B	53.14	B	415,419	B
ThPM(0.90)-NoOpp	59.38	A	445,163	A	61.20	A	459,018	A

For Scenario 1.5*CDC–1.5*CDT, the unit downtime cost of corrective maintenance is multiplied by 1.5, and the maintenance duration of corrective maintenance is also multiplied by 1.5 according to the base scenario. According to Table 5.35, unlike the previous scenario, there is an improvement in the Total Cost test results in ThPM(0.95) with respect to DB maintenance. Here, ObsOpp policy is significantly better than NoOpp policy; however, there is still no significant difference between Opp and NoOpp policies. Opportunistic maintenance policies and NoOpp policy are not significantly different in ThPM(0.95) strategy for CB maintenance. At thr=0.90 value, for CB maintenance, we still cannot say that both opportunistic policies are better than NoOpp policy. In this scenario, we expect an improvement in the opportunistic maintenance on proactive by worsening the corrective maintenance conditions.

However, at thr=0.95 where proactive maintenance is more frequently observed, worsening corrective maintenance conditions even more does not improve the results of opportunistic policies on proactive maintenance. That’s why, we create a new scenario by worsening the proactive conditions.

Table 5.35 Scenario 1.5*CDC–1.5*CDT Post-ANOVA Results

Strategy-Policy	DB				CB			
	Dt. Duration	Group	Total Cost	Group	Dt. Duration	Group	Total Cost	Group
CM-ObsOpp	73.02	B	563,036	B	72.72	B	560,508	B
CM-Opp	73.26	B	564,650	B	73.02	B	561,761	B
CM-NoOpp	81.00	A	610,568	A	82.8	A	623,997	A
ThPM(0.95)-ObsOpp	78.20	B	480,785	B	77.82	B	473,385	A
ThPM(0.95)-Opp	80.72	B	496,505	A,B	78.16	B	472,471	A
ThPM(0.95)-NoOpp	86.26	A	527,786	A	83.76	A	497,787	A
ThPM(0.90)-ObsOpp	71.14	B	545,582	B	71.14	B	546,466	B
ThPM(0.90)-Opp	72.54	B	555,377	B	76.16	B	581,134	A,B
ThPM(0.90)-NoOpp	81.16	A	602,551	A	83.40	A	620,200	A

Since the conditions are already good for proactive maintenance in our problem, it is unnecessary to perform opportunistic maintenance on a proactive strategy, and therefore, no improvement in costs and durations can be achieved. Therefore, we aim to improve the effect of opportunistic policies on proactive maintenance by worsening the proactive maintenance conditions. That's why, Scenario 1.5*PDC is considered. In this scenario, the unit downtime cost of proactive maintenance is multiplied by 1.5 according to the base scenario. Dt. Duration and Total Cost test results for DB and CB indicate that ObsOpp and Opp policies yield significantly better results than NoOpp policy in all strategy groups.

Table 5.36 Scenario 1.5*PDC Post-ANOVA Results

Strategy-Policy	DB				CB			
	Dt. Duration	Group	Total Cost	Group	Dt. Duration	Group	Total Cost	Group
CM-ObsOpp	53.20	B	296,366	B	53.04	B	292,515	B
CM-Opp	52.36	B	291,177	B	53.60	B	294,809	B
CM-NoOpp	62.08	A	329,666	A	62.60	A	330,174	A
ThPM(0.95)-ObsOpp	64.16	B	317,072	B	64.14	B	314,554	B
ThPM(0.95)-Opp	65.04	B	318,749	B	66.38	B	325,192	B
ThPM(0.95)-NoOpp	72.06	A	352,142	A	71.84	A	349,231	A
ThPM(0.90)-ObsOpp	49.90	B	277,793	B	52.54	B	288,761	B
ThPM(0.90)-Opp	51.64	B	286,602	B	53.58	B	293,202	B
ThPM(0.90)-NoOpp	60.70	A	319,918	A	61.92	A	324,266	A

The effect of opportunistic maintenance policies on corrective maintenance is more significant than that of proactive maintenance. When examining ThPM strategies, ThPM(0.90) is a strategy closer to CM strategy because less proactive maintenance is done since it has a threshold parameter of 0.90. Therefore, the opportunistic maintenance effect can be observed better at ThPM(0.90) than at ThPM(0.95). In other words, proactive maintenance overshadows the impact of opportunistic maintenance. It can be concluded that opportunistic maintenance policies perform better in the 0.90 strategy. This is because proactive maintenance already has a cost advantage compared to corrective maintenance due to its low downtime cost and duration. Therefore, the extra advantage of applying opportunistic maintenance is not reflected very much in the results. When opportunistic maintenance is performed on proactive maintenance, the system is again subject to excessive maintenance because doing too much proactive maintenance, which also includes opportunistic ones, becomes unnecessary after a certain stage. For this reason, the effect of opportunistic maintenance in proactive is not the same as in corrective. Therefore, instead of worsening corrective maintenance conditions, worsening proactive maintenance conditions gives more positive results in terms of opportunistic maintenance.

It is observed that duration-based results are generally better than cost-based results. Regardless of the objective function, the duration results of opportunistic policies are better than their cost results. Overall, opportunistic policies give better outcomes in terms of duration. In duration-based maintenance, the method only looks at duration whereas in cost-based maintenance, both the duration and maintenance cost of the components are taken into account. When performing cost-based maintenance, the method looks locally, it can choose the component whose cost is advantageous at that moment, even though its duration is longer. When the method takes cost into account, it loses duration focus. As a result, when duration and cost-based maintenance are evaluated, it is more meaningful to prioritize duration-based maintenance.

5.5 SENSITIVITY ANALYSIS TO PROACTIVE THRESHOLD

To justify using opportunistic maintenance in the maintenance decision-making process, we compare the two strategies ObsOpp and Opp that we propose with NoOpp policy in which the opportunistic policy is not considered. We analyze them using the ThPM and CM strategies.

Within the scope of the base scenario, we obtain results with proactive thresholds of 0.90 and 0.95 (See: Section 5.1-5.2). In this section, results are also generated for 0.80, 0.85, and 0.97 proactive threshold values for ThPM strategies in the same scope to understand how the methodologies behave with different proactive threshold values. A comparison of strategies under the DB base scenario regarding downtime and total cost is given in Figure 5.5 and Figure 5.6, respectively, according to increasing thr values (0.80, 0.85, 0.90, 0.95, and 0.97).

According to Figure 5.5, CM-ObsOpp and CM-Opp are not significantly different in any thr values, and their downtime durations are statistically less than those of CM-NoOpp. In addition, ThPM-ObsOpp and ThPM-Opp are not significantly different in any thr values.

When moving from thr=0.80 to thr=0.90, it is observed that as the threshold value increases, the Dt. Duration value almost remains constant in the

ThPM-ObsOpp and ThPM-Opp strategies which are not significantly different from their CM counterparts, i.e., CM-ObsOpp and CM-Opp respectively. In addition, ThPM-NoOpp strategy gives the highest downtime at all thr values, while CM-Opp gives the lowest downtime at all thr values. In addition, there is no significant difference among all opportunistic policies except the case at thr=0.85 where ThPM-ObsOpp gives significantly greater Dt. Duration than CM-Opp.

When both thr=0.95 and thr 0.97 are examined, each ThPM strategy yields a higher duration than its corresponding CM counterparts. When examining ThPM strategies, it is seen that opportunistic policies are significantly more effective than the non-opportunistic policy, and there is no significant difference between them.

For the lower values of thr, ThPM strategies do not differ much from corrective strategies when applying any opportunistic policy. At 0.80, 0.85, and 0.90, opportunistic polices are significantly better than NoOpp spolicy. When thr value increases, a significant amount of proactive maintenance is applied i.e., at 0.95 and 0.97 thr values. When too much proactive maintenance occurs at a given strategy, opportunistic policies demonstrate minimal contribution. Therefore, proactive maintenance has no advantage over corrective maintenance for increasing thr values. At thr=0.95 and beyond, ThPM-ObsOpp and ThPM-Opp have greater dt duration than CM-NoOpp; however, they are still significantly better than ThPM-NoOpp. Thus, starting from thr=0.95, there is an improvement when applying opportunistic methods in ThPM strategies compared to not using them; however, they are worse than corrective maintenance. For reliability threshold values of 0.90 and lower, there is not much opportunity for proactive maintenance, causing ThPM strategy to turn to CM strategy. That’s why, comparisons are made in the base scenario for threshold values of 0.90 and 0.95 in ThPM, since it does not make much sense to try for lower values.

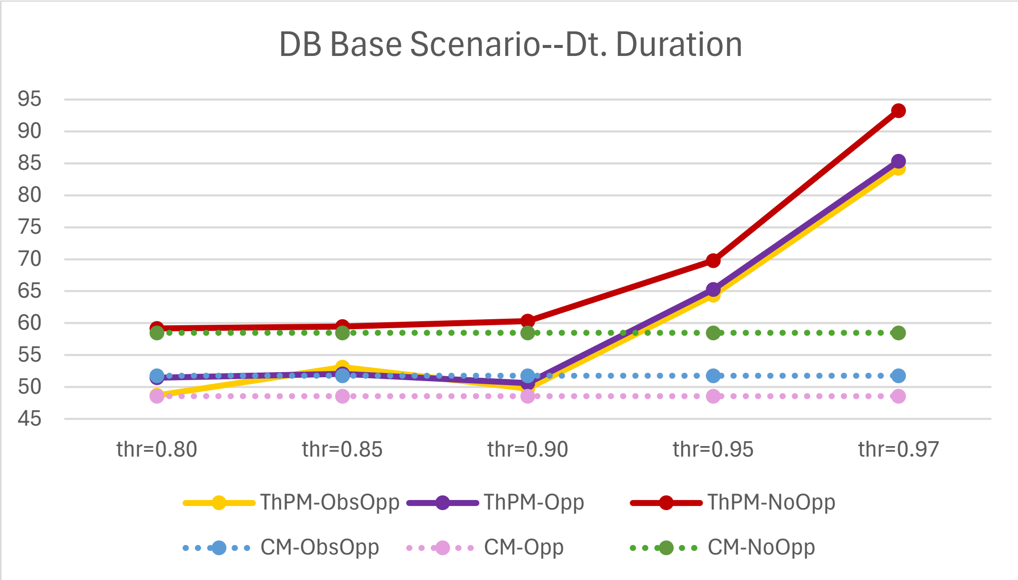

Figure 5.5 Comparison of Strategies under DB Base Scenario wrt Dt. Duration

In addition to sensitivity analysis within the scope of the Dt. Duration, we also conduct sensitivity analysis wrt cost of which results are given in Figure 5.6. CM-ObsOpp and CM-Opp are not significantly different in any thr values. In addition, ThPM-ObsOpp and ThPM-Opp are also not significantly different in any thr values.

When moving from thr = 0.80 to thr = 0.85, it is observed that the total cost increases in ThPM-ObsOpp and ThPM-Opp strategies which are not significantly different from their CM counterparts, i.e., CM-ObsOpp and CM-Opp respectively. However, the total cost decreases when switched to thr = 0.90 where the strategies behave as in thr = 0.80. In addition, ThPM-NoOpp strategy gives the highest total cost at thr=0.97. CM-Opp gives the lowest total cost at all thr values.

After thr=0.95, ThPM strategies show an increase in cost. Although using opportunistic maintenance still has an advantage over not using it at thr=0.97, ThPM strategies with opportunistic maintenance result in much higher costs than their CM counterpart strategies.

Both opportunistic policies and proactive strategies require excessive maintenance. Excessive maintenance becomes unnecessary for reliability threshold values greater than a certain value. More maintenance is done when the opportunistic and the proactive strategies (i.e, ThPM in this study) are used together. Because of this double effect, we observe the advantage of opportunistic proactive maintenance on cost over its corrective counterpart when the threshold value is smaller i.e., thr=0.90. We should emphasize that this is not a significant advantage as seen in the non-opportunistic case where the advantage of proactive maintenance on cost appears when the threshold value is a little larger i.e., thr=0.95. As a result, ThPM-ObsOpp and ThPM-Opp have the disadvantage of over-maintenance after thr = 0.90, while ThPM-NoOpp has it after thr=0.95. At thr=0.97, although opportunistic maintenance policies perform better than their non-opportunistic maintenance counterparts, they are worse than their CM counterparts.

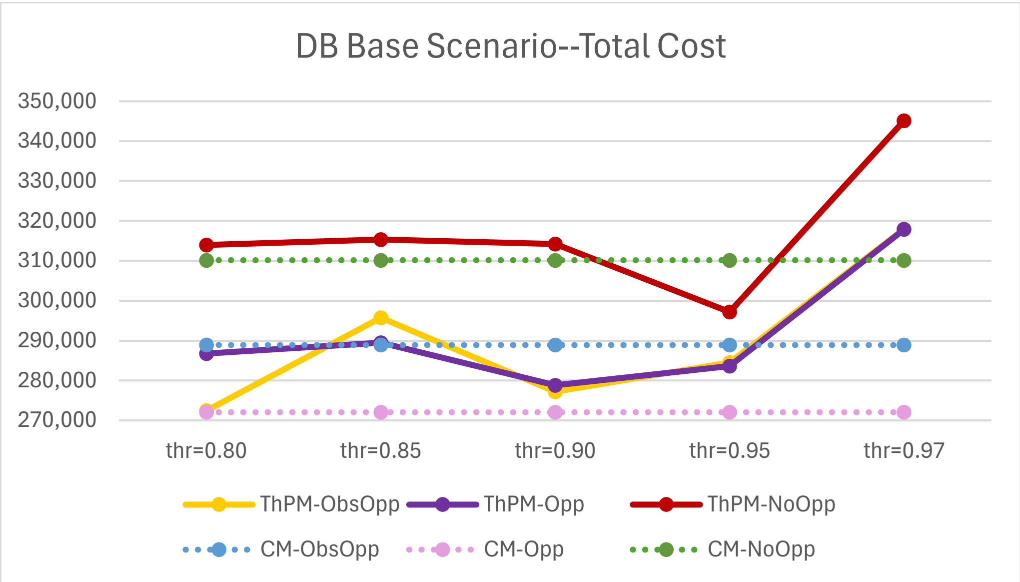

Figure 5.6 Comparison of Strategies under DB Base Scenario wrt Total Cost

Considering the cost of ThPM-NoOpp and CM-NoOpp, they are not significantly different at thr=0.95. However, they are significantly different when considering duration. It can be concluded that when the duration is considered, a more specific distinction can be made due to the much better performance of the proposed opportunistic policies.

CONCLUSION AND SUGGESTIONS

This study presents a maintenance approach for complex systems with partial observations and multiple components. It is very important to determine an effective maintenance strategy when a malfunction occurs in the system. On the other hand, dependencies between components can make the decision-making process difficult. Dynamic Bayesian Networks (DBNs) are effective and have an advantage in modeling complex relationships.

We consider the Axis System which has eleven components with stochastic dependencies within a CNC machine in a production facility. We identify cause-and-effect relations in the system using HAZOP analysis. Then, we use DBNs to model the components' aging and the system's causal relations, and to calculate the probabilistic inferences. We offer an opportunistic maintenance method under both corrective and proactive maintenance policies for this dynamic system. We propose two opportunistic maintenance policies (ObsOpp, Opp) with two objectives: minimizing total cost and downtime duration. By changing the component selection efficiency measure that we use to select the component at a maintenance time, we implement the proposed opportunistic maintenance policies under the given objectives. We compare the performance of the opportunistic policies with a non-opportunistic policy (NoOpp) under corrective and proactive maintenance strategies with the objectives of minimizing downtime duration and total cost separately. We observe that our studies based on downtime duration give better results than those based on cost. We also see that proposed opportunistic policies have less downtime duration and less total cost compared to the non-opportunistic one based on both objectives.

We also examine the results of opportunistic maintenance approaches on a component-detailed basis. From an opportunistic maintenance perspective, the duration of the component to be maintained should be equal to or shorter than the duration of the selected component, and the reliability of the component should fall below the opportunistic threshold. It is observed that components with long maintenance durations are not considered for opportunistic maintenance. Therefore, such components cannot benefit from this approach. In addition, since they also have very high maintenance costs because of their long maintenance durations they cannot also be evaluated for regular maintenance at a corrective or proactive maintenance time. Components with short maintenance durations have an advantage in the scope of opportunistic maintenance. However, among these, the ones whose reliability decreases slowly may not be considered within the scope of opportunistic maintenance if their reliability is high during the opportunistic maintenance, even if they meet the duration criteria.

To test the efficiency of the proposed opportunistic policies, three scenarios are designed by referencing the base scenario: increasing unit corrective downtime cost, then increasing both unit corrective downtime cost and corrective maintenance durations of components, and finally increasing unit proactive downtime cost. When the maintenance conditions in the corrective maintenance worsen, a significant advantage of opportunistic policies under the corrective maintenance is seen, but this effect is not always seen in proactive maintenance since too much maintenance is already done there. Consequently, the benefits of increased maintenance through opportunistic policies may not be sufficiently realized in proactive maintenance. As the unit downtime cost in proactive maintenance increases, the impact of opportunistic policies becomes more significant there.

We apply sensitivity analysis to the reliability threshold parameter in proactive maintenance concerning the downtime duration and total cost to understand how the policies behave with different threshold values. For the lower reliability threshold values, the proactive strategies do not differ much from their corrective counterpart strategies whether any opportunistic maintenance is applied. Regardless of the threshold value, opportunistic maintenance policies are better than NoOpp policy. However, as the threshold value increases, i.e.,0.90, when minimization of downtime duration is considered, even if opportunistic policies provide an improvement, proactive maintenance loses its advantage over the corrective one because of excessive maintenance. When minimization of total cost is considered, it is observed that, in the absence of opportunistic policies, the reliability threshold at which the total cost of proactive maintenance begins to increase compared to corrective maintenance is shifted to 0.95. This shows that achieving the objective of cost minimization is more difficult than achieving the objective of minimizing downtime duration. The underlying reason for this is thought to be the component selection methods used in this study. In duration-based maintenance, the method looks only at duration, whereas in cost-based maintenance, total maintenance cost, which is calculated by considering also the duration of the component, is considered. When performing cost-based maintenance, the method looks locally, it can choose the component whose cost is advantageous at that moment, even though its duration is longer. Hence, when the method takes cost into account, it loses duration focus.

As a future study, additional observations can be added to the existing system and further opportunistic policies can be developed using these observations. As obtaining more data may become increasingly difficult, research can focus on the dynamic updating of the DBN model using real-time monitoring data. This approach can enable maintenance strategies to be instantly implemented based on the system's status predicted via sensors such as temperature, vibration, pressure, humidity, etc.

Developing a hybrid model with machine learning algorithms to support the DBN model can increase the predictability of systems. For instance, integration of methods such as deep learning or reinforcement learning with DBN can be examined to improve breakdown predictions.

In addition to the above, the proposed opportunistic maintenance methodologies can be applied to different systems where a breakdown leads to high downtime costs. We discuss the CNC machines in this study, but many other systems can be handled in production facilities. For example, a production line system can be considered in a future study since when one of its key components is damaged, it can halt the entire production line causing serious profit losses. The opportunistic maintenance approaches can also be applied in other areas such as wind turbines and aviation.

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APPENDICES

APPENDIX A. HAZOP ANALYSIS

Element	Deviation	Possible Causes	Consequences	Safety Precautions
RB	Bearing vibration+*"MORE"*	1. There is friction, heat, and wear in bearing housings.	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform regular maintenance on the rotor bearings. 2. Check the lubrication of the rotor bearings.
	Load on bearing+*"MORE"*	1. There is wrong bearing selection and wrong alignment (assembling).	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. It shortens the operating life of the bearing and causes wear on the bearing. For this reason, the rotation of the rotor shaft is restricted or hindered.	1. Ensure that the correct bearing is selected for the rotor shaft. 2. Ensure proper alignment during the assembly process.
	Creepage+*"MORE"*	1. There is high heat generated due to rotation and an excessive number of revolutions.	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. As the bearing heats up, it becomes deformed and unable to function properly, restricts or hinders rotor shaft rotation.	1. Make sure that the bearing housing has high durability. 2. Avoid overloading and high-speed operation.
	Corrosion+*"MORE"*	1. There are worn or damaged seals. 2. Bearings have come into contact with water. 3. Bearings have been exposed to electric current. 4. There is a wrong grease oil selection.	1. It negatively affects the functions of the encoder, rotor shaft, and motor on the system. 2. The rotation of the rotor shaft is restricted or hindered.	1. Check seals regularly. 2. Avoid contact of the bearings with water. 3. Prevent electric current from passing through the bearings. 4. Make sure to choose the correct type of grease oil.
Enc	Speed value read incorrectly on the computer+*"OTHER THAN"*	1. There is friction and wear in encoder. 2. There is rotor bearing vibration. 3.There is operation at high speeds.	1. The speed value is misread and movement tracking cannot be done. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform regular maintenance on the encoder (Encoder must be replaced completely after 10,000 hours of operation).
	Intermittent signals+*"MORE"*	1. There is wear in encoder.	1. There are fluctuations and interruptions in the signal. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform the encoder's connection checks.
	Heating+*"MORE"*	1. There is dirt and dust accumulation on encoder surfaces. 2. Components inside the encoder are defective or damaged. 3. There is operation at high speeds.	1. Overheating of the encoder negatively affects signal accuracy and sensitivity. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform the maintenance of cooling fans on time. 2. Perform regular maintenance on the encoder.

Element	Deviation	Possible Causes	Consequences	Safety Precautions
RS	Voice+*"MORE"*	1. There is wear or imbalance in rotor bearings.	1. Impulses negatively affect the rotation movement of the rotor shaft.	1. Perform periodic maintenance of the rotor bearings.
	Vibration+*"MORE"*	1. There is wear or imbalance in rotor bearings.	1. Impulses negatively affect the rotation movement of the rotor shaft.	1. Perform periodic maintenance of the rotor bearings.
	Heating+*"MORE"*	1. There is friction, wear, or imbalance in rotor bearings.	1. It negatively affects rotational motion by increasing friction on the rotor shaft.	1. Perform the periodic maintenance of cooling fans and rotor bearings. 2. Check the lubrication of the rotor bearings.
Mot	Voltage difference+*"MORE"*	1. Mains voltage is lower than motor operating voltage.	1. It may cause the motor to draw excessive current, so the windings heat up and the motor insulation weakens. This increases the risk of motor burnout. 2. The rotation of the rotor shaft is restricted or hindered.	1. Consider the relationship between mains current and motor current when choosing a motor.
	Heating+*"MORE"*	1. There is wear or imbalance in rotor bearings. 2. Motor draws excessive current or operates in bad environmental conditions.	1. It constantly causes short circuits and increases the risk of motor burnout. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform periodic maintenance of the rotor bearings. 2. Keep the environment in which the motor operates at the desired level (The temperature should be appropriate and the environment should be dry and clean,etc.). 3. Make sure the motor cooling fan is intact and clean.
	Sudden voltage changes+*"MORE"*	1. The switching on and off of large load causes overvoltage.	1. It causes deterioration of motor insulation and damage to the motor. This increases the risk of motor burnout. 2. The rotation of the rotor shaft is restricted or hindered.	1. Check the mains current. 2. Regularly measure the voltage and frequency on the system and keep them within the desired ranges.
	Phase losses+*"MORE"*	1. The absence of one of the motor phases causes current draw.	1. Overheating occurs, leading to insulation breakdown and short circuits. This increases the risk of motor burnout. 2. The rotation of the rotor shaft is restricted or hindered.	1. Make good cable and terminal connections, and check regularly.
	Load on motor+*"MORE"*	1. There is wear or imbalance in rotor bearings. 2. There is a load higher than motor power is connected.	1. Overheating occurs, leading to insulation breakdown and short circuits. This increases the risk of motor burnout. 2. Motor cannot provide the required torque. 3. The rotation of the rotor shaft is restricted or hindered.	1. When choosing a motor, choose the one that suits the tolerances and system.
	Insulation resistance+*"LOW"*	1. There is physical damage or corrosion on the motor winding. 2. There is poor quality material selection.	1. It constantly causes short circuits and increases the risk of motor burnout. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform periodic maintenance of the motor. 2. Measure insulation resistances regularly.

Element	Deviation	Possible Causes	Consequences	Safety Precautions
Dri	Heating+*"MORE"*	1. There is wear in drivers.	1. Drivers burn out. 2. The rotation of the rotor shaft is restricted or hindered.	1. Clean air conditioners that cool drivers.
	Processing performance+*"LOW"*	1. There is wear in drivers.	1. It causes pauses during processing. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform periodic maintenance of drivers.
	Error warnings+*"MORE"*	1. There is wear in drivers.	1. The system stops every time it gives an error. 2. The rotation of the rotor shaft is restricted or hindered.	1. Perform periodic maintenance of drivers.
SOQ	Quality+*"LOW"*	1. There are particles in the slide oil. 2.There is wrong slide oil selection.	1. It causes friction on slide surfaces. 2. It makes axis movements difficult. 3. Noise and vibrations occur during processing. 4. It affects the surface quality of the workpieces. 5. It causes clogging of oil distributor elements. 6. It causes wear of the axis shaft bearings, axis shaft and nut, and slide surfaces.	1. Change slide oil periodically. 2. Make sure to choose the correct type of slide oil.
ODE	Clogging+*"MORE"*	1. There are sediments and residues. 2. The slide oil quality is poor.	1. It causes wear of the axis shaft bearings, axis shaft and nut, and slide surfaces.	1. Perform periodic maintenance of oil distributor elements. 2. Make sure to choose the correct type of slide oil.
	Lubrication level+*"LOW"*	1. There are sediments and residues. 2. The slide oil quality is poor.	1. It causes wear of the axis shaft bearings, axis shaft and nut, and slide surfaces.	1. Perform periodic maintenance of oil distributor elements. 2. Make sure to choose the correct type of slide oil.
ASB	Bearing vibration+*"MORE"*	1. There is friction, heat and damage to the bearing housings.	1. It negatively affects the functions of the coupling, axis shaft and nut on the system. 2. The rotation of the axis shaft is restricted or hindered.	1. Perform periodic maintenance of the axis shaft bearings. 2. Measure the axis movement and ensure that it goes to the desired extent. 3. Check the lubrication level.
	Load on bearing+*"MORE"*	1. There is wrong bearing selection and wrong alignment (assembling).	1. It negatively affects the functions of the coupling, axis shaft and nut on the system. 2. It shortens the operating life of the bearing and causes damage to the bearing. For this reason, the axis shaft rotation is negatively affected and the desired rotation is not achieved.	1.Ensure that the correct bearing is selected for the axis shaft. 2. Ensure proper alignment during the assembly process.
	Creepage+*"MORE"*	1. There is high heat generated due to rotation and an excessive number of revolutions.	1. It negatively affects the functions of the coupling, axis shaft and nut on the system. 2. As the bearing heats up, the bearing is deformed and cannot function. Therefore, the desired movement is not achieved.	1. Make sure that the bearing housing has high durability. 2. Avoid overloading and high-speed operation.
	Corrosion+*"MORE"*	1. There are worn or damaged seals. 2. Bearings have come into contact with water. 3. Bearings are exposed to electric current. 4. There is insufficient lubrication or poor quality slide oil/grease oil selection. 5. Oil distributor elements are clogged.	1. It negatively affects the functions of the coupling, axis shaft and nut on the system. 2. The rotation of the axis shaft is restricted or hindered.	1. Check seals regularly. 2. Avoid contact of the bearings with water. 3. Prevent electric current from passing through the bearings. 4. Make sure to choose the correct type of oil. 5. Maintain the lubrication system regularly.

Element	Deviation	Possible Causes	Consequences	Safety Precautions
Cou	Loosening+*"MORE"*	1. There is wear on the axis shaft bearings.	1. It negatively affects the energy transfer on the shafts and causes the rotation not to be as desired.	1. Perform periodic maintenance of the axis shaft bearings.
ASN	Voice+*"MORE"*	1. There is wear or imbalance in axis shaft bearings.	1. Impulses negatively affect the rotation movement of the axis shaft. 2. It prevents the axis movement from being accurate.	1. Perform periodic maintenance of the axis shaft bearings.
	Vibration+*"MORE"*	1. There is wear or imbalance in axis shaft bearings.	1. Impulses negatively affect the rotation movement of the axis shaft. 2. It prevents the axis movement from being accurate.	1. Perform periodic maintenance of the axis shaft bearings.
	Heating+*"MORE"*	1. There is friction, wear, or imbalance in rotor bearings. 2. There is insufficient lubrication or poor quality slide oil selection. 3. Oil distributor elements are clogged.	1. It negatively affects rotational motion by increasing friction on the axis shaft.	1. Perform the maintenance of cooling fans on time. 2. Maintain the lubrication system regularly.
SS	Corrosion+*"MORE"*	1. The slide plastic and metal surfaces of the slides are damaged. 2. Axis protection plate does not fulfill its function. 3. There is insufficient lubrication or poor quality slide oil selection. 4. Oil distributor elements are clogged.	1. Axis movement does not occur as desired.	1. Clean and maintain the slide surfaces at regular intervals. 2. Maintain the lubrication system regularly.
LS	Uncontrolled movement+*"MORE"*	1. There is friction, impulses, pollution, and high operating speed. 2. If the axis protection plate does not function, the slide oil will pass to the bottom and damage the limit switches.	1. Axis movement does not stop in a controlled manner. The parts that enable the axis movement stop by hitting the workbench or part. This will cause serious damage to the machine.	1. Manually check limit switches whether it is working or not to avoid possible major damage.

APPENDIX B. INITIAL PROBABILITIES

Initial Probabilities of Rotor Bearings

RB M.	Replace	Do Nothing
Good	1	1
Worn	0	0

Initial Probabilities of Encoder

RB	Good		Worn	
Enc M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0

Initial Probabilities of Rotor Shaft

RB	Good		Worn	
RS M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0

Initial Probabilities of Motor

RB	Good		Worn	
Mot M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Burn	0	0	0	0

Initial Probabilities of Drivers

Dri M.	Replace	Do Nothing
Good	1	1
Burn	0	0

Initial Probabilities of Slide Oil Quality

Good	0.9
Bad	0.1

Initial Probabilities of Oil Distributor Elements

SOQ	Good		Bad	
ODE M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Clogged	0	0	0	0

Initial Probabilities of Axis Shaft Bearings

ODE	Good			
SOQ	Good		Bad	
ASB M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0
ODE	Clogged			
SOQ	Good		Bad	
ASB M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0

Initial Probabilities of Coupling

ASB	Good		Worn	
Cou M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Loose	0	0	0	0

Initial Probabilities of Limit Switches

LS M.	Replace	Do Nothing
Good	1	1
Cracked	0	0

Initial Probabilities of Axis Shaft and Nut

ASB	Good			
ODE	Good			
SOQ	Good		Bad	
ASN M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0
ASB	Good			
ODE	Clogged			
SOQ	Good		Bad	
ASN M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0
ASB	Worn			
ODE	Good			
SOQ	Good		Bad	
ASN M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0
ASB	Worn			
ODE	Clogged			
SOQ	Good		Bad	
ASN M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0

Initial Probabilities of Slide Surfaces

ODE	Good			
SOQ	Good		Bad	
SS M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0
ODE	Clogged			
SOQ	Good		Bad	
SS M.	Replace	Do Nothing	Replace	Do Nothing
Good	1	1	1	1
Worn	0	0	0	0

APPENDIX C. TRANSITION PROBABILITIES

Transition Probabilities of Rotor Bearings

RB M.	Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn
Good	1	1	0.99933	0
Worn	0	0	0.00067	1

Transition Probabilities of Encoder

RB	Good				Worn			
Enc M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99967	0	1	1	0.99933	0
Worn	0	0	0.00033	1	0	0	0.00067	1

Transition Probabilities of Rotor Shaft

RB	Good				Worn			
RS M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99967	0	1	1	0.99933	0
Worn	0	0	0.00033	1	0	0	0.00067	1

Transition Probabilities of Motor

RB	Good				Worn			
Mot M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Burn	Good	Burn	Good	Burn	Good	Burn
Good	1	1	0.99978	0	1	1	0.99952	0
Burn	0	0	0.00022	1	0	0	0.00048	1

Transition Probabilities of Drivers

Dri M.	Replace		Do Nothing	
(Self) [t-1]	Good	Burn	Good	Burn
Good	1	1	0.99978	0
Burn	0	0	0.00022	1

Transition Probabilities of Oil Distributor Elements

SOQ	Good			
ODE M.	Replace		Do Nothing	
(Self) [t-1]	Good	Clogged	Good	Clogged
Good	1	1	0.99933	0
Clogged	0	0	0.00067	1
SOQ	Bad			
ODE M.	Replace		Do Nothing	
(Self) [t-1]	Good	Clogged	Good	Clogged
Good	1	1	0.99889	0
Clogged	0	0	0.00111	1

Transition Probabilities of Axis Shaft Bearings

ODE	Good							
SOQ	Good				Bad			
ASB M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99933	0	1	1	0.99917	0
Worn	0	0	0.00067	1	0	0	0.00083	1
ODE	Clogged							
SOQ	Good				Bad			
ASB M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99889	0	1	1	0.99833	0
Worn	0	0	0.00111	1	0	0	0.00167	1

Transition Probabilities of Coupling

ASB	Good				Worn			
Cou M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Loose	Good	Loose	Good	Loose	Good	Loose
Good	1	1	0.99967	0	1	1	0.99917	0
Loose	0	0	0.00033	1	0	0	0.00083	1

Transition Probabilities of Limit Switches

LS M.	Replace		Do Nothing	
(Self) [t-1]	Good	Cracked	Good	Cracked
Good	1	1	0.99933	0
Cracked	0	0	0.00067	1

Transition Probabilities of Axis Shaft and Nut

ASB	Good							
ODE	Good							
SOQ	Good				Bad			
ASN M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99958	0	1	1	0.99952	0
Worn	0	0	0.00042	1	0	0	0.00048	1
ASB	Good							
ODE	Clogged							
SOQ	Good				Bad			
ASN M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99933	0	1	1	0.99889	0
Worn	0	0	0.00067	1	0	0	0.00111	1
ASB	Worn							
ODE	Good							
SOQ	Good				Bad			
ASN M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99933	0	1	1	0.99889	0
Worn	0	0	0.00067	1	0	0	0.00111	1
ASB	Worn							
ODE	Clogged							
SOQ	Good				Bad			
ASN M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99833	0	1	1	0.99667	0
Worn	0	0	0.00167	1	0	0	0.00333	1

Transition Probabilities of Slide Surfaces

ODE	Good							
SOQ	Good				Bad			
SS M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99983	0	1	1	0.99978	0
Worn	0	0	0.00017	1	0	0	0.00022	1
ODE	Clogged							
SOQ	Good				Bad			
SS M.	Replace		Do Nothing		Replace		Do Nothing	
(Self) [t-1]	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Good	1	1	0.99972	0	1	1	0.99967	0
Worn	0	0	0.00028	1	0	0	0.00033	1

APPENDIX D. CONDITIONAL PROBABILITIES

Conditional Probabilities of Rotor Shaft Rotation

Dri	**Good**							
Mot	**Good**							
RS	**Good**				**Worn**			
Enc	**Good**		**Worn**		**Good**		**Worn**	
RB	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Rotate	1	0.6	0.75	0.45	0.5	0.3	0.4	0.2
Not Rotate	0	0.4	0.25	0.55	0.5	0.7	0.6	0.8
Dri	**Good**							
Mot	**Burn**							
RS	**Good**				**Worn**			
Enc	**Good**		**Worn**		**Good**		**Worn**	
RB	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Rotate	0	0	0	0	0	0	0	0
Not Rotate	1	1	1	1	1	1	1	1
Dri	**Burn**							
Mot	**Good**							
RS	**Good**				**Worn**			
Enc	**Good**		**Worn**		**Good**		**Worn**	
RB	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Rotate	0	0	0	0	0	0	0	0
Not Rotate	1	1	1	1	1	1	1	1
Dri	**Burn**							
Mot	**Burn**							
RS	**Good**				**Worn**			
Enc	**Good**		**Worn**		**Good**		**Worn**	
RB	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**	**Good**	**Worn**
Rotate	0	0	0	0	0	0	0	0
Not Rotate	1	1	1	1	1	1	1	1

Conditional Probabilities of Axis Shaft Rotation

ASN	Good			
Cou	Good			
ASB	Good		Worn	
RSR	Rotate	Not Rotate	Rotate	Not Rotate
Rotate	1	0	0.8	0
Not Rotate	0	1	0.2	1
ASN	Good			
Cou	Loose			
ASB	Good		Worn	
RSR	Rotate	Not Rotate	Rotate	Not Rotate
Rotate	0.75	0	0.45	0
Not Rotate	0.25	1	0.55	1
ASN	Worn			
Cou	Good			
ASB	Good		Worn	
RSR	Rotate	Not Rotate	Rotate	Not Rotate
Rotate	0.55	0	0.4	0
Not Rotate	0.45	1	0.6	1
ASN	Worn			
Cou	Loose			
ASB	Good		Worn	
RSR	Rotate	Not Rotate	Rotate	Not Rotate
Rotate	0.3	0	0.2	0
Not Rotate	0.7	1	0.8	1

Conditional Probabilities of Axis Movement

LS	Good							
ASR	Rotate				Not Rotate			
SS	Good		Worn		Good		Worn	
ASN	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Accurate	1	0.85	0.95	0.75	0	0	0	0
Inaccurate	0	0.15	0.05	0.25	0	0	0	0
No Movement	0	0	0	0	1	1	1	1
LS	Cracked							
ASR	Rotate				Not Rotate			
SS	Good		Worn		Good		Worn	
ASN	Good	Worn	Good	Worn	Good	Worn	Good	Worn
Accurate	0.95	0.8	0.9	0.7	0	0	0	0
Inaccurate	0.05	0.2	0.1	0.3	0	0	0	0
No Movement	0	0	0	0	1	1	1	1

Conditional Probabilities of Laser Measurement

AM	Accurate	Inaccurate	No Movement
Accurate	0.99	0.01	0
Inaccurate	0.01	0.99	0
No Movement	0	0	1

Conditional Probabilities of Rotor Shaft Vibration

RS	Good	Worn
No Vibration	0.99	0.01
Vibration	0.01	0.99

Conditional Probabilities of Axis Shaft Vibration

ASN	Good	Worn
No Vibration	0.99	0.01
Vibration	0.01	0.99

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