

**MAXIMIZING OVERALL EQUIPMENT
EFFECTIVENESS (OEE) USING MARKOV
DECISION PROCESS MODEL (MDP)**

BY

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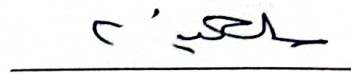
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I dedicate this thesis to my parents, teachers, and friends for their prayers, guidance, and unwavering support throughout this journey.

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THESIS ABSTRACT

NAME: RAFT MOHMMAD SAEED QAID ALREBATI

TITLE OF STUDY: MAXIMIZING OVERALL EQUIPMENT EFFECTIVENESS (OEE) USING MARKOV DECISION PROCESS MODEL (MDP)

MAJOR FIELD: INDUSTRIAL AND SYSTEMS ENGINEERING

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This thesis introduces a novel Markov Decision Process (MDP) model to optimize Overall Equipment Effectiveness (OEE) in production systems. A novel high-level decision-making framework for optimizing the OEE . The model can be used to schedule the daily production and maintenance tasks to maximize the OEE—a topic that is seldom addressed in the existing literature within dynamic settings. The approach involves maximizing the OEE by taking the optimal decisions for production and maintenance planning based on the availability and quality rate of the system using the MDP model. The MDP model was solved by the policy iteration algorithm to select the optimal policy that will maximizing the OEE. A case study of a food factory demonstrates

the approach's effectiveness. This research offers a unique contribution to the field by modeling Overall Equipment Effectiveness (OEE) using the MDP framework, with daily availability and quality as the system state. Unlike most studies in the literature that focus on measuring OEE, this research aims to facilitate optimal control of OEE, and with the increasing availability of sensory data in modern industries, this direction holds significant potential for practical application.

This thesis provides valuable insights for decision-makers in industry.

ملخص الرسالة

الاسم: رافت محمد سعيد قائد الرباطي

عنوان الدراسة: تعظيم الفعالية الشاملة للمعدات باستخدام نموذج ماركوف (MDP)

التخصص: قسم الهندسة الصناعية والنظم

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تقدم هذه الأطروحة نموذجاً جديداً لعملية اتخاذ القرار ماركوف (MDP) لتحسين فعالية المعدات الإجمالية (OEE) في أنظمة الإنتاج. وهو يمثل إطاراً جديداً لاتخاذ القرارات على مستوى عالٍ لتحسين فعالية المعدات الإجمالية في أنظمة الإنتاج. يمكن استخدام النموذج لجدولة مهام الإنتاج والصيانة اليومية لتعظيم فعالية المعدات الإجمالية - وهو موضوع نادراً ما يتم تناوله في الأدبيات الحالية ضمن الإعدادات الديناميكية. يتضمن النهج تعظيم فعالية المعدات الإجمالية من خلال اتخاذ القرارات المثلى لتخطيط الإنتاج والصيانة بناءً على معدل توفر وجودة النظام باستخدام نموذج عملية اتخاذ القرار ماركوف. تم حل نموذج عملية اتخاذ القرار ماركوف من خلال خوارزمية Policy Iteration Algorithm لاختيار السياسة المثلى التي ستزيد من فعالية المعدات الإجمالية. توضح دراسة حالة لمصنع أغذية فعالية النهج. يقدم هذا البحث مساهمة فريدة في هذا المجال من خلال نمذجة فعالية المعدات الإجمالية (OEE) باستخدام إطار عمل عملية اتخاذ القرار ماركوف، مع التوافر اليومي والجودة كحالة للنظام. على عكس معظم الدراسات في الأدبيات التي تركز على قياس OEE، يهدف هذا البحث إلى تسهيل التحكم الأمثل في OEE، ومع تزايد توافر البيانات في الصناعات الحديثة، فإن هذا الاتجاه يحمل إمكانات كبيرة للتطبيق العملي. تقدم هذه الأطروحة رؤية قيمة لصناع القرار في OEE.

CHAPTER 1

INTRODUCTION

1.1 Overall Equipment Effectiveness

In today's highly competitive industrial environments, optimizing overall equipment effectiveness (OEE) is critical for improving productivity and operational efficiency. It is a standard metric combining the performance, availability and quality rate to measure the equipment effectiveness Nakajima, (1988) . Overall equipment effectiveness (OEE) defined as a measure of total equipment performance. That is, the degree to which the equipment is doing what it is supposed to do according to Williamson et al.(2006). It shows the hidden capacity in the production process and lead to balanced production flow line. According to Bulent et al. (2000), OEE used to track and trace improvements or decline in equipment effectiveness over a period.

It is used to find points where operational improvement needs to be sought and ensures the best output is guaranteed for production. It is a three-dimensional analysis tool for equipment performance based on its availability, process rate, and the quality rate of the output. Availability refers to the proportion of actual production

time to the time the equipment has been scheduled to operate, which also counts the downtime created by breakdowns, maintenance, or changeovers. Performance indicate how much faster the equipment performs to the designed capacity in maximum utilization. It captures losses due to reduced speed or inefficiency. Quality refers to the percentage of products manufactured to specification that are required, discounting defective products or those that have to be reworked. These three are combined to give OEE; the score stands at 100 percentage in an ideal setting, meaning production was perfect—no downtime, best speed, and best product quality. It is widely regarded as a benchmark because an operational efficiency ratio above 85 percentage is considered world-class, meaning highly optimized production. The analysis of OEE therefore enables the manufacturers to find and eliminate inefficiencies systematically for ongoing improvements in production systems to get rid of wastes and enhance competitiveness.

1.2 Problem Statement

Maximizing overall equipment effectiveness in today’s highly competitive production environment is one of the major challenges that many organizations are trying to surmount in order to enhance their operation efficiency and reduce production costs. Appropriately, despite tremendous improvement in technology and automation, many manufacturers are unable to achieve optimum OEE as various problems relating to equipment downtime, suboptimal production speeds, and high defect rates remain persisting. These inefficiencies not only impact productivity but also increase waste

and operational costs, and decrease profitability. It is complex to find and eliminate the root causes impacting the three key components of OEE , availability, process rate, and quality, balancing the needs of production targets, maintenance schedules, and quality control. The problem, therefore, involves developing effective strategies and solutions that reliably enhance OEE by minimizing equipment downtimes, optimizing process rate and production line availability , and ensuring high product quality within dynamic constraints in industr.

1.3 Objectives

1. Conducting data analysis for the OEE components.
2. Proposing a novel sequential decision-making model to maximize the OEE.
3. Proposing a solution methodology for the model.
4. Demonstrating the applicability of the model through a real case study.

1.4 Contribution

In the first part of the thesis, Chapter 3, this research makes a contribution to the field of OEE by analyzing the correlation between the OEE component based on a case study and the second part of the chapter makes a contribute to availability prediction techniques by build mathematical models using autoregressive integrated moving average (ARIMA) .

In the second part of the thesis, Chapter 4, introduces a novel MDP-based with unique state and action spaces. offering a practical solution for optimizing OEE for the situation where detailed sensory data is missing. Second, it demonstrates the real-world applicability of the model through an industrial case study, showcasing significant improvements over the existing main intuitive approaches .Policy iteration algorithm used to solve the MDP model and get the optimal decisions.

The third part introduce a new model to maximizing the availability with budget constrain to develop strategies for optimizing maintenance that will enhance system availability and ensure financial sustainability in an industrially demanding environment. Linear programming technique used to solve the model , this part is the basis for new future researches .

1.5 Thesis organization

This thesis is structured into six chapters. Chapter 2 provides a comprehensive literature review and explores OEE and its component's and optimization. Chapter 3 analyze the OEE components and the case study data, study the correlations , build mathematical models for availability prediction using ARIMA ,discussion the results. Chapter 4 reviews the literature related to OEE optimization, presents a novel MDP model for OEE optimization, discusses the experimentation, results. Chapter 5 presents a novel MDP model for optimizing the availability with budget constrain , and discusses the experimentation, results. Chapter 6 summarizes the conclusions, discusses the findings, and outlines future research directions.

CHAPTER 2

LITERATURE REVIEW

2.1 Overall Equipment Effectiveness Definition

Overall equipment effectiveness (OEE) is defined as a measure of total equipment process rate. That is, the degree to which the equipment is doing what it is supposed to do according to Williamson et al. (2006). It is a three-dimensional analysis tool for equipment process rate based on its availability, process rate, and the quality rate of the output. OEE categorizes major losses or reasons for poor process rate and therefore provides the basis for setting improvement priorities. It can point to hidden capacity in a manufacturing process and lead to balanced flow. According to Bulent et al. (2000), OEE is used to track and trace improvements or decline in equipment effectiveness over a period.

2.2 Overall equipment effectiveness components

The three components of OEE are availability, process rate efficiency, and quality rate. These components assess different aspects of production losses and assist in identifying the underlying reasons for breakdown losses and speed losses. The three components will be discussing through this study.

2.2.1 Availability

Availability is one of the components of OEE and it is defined as the ability of a system to perform its required function in given conditions up to a given point in time or during a given time interval Lazzaroni et al . (2011). The availability term in maintainability engineering refers to quality of service of the system and it is calculated as percentage of actual working time to the total time according to Djenadic et .al (2019). Availability it is also concept used to characterize the process rate of a machine, component, or system with respect to its ability to fulfill its intended function (Zio et al . 2010). It is an overall indicator that includes partial indicators related to reliability, maintenance, and process rate. To increase the OEE, it is important to focus on improving availability by reducing downtime and increasing the amount of time that equipment is available for use. Several papers discuss the importance of availability in enhancing OEE. For example, Hung et al (2022). proposed a novel metric called value-added overall equipment effectiveness (VAOEE) that measures all identified losses, including those related to availability, reducing this loss will improve the availability and increase the OEE. Zineb et al . (2019) used stochastic Petri nets

to model maintenance and improve machine availability, leading to increased OEE. Wiranata et al . (2019) identified availability as one of the factors needed to prevent and overcome problems in a processing plant, ultimately improving efficiency and effectiveness also Chikwendu et al . (2020) emphasized the need to address availability in order to reduce downtime and improve OEE. In pharmaceutical companies Suryaprakash et al . (2021) presented a case study where implementing TPM and reducing tool changeover time increased availability and improved the OEE. To reduce breakdowns, failure rates, and increase the operating time different maintenance strategies such as total productive maintenance (TPM), condition-based maintenance (CBM), and others have been reported in the literature. Next, we summarize some of these studies

Availability maximization using condition-based maintenance

Condition-based maintenance (CBM) is a strategy that aims to maximize system availability by making maintenance decisions based on the condition of the system. CBM considers the availability and safety of the system as priorities in maintenance decision-making Fallahi et al . (2022) . It involves monitoring the condition of the system using real-time sensor data from condition monitoring (CM) systems Kumar et al . (2023) .By leveraging CM, machines operators can gain insights into evolving asset failure risks for machines , which can be used to optimize maintenance scheduling and improve availability Dziula et al . (2022).

Condition-based maintenance and production modeling can be used in maximizing the OEE of a system by optimizing decisions on maintenance with regard to the state

of components, the system can work at a good level Aldurgam et al. (2013). The semi-Markov method is an effective approach needed in the modeling of complex mechanical systems that deteriorate with age, thus applicable in assessing system availability. Li et al. (2021). Generally speaking, of late, multistate models have always been used when analyzing the availability of machines. This will often take into consideration inspections, and repairs, and degradation. Ghandali et al. (2018). From these two approaches, the maintenance policies can be determined in such a way as to maximize the system availability and profitability. Condition-based maintenance strategies enable proactive and resource-effective maintenance undertakings that contribute to high system availabilities.

Availability optimization using preventive maintenance

The optimization of availability with a preventive maintenance policy for repairable systems has been explored by a number of papers. Zhixia et al. (2013) developed a deterioration mathematical model and deduced the spectrum formula for calculation of the steady availability. Xu et al. (2008) considered both preventive and corrective maintenance and used strong continuous semi-group theory to calculate the steady state's availability of degrading equipment. In this direction, the optimal preventive maintenance strategy for a single-unit system was proposed by Samet et al. and further developed using the mathematical model approach in order to study the evolution of system availability. A complementary optimal age maintenance policy has been proposed by Udoh et al. in the case of repairable systems in order to reach an optimum between high availability and safety standards. Coster et al. (2015) presented

the determination of an optimum maintenance policy for a repairable system with a linearly increasing hazard rate and constant repair rate. These papers provide insights into optimizing availability through preventive maintenance strategies for repairable systems..

Availability maximization using total productive maintenance

Total productive maintenance (TPM) can increase system availability by improving the OEE and reducing downtime. TPM focuses on proactive maintenance strategies to prevent breakdowns and optimize equipment process rate. It involves calculating OEE and identifying the six big losses to prioritize maintenance efforts Guritno et al . (2021) . By implementing TPM pillars such as autonomous maintenance and planned maintenance, operators gain knowledge and skills to take responsibility for machine maintenance, leading to increased availability Nurprihatin et al . (2019). TPM also emphasizes preventive and predictive maintenance, reducing unexpected equipment failures and minimizing downtime (Kiran, 2022). Through TPM, organizations can eliminate breakdowns, optimize equipment effectiveness, and improve availability by addressing maintenance issues proactively Shetty et al . (2016).

Availability maximization under partial observations

Availability maximization under partial observations involves determining optimal control policies for maintenance applications in systems with unobservable operational states. One objective is to maximize the long-run expected average availability per unit time Jiang et al .(2013). This problem is often formulated as an optimal

stopping problem with partial information, where only the failure state is observable Jiang et al . (2012). This problem is addressed by utilizing the partially observable Markov decision process (POMDP), which can take into account both cost and availability when determining the most optimal inspection and maintenance strategies. Lefèvre et al. (2001).

Maximization of system availability with failure dependency

Maximizing system availability in the presence of failure dependency is a challenging problem in the design of complex systems. The inclusion of redundant components and maintenance teams can enhance availability but also increase system cost Habib et al . (2016) . The optimization of repair rates and component failure rates can maximize steady-state availability while considering constraints on repair and failure rates Joshi et al . (1989). Failure dependency and limited repair teams can affect the state distribution and availability of a series-parallel system Hu et al . (2012). Failure prediction and proactive actions can impact steady-state availability, and optimizing failure prediction involves selecting the appropriate precision and recall trade-off Kaitovic et al . (2016). The design of redundant systems with failure dependency is important for system reliability and availability optimization, and the classification of redundant dependencies can aid in system design optimization Haiyang et al . (2007).

2.2.2 Process rate

Production process rate refers to analyzing and measuring the efficiency and effectiveness of a production system Nouri et al . (2017). It plays a vital role in supporting

decision-making processes for managers and engineers who are involved in optimizing the system Grace et al . (2016). Key process rate indicators (KPIs) are commonly employed to measure production process rate in industries that use batch processing Emerson et al . (2004) and can encompass measurements of overall process rate, meeting targets or specifications, and making comparisons with similar batches Kurmar et al . (2007). process rate evaluation is widely utilized to ensure organizational success in the complex business environment of today. Optimizing production process rate involves improving the productivity and efficiency of production systems to maximize output and minimize costs. Various methods and strategies are used to achieve this goal. One approach is to evaluate and improve the process rate of closed-loop production lines, considering factors such as the quality dependent on the level of degradation and the procedures for rework Zhou et al . (2023). Another approach is to integrate advanced digital platforms with predictive analytical models to optimize production planning and cost Alsaeed et al . (2022). . Additionally, analysis and optimization of specific equipment, such as electric submersible pumps, can be performed using mathematical calculations and nodal variable speed drive analysis .according to Biantoro et el .(2022) . The implementation of Industry 4.0 technologies, such as robotics and lean manufacturing, can also contribute to optimizing production system process rate Dossou et al . (2022). Production rates have an impact on machine availability. The degradation of a manufacturing system, caused by its production rate and availability, can lead to unavailability due to maintenance actions Ayed et al . (2017). In intermittent production situations, the completion of a production run can result in the unavailability of the facility for a random amount of time, affecting stock-out

situations Jaber et al .(2001). The availability of working machines and equipment is crucial for operational efficiency in the production process kolinki et al . (2017). Optimal production control and maintenance planning can improve the availability of a manufacturing system and minimize surplus and repair costs Kenne et al .(2003). The volume of production and the effectiveness of the system are influenced by factors such as production rates, renewal capacity, and the number of redundant units Nanasi et al . (2013). To improve production rates and increase availability, several approaches can be taken. One method is to analyze the reliability and failure metrics of the manufacturing system using a Markov approach, as demonstrated by Yaghoubi et al .(2021). Identifying critical components and increasing repair rates can also enhance the availability of the production line according to .Noji et al .(2000). Continuous monitoring of process states, such as equipment parameters, can indirectly detect changes in production characteristics and prevent problems in production processes Lin et al. (2022).

2.2.3 Quality Rate

Production quality rate refers to the level of quality maintained during the production process. It is an important factor in operations management as it directly impacts customer judgment and satisfaction Grosset et al (2020). In the context of production models, the optimal choices of production rate and quality level can be treated as an optimal control problem Sarkar et al . (2018). The relationship between production rate and quality level can vary depending on the specific model. In some cases, the optimal production rate and quality level are independent of each other Chiu et al .

(2014). However, in other cases, they are interdependent, and the optimal production and quality levels are determined in a more complex manner Jauhari et al. (2017). The goal is to find the optimal balance between production rate and quality level to minimize costs and maximize customer satisfaction Nandra et al .(2021) .

2.2.4 Optimization production process rate and quality rate

Optimizing production rate and quality is a relevant issue in operations management. In a short-term production model, the optimal choices of production rate and quality level can be treated as an optimal control problem with a parameter according to Grosset et al .(2023) . AlDurgam Shokri Selim. (2019) discusses a model that determines the economic production quantity and the rate of production, taking into account variable machining rates and product quality. Hit rate, which represents the percentage of products accepted within a controlled range of quality, is a key process rate metric in predicting process product quality. Optimizing hit rate is a non-convex problem, but a data-driven quasi-convex approach combining factorial hidden Markov models, multitask elastic net, and quasi-convex optimization can convert it into a set of convex feasible problems, achieving an optimal hit rate Yang et al .(2023). Tolerance allocation models traditionally focus on minimizing cost and tend to ignore waste. A proposed tolerance allocation model considers both tolerance selection in product design and production rate selection in operation planning, aiming to minimize cost and waste Doti et al .(2023).

2.2.5 Optimization Availability and Quality rate

The relationship between production system availability and quality rate has been explored in several studies . One study by Farahani and Tohidiet al . (2021) provides a comprehensive review of papers that optimize decisions for maintenance, quality, and production. Baltag and Morariu (2022) focuses on the use of risk management and maintenance activities as facilitators for quality improvement. Boumallessa et al. (2019) highlight the interdependence of production scheduling, quality management, and maintenance planning, and the need for integrated models to improve efficiency . Dutoit et al . (2019) propose on techniques to optimize maintenance and quality control, with a focus on measuring quality indicators . Overall, these studies provide insights into the integration of maintenance, quality, and production for improving the quality rate in production systems. It is difficult to achieve the minimum unavailability in the production system along with maximum quality rate simultaneously. This may be achieved by developing an integrated model of maintenance policies with the improvement of product quality and availability. Shi et al. (2023) present a joint model of OM and improvement of product quality and availability in an MMPS. The other ways are through TDSA analysis and optimization methodologies. Aggarwal et al. 2017 discusses the methodology on TDSA analysis of a butter oil production system and optimizes its process rate through genetic algorithms. Another method to improve availability is through RMS. Junliang et al., (2020) uses a simulation-based multi-objective optimization approach to find optimal task allocation and assignment to workstations considering different availability scenarios. Ansari et al . (2021) intro-

duce an AI-enhanced methodology for digital shift books in the automotive industry, leading to an increase in the OEE .

2.3 Overall Equipment Effectiveness Modeling and Optimization

When a manufacturing facility deploys an OEE tracking system effectively, the facility can get a better handle on production and process rate metrics. These metrics can help managers make faster and more informed decisions about optimizing manufacturing processes. Managers can track downtime, production levels, and waste, and can determine causes or effects of system events in real time, allowing them to respond faster, and in turn improve OEE. process rate can be compared shift by shift and hour by hour, or product to product. While most of the OEE-related studies in the literature focused on measuring the OEE rather than maximizing it according to Carmen et al. (2020) , Prakash et al.(2019), few studies developed quantitative models and optimization techniques to maximize the OEE. Aldurgam and Duffuaa (2013) modeled a single-stage with multi-state system as a partly observable markov decision process in order to optimize the OEE by taking into consideration the condition of the production system . Vivek Prabhu et al. (2014) Optimized OEE using genetic algorithms, enhancing utilization of plant resources. Tobe et al. (2018) Integrated OEE measurement with lean manufacturing concepts to enhance production system process rate in a fertilizer company. Carmen et al. (2020), Prakash et al. (2019) reviewed literature focused mainly on measuring OEE. Prasetyo Veroya (2020) utilized OEE to identify

and minimize bottlenecks in semiconductor manufacturing through integration with Lean Six Sigma DMAIC. Sukma et al. (2022) carried out total productive maintenance in order to enhance the overall equipment effectiveness of the linear accelerator synergy platform, a medical device used in cancer treatment, Sukma concluded that TPM plays an important role in the optimization of medical devices for dependability of operation and sustainability of treatment continuously. Thiede et al. (2023) used energy data as a predictor for OEE, by state-based and machine learning methods, they propose a cost-effective method of process rate optimization. Ullah et al. (2023) work on detailed analysis of OEE's components and best practices for implementation to optimize operational efficiency.

Hernandez-Vázquez et al. (2024) build meta model using experiments (DOE) and simulations to optimize the OEE in the buffer allocation problem, instances showed that buffered strategic locations enhance OEE while sciatic buffers degrade process rate. Joyeshree Biswas, (2024), throws light on implementing total productive maintenance to enhance overall equipment effectiveness. More focus has been placed on how TPM practices impact on the process rate of the equipment regarding availability and quality. Main focus was placed on the measurement methods of OEE. Biswas depicts the need for continuous monitoring with structured maintenance strategies as a way of ensuring maximum operational productivity.

Based on our extensive literature review, which shows the importance of OEE and its components. However, modelling and optimizing of the OEE have been less addressed. Most of the studies and models that used to optimize the OEE failed to handle all OEE components. It's often optimizing availability, process rate, or

quality in isolation without considering all components together, which this thesis address it in the proposed MDP model , which allows for better decision-making under uncertainty. This research introduces a novel approach to optimizing Overall Equipment Effectiveness (OEE) in production lines through the innovative application of the Markov Decision Process (MDP) framework. Unlike traditional models, this study develops an MDP model that concurrently optimizes all key components of OEE—availability, process rate, and quality. By addressing a significant research gap, it bridges the divide between theoretical MDP models and their application in dynamic, real-world production environments.

The inclusion of a real case study further enhances this contribution, providing empirical insights that validate the model’s practical impact. This work not only establishes a systematic approach to optimal decision-making in production systems but also highlights the influence of varying maintenance strategies and production levels on OEE. As a decision-support tool, it offers a pathway to increased operational efficiency in production processes, contributing meaningfully to the literature on OEE optimization through the practical application of MDP.

CHAPTER 3

OEE DATA ANALYSIS

3.1 Introduction

The food company under study is considered one of the largest leading companies in the production of foods in Yemen and the Middle east .It has many accredited international quality certificates. Based on the privacy of the data obtained for the study, the name of the company will not be mentioned; instead, "the food factory" will be used to indicate the company. The production line is represented in Fig(3.1). The production line data was recorded on a daily basis and includes detailed records of system uptime, idle time, downtime, and overall availability, good products, scrap, production quantity, and overall equipment effectiveness.

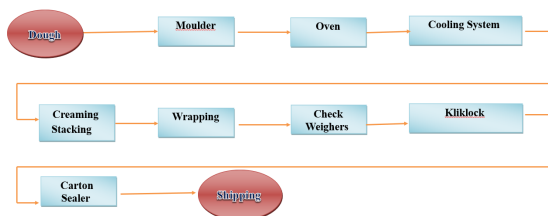


Figure 3.1: Food production line processes

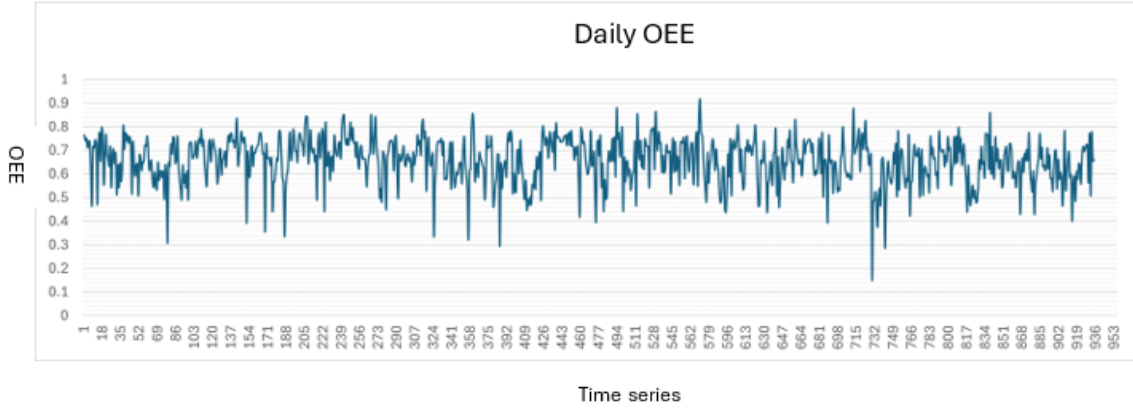


Figure 3.2: OEE time series

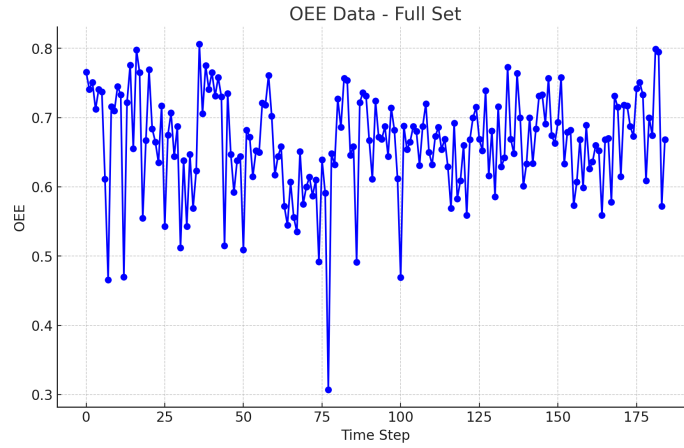


Figure 3.3: OEE time series

3.2 Data Collection

This study utilizes data from a food factory over the course of three years of operation. System parameters are reflected in the data as daily instances . Data cleaning and preprocessing were performed to ensure uniformity and correctness, addressing missing values and outliers as necessary. The following graphs show the time series and the histograms for OEE .The line chart for OEE daily values in the three years data represented in figures Fig (3.2) and fig(3.3) .The OEE histogram showed in Fig 3.4

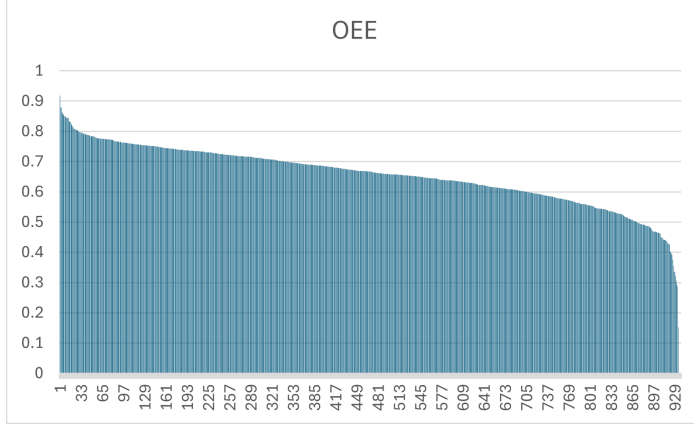


Figure 3.4: OEE Histogram

3.3 Corelation Analysis

The correlation matrix provides the analysis of the association of key operational variables at availability (t), quality (t), and process rate to OEE ($t+1$). of the variables considered, availability (t) is the one that has the highest positive association with OEE($t+1$), with a correlation coefficient of 0.497; hence, the equipment uptime occurring in the current period may be a main determinant of the overall effectiveness of the equipment in the subsequent period. In manufacturing and industrial processes, availability refers to that fraction of time where equipment is available and operational when needed. The strength of this relation then makes it imperative to minimize downtime and ensure continuity of machinery operation without interruptions to maintain or improve the OEE levels in the next period.

Quality (t) and process rate are less strongly related to OEE ($t+1$), equaling 0.124 and -0.160, respectively. Quality (t) shows, rather weakly, a positive relationship, indicating that producing outputs within the circle of quality standards is important, but compared to availability, immediate OEE in the next period is rather limited. This

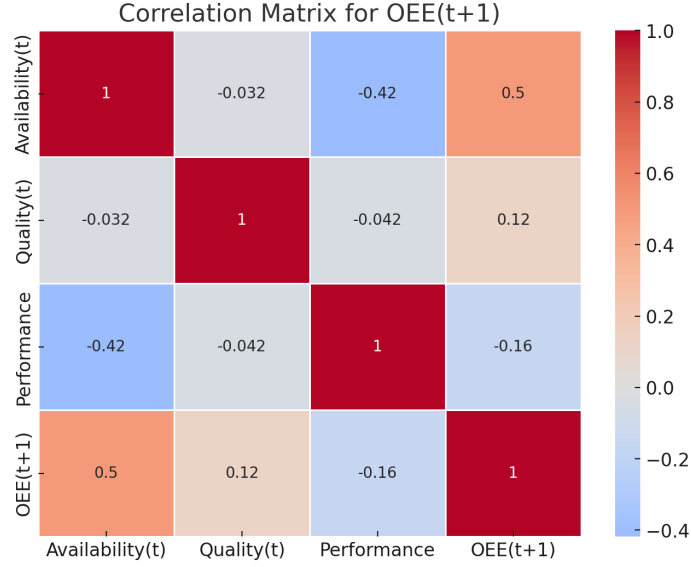


Figure 3.5: Correlation matrix

is so because high-quality outputs can be offset by equipment downtime or process rate losses for the potential gains in OEE. The correlation of the process rate metric is -0.160, indicating that poor-speed or low-capacity equipment operation reduces OEE. The strength of the relationship to OEE is not quite as pronounced as that which is found with availability, and this might be because process rate too, tends to have much other dependence, such as on the operational load or external constraints. These results point out that strategies oriented toward maximizing plant availability, such as routine maintenance and quick reactions in case of any downtime event, are preferred by industrial managers in order to achieve improvement in OEE. This could yield the most significant long-term benefit regarding optimization of uptime, operational efficiency, and productivity.

3.4 Availability analysis

Availability is one of the components of OEE and is defined as the ability of a system to perform its required function in given conditions up to a given point in time or during a given time interval Lazzaroni et al.(2011).The correlation between the OEE and the availability of systems is more than the other OEE component, so we will focus more in our study on it and make more analysis ,to do that the production line data was recorded on a daily basis and includes detailed records of system a, idle time, downtime, and overall availability ,quality and process rate .

- System Uptime (hours per day): The total time during which the production line was operational.
- System Idle Time (hours per day): The total time during which the production line was not in use but available for operation.
- System Downtime (hours per day): The total time during which the production line was not operational due to maintenance or failures.
- Overall Availability : The percentage of total time the production line was operational out of the total available time in a day.

Asample of the production line data presented in the table (3.1) .

The analysis include correlation analysis for the availability at time (t) and it is values previous period . The technique used to do that called ARIMA .The model build to study the correlation and used to predict the availability .

Table 3.1: Production Data

Day	Production	PT	Up Time	DT	Idle Time	Availability
1	2714	12	8.5	3.5	12	0.35
2	5236	24	19	5	0	0.79
3	5847	24	21	3	0	0.88
4	7105	24	22	2	0	0.92
5	6985	24	21.5	2.5	0	0.90
6	5591	24	21	3	0	0.88
7	3095	12	10.5	1.5	12	0.44

3.4.1 ARIMA Model Development

To build an ARIMA model using this data, the following steps will be taken:

3.4.2 Check for stationarity of the time series

The Augmented Dickey-Fuller test indicates that the time series is stationary, as the p-value is less than 0.05. Therefore, differencing ($d = 0$) is not needed to make the series stationary. The ADF test is used to check the stationarity of a time series. The test equation is:

$$\Delta A_t = \alpha + \beta t + \gamma A_{t-1} + \delta_1 \Delta A_{t-1} + \dots + \delta_p \Delta A_{t-p} + \epsilon_t \quad (3.1)$$

Where:

- ΔA_t is the first difference of the series
- α is a constant
- βt is the coefficient on a time trend
- γ is the coefficient used to test for a unit root

- $\delta_1, \delta_2, \dots, \delta_p$ are the coefficients of the lagged difference terms
- ϵ_t is white noise

The tested data showed that it was stationary. Next, the parameters p and q for the ARIMA model will be identified.

3.4.3 Model Identification

- **Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plots:** These plots are examined to determine the potential values of the autoregressive order (p) and the moving average order (q).
- **Selection of p , d , and q :** Based on the ACF and PACF plots, the values of p and q are selected, and the value of d is taken from the differencing step.

The data was divided into 10 lags, and ACF and PACF were calculated for each lag. The Minitab program was used to calculate the ACF and PACF. The table (3.2) and the fig(3.6) show the ACF for availability and table (3.3) and fig (3.7) show the PACF .

The fig(3.6) illustrates the autocorrelation function (ACF) for the availability time series, accompanied by the 5-percent significance limits for the autocorrelations. The initial lags, specifically up to lag 2, demonstrate significant autocorrelation values exceeding the 5-percent significance limits, indicating a robust correlation with their preceding values. These significant autocorrelation values progressively diminish, with most of the subsequent lags residing within the significance limits. The notable positive spikes at lags 1 and 2 suggest a positive correlation with recent past values,

Table 3.2: Autocorrelation Function (ACF)

Lag	ACF	T
1	0.417891	12.77
2	0.265379	6.98
3	0.188313	4.71
4	0.147081	3.60
5	0.101967	2.46
6	0.081058	1.94
7	0.084073	2.01
8	0.049396	1.17
9	0.042653	1.01
10	0.063005	1.49

whereas the weaker autocorrelations beyond lag 2 indicate minimal correlation with further lags. This pattern suggests that an autoregressive (AR) component should be incorporated into the ARIMA model, likely with a lower order around 1 or 2. Given the attenuation in autocorrelation values, a higher-order AR model or a moving average (MA) component may not be essential for capturing the dependencies in the data. Consequently, an ARIMA model with parameters p approximately 1 or 2, $d = 0$, potentially a low or zero q could serve as an appropriate initial model for this time series. Subsequent refinement and validation will be necessary to determine the optimal parameters.

The fig(3.7) and table (3.4) illustrates the Partial Autocorrelation Function (PACF) for the availability time series, including the 5-percent significance limits for the partial autocorrelations. The PACF indicates a significant partial autocorrelation value at the first lag, suggesting a strong direct correlation with its immediate past value. Subsequent lags do not exhibit significant partial autocorrelations, as their values fall within the significance limits, indicating minimal direct correlation with

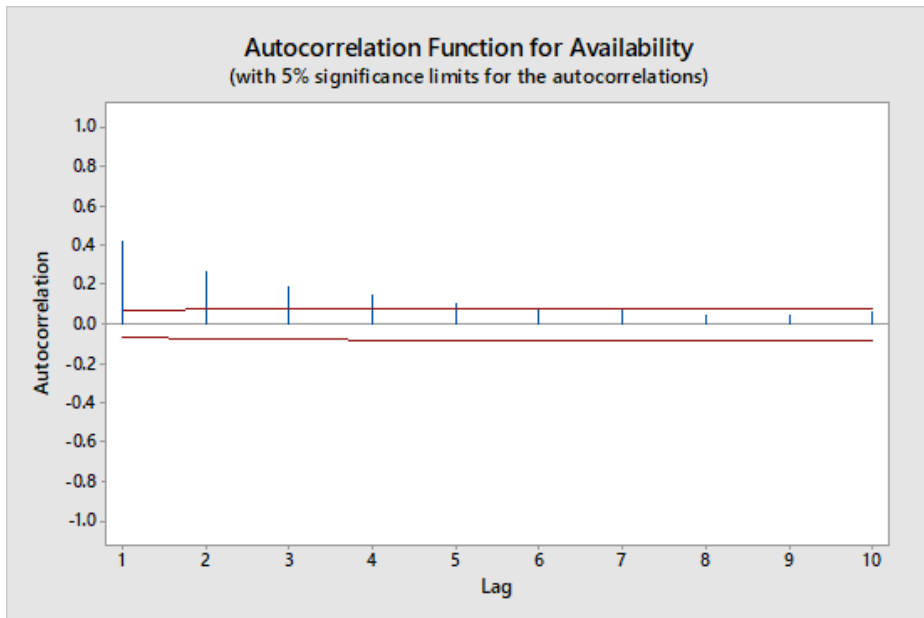


Figure 3.6: Autocorrelation for Availability.

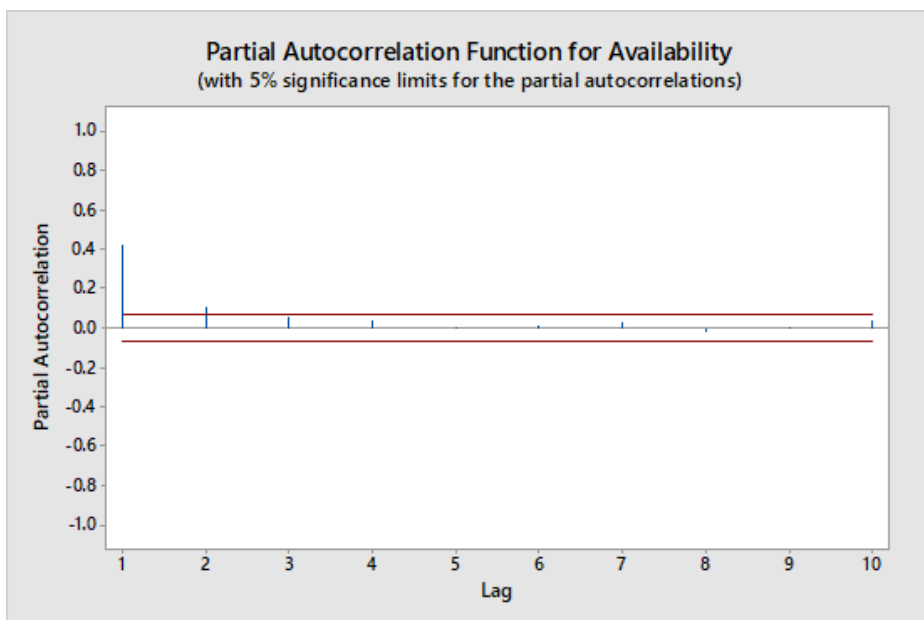


Figure 3.7: Partial Autocorrelation for Availability.

Table 3.3: Partial Autocorrelation Function (PACF)

Lag	PACF	T
1	0.417891	12.77
2	0.109947	3.36
3	0.053545	1.64
4	0.039209	1.20
5	0.006603	0.20
6	0.014152	0.43
7	0.033584	1.03
8	-0.013773	-0.42
9	0.007423	0.23
10	0.038471	1.18

further past values once the effect of intervening lags is considered. This observation implies that an autoregressive (AR) term of order 1 ($p = 1$) is appropriate for capturing the dependency structure in the data, and higher-order AR terms are unnecessary. Given the established stationarity ($d = 0$) and the PACF insights, an ARIMA model with parameters $p = 1$, $d = 0$, and a potentially low or zero q could serve as an initial model. Further refinement and validation will be required to determine the optimal parameters.

3.4.4 Parameter Estimation

Autocorrelation analysis for the availability The autocorrelation for data and the Partial shown in Figs(3.6,3.7) and the detailed value shown in Tables (3.2,3.3) which 10 lag used in the analysis. It is clear that from Fig(3.6) the exponential decay of ACF and sharp drop of PACF at lag 1, both suggest the significance of the autoreactive part without the need for the moving average and the AIC will used to prove that choose the best ARIMA model using the Akaike Information Criterion (AIC), we can

fit multiple ARIMA models with different orders of autoregressive (p), differencing (d), and moving average (q) terms, and then select the model with the lowest AIC value. The AIC is a measure of the relative quality of statistical models for a given set of data. It balances the model's fit with its complexity, rewarding models that fit well but penalizing those with too many parameters. Programming code using python language is used to evaluate the different ARIMA model that can be constructed , calculate the AIC , choose the best model, and calculate the model parameter in equation (3.3) . The table (3.4) show the different model of ARIMA. The P parameter it select from the ACF graph in fig (3.6) and the d parameter from PACF graph in fig(3.7) it is the number of lags that pass the significant level 0.05 , The dicky filler test is used to test if the data is stationary or not .Based on the d value selected , The data is stationary so d equal zero .The different models build by changing the values of the parameters p, q until achieve the lowest AIC .The best model was selected which have the lowest AIC value .

3.4.5 ARIMA Model Selection

Performing stepwise search to minimize AIC yielded the following results in table (3.4).

After evaluating different models, it found that the ARIMA(1,0,1) model had the lowest AIC value of -1733.6 among the models we considered, So this model used as the optimal ARIMA model for the production system.

Table 3.4: Different ARIMA Models with AIC

ARIMA	AIC
ARIMA(1,0,2)(0,0,0)[0]	-1683.056
ARIMA(0,0,0)(0,0,0)[0]	2293.030
ARIMA(1,0,0)(0,0,0)[0]	inf
ARIMA(0,0,1)(0,0,0)[0]	1220.195
ARIMA(0,0,2)(0,0,0)[0]	502.128
ARIMA(1,0,1)(0,0,0)[0]	-1644.206
ARIMA(2,0,2)(0,0,0)[0]	-1705.605
ARIMA(2,0,1)(0,0,0)[0]	-1708.331
ARIMA(2,0,0)(0,0,0)[0]	inf
ARIMA(3,0,1)(0,0,0)[0]	inf
ARIMA(3,0,0)(0,0,0)[0]	inf
ARIMA(3,0,2)(0,0,0)[0]	inf
ARIMA(2,0,1)(0,0,0)[0] intercept	-1732.974
ARIMA(1,0,1)(0,0,0)[0] intercept	-1733.602
ARIMA(0,0,1)(0,0,0)[0] intercept	-1676.649
ARIMA(1,0,0)(0,0,0)[0] intercept	-1721.047
ARIMA(1,0,2)(0,0,0)[0] intercept	-1732.791
ARIMA(0,0,0)(0,0,0)[0] intercept	-1543.902
ARIMA(0,0,2)(0,0,0)[0] intercept	-1709.005
ARIMA(2,0,0)(0,0,0)[0] intercept	-1730.544
ARIMA(2,0,2)(0,0,0)[0] intercept	-1730.299

3.4.6 Mathematical Model

The mathematical model for an ARIMA(1,0,1)(0,0,0)[0] with intercept can be expressed as in Equations (3.2) and (3.3):

$$A_t = \mu + \phi_1 A_{t-1} + \epsilon_t + \theta_1 \epsilon_{t-1} \quad (3.2)$$

Where:

A_t : Availability at time t

A_{t-1} : Availability at time $t-1$

μ : Intercept (constant term)

ϕ_1 : Coefficient for the autoregressive term A_{t-1}

ϵ_t : Error term at time t

θ_1 : Coefficient for the moving average term ϵ_{t-1}

The coefficient and parameters of equation(3.2) founded using python code and the model developed to be in the following expression.

$$A_t = 0.26 + 0.672y_{t-1} + \epsilon_t - 0.031\epsilon_{t-1} \quad (3.3)$$

3.4.7 Model Evaluation

Fit the ARIMA model and evaluate its process rate. The figures (3.8, 3.9) show model process rate. The graphs show the process rate of a time series forecasting model, presumably ARIMA(1,0,1), in predicting system availability.

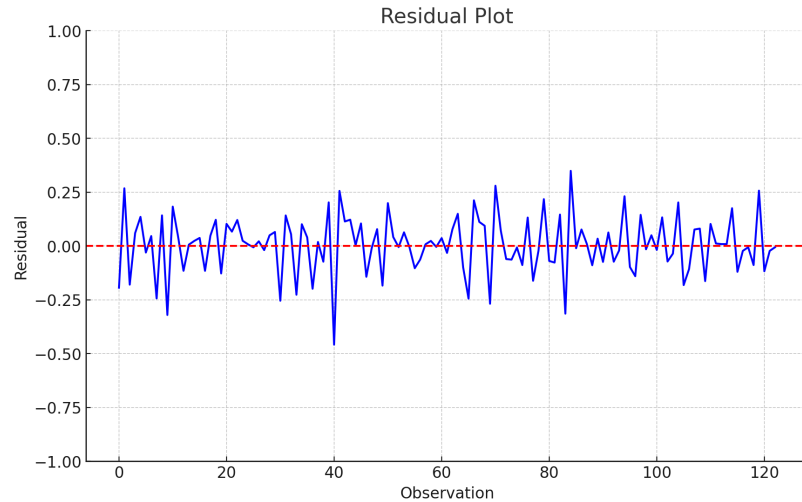


Figure 3.8: The Residuals of ARIMA

3.4.8 Actual vs Predicted Availability

This graph compares the actual availability data with the predicted availability data (in dashed black) over time. The predicted values seem to follow the general trend of the actual data quite closely, indicating that the model is capturing the underlying pattern in the availability data.

However, there are noticeable discrepancies where the predicted values deviate from the actual ones, particularly at points where the actual data has sharp peaks or troughs. This could suggest that while the model is good at capturing the overall trend, it may struggle with sudden changes or anomalies in the data.

3.4.9 Residuals of the ARIMA Model

The residuals represent the differences between the actual and predicted values, which are shown in Figure 5. Ideally, you would want the residuals to be randomly scattered around the zero line, which would indicate that the model has captured all the patterns

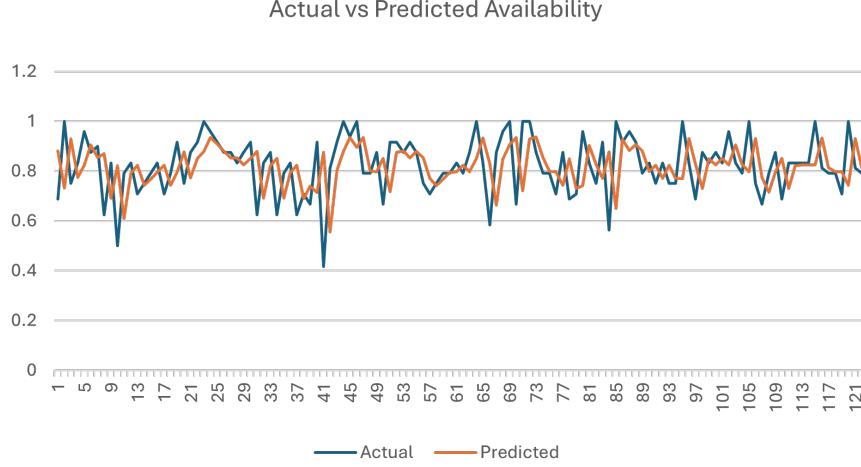


Figure 3.9: The Actual vs Predicted Availability of ARIMA

in the data. In this graph, while the residuals are centered around zero, which is good, there is significant fluctuation and some patterns appear to be present, which suggests that the model is not capturing all aspects of the data. The spikes (large residuals) indicate points in time where the model predictions were significantly different from the actual values.

For a more comprehensive evaluation, statistical measures like mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are used to examine the model.

3.5 Results and Discussion

From analysing the OEE data correlation it observed that ,there is a correlation between the OEE at time (t) and the OEE at time (t+1) . Availability is the OEE parameter wich have the high correlation to the OEE ,so we take in detailes and use ARIMA model to analysis it and build predicting model using ARIMA.

Table 3.5: Evaluation Table for ARIMA Model

Evaluating Metric	MSE	RMSE	MAE	MAPE
Model 1 (ARIMA)	0.018	0.136	0.104	13.54

The process rate of ARIMA Model is measured using different evaluation metrics, as represented in Table (3.5) . The results show that the model work with a good accuracy and it will help tp predict the availability of the production line .

CHAPTER 4

MAXIMIZATION OVERALL EQUIPMENTS EFFECTIVENESS USING MDP MODEL

4.1 Introduction

Markov decision process (MDP) is a popular mathematical framework used in a stochastic decision-making . MDPs provide a systematic method to evaluate and optimize a decision-making process by taking into consideration the present situation, future situation, and actions that can be performed. This work aims to model the stochastic character of equipment failures and other operational variables that affect OEE by modeling a production flow line by an MDP. Based on MDP, this work strives to find optimal decision-making policies that maximize OEE for a production flow line. Entering different scenarios analyses, the impact evaluation of various decision variables, and the determination of the optimal actions that would enhance equipment availability, process rate, and quality. Decision makers can increase the overall operational efficiency, decrease downtime, and thereby achieve higher OEE with the help of proposed techniques and decision policies. In fact, the results of this study throw important insight on how MDP can be applied for optimizing OEE in a production flow line. The efficiency of the developed mathematical framework in handling the complexity of production processes will add to the existing knowledge. The application of the suggested techniques and decision policies by a decision maker will contribute to an increase in general operational efficiency, a reduction in downtime, and an attainment of higher OEE.

4.2 MDP Model

This section presents a novel MDP model to maximize OEE. The main notations used in this paper are given in Table 4.1.

Table 4.1: Notations

Parameter	Description
a_{t+1}	The maintenance action at time $t + 1$
b_{t+1}	The production action at time $t + 1$
γ	Discount factor to account for the time value of money
A_t	The system availability at time t
Q_t	The system quality rate at time t
A_{t+1}	The system availability at time $t + 1$
Q_{t+1}	The system quality rate at time $t + 1$
M_{t+1}	The system Process rate at time $t + 1$

An MDP is defined by the tuple S, A, P, R, T where:

1. T denotes the planning horizon, which can be either finite or infinite, and encompasses time t .
2. S represents the set of potential system states.
3. Z signifies the set of actions available to the decision maker at discrete time points within T .
4. P represents the collection of Markovian transition probability matrices that

correspond to different actions.

5. R indicates the reward obtained from taking actions a_{t+1} and b_{t+1} at time t when the system is in state s . The reward depend on the initial and future system states and can be either deterministic or stochastic.

The MDP model for maximizing the OEE for a production line is formulated as follows:

1. Decision/time epochs ($t \in T$): Our analysis assumes a finite time planning horizon of T . In this thesis, without loss of generality, a day is the time epoch.
2. State space ($S_t = A_t, Q_t$): At each decision epoch, the system is fully described by its state, S , the state of the system is comprised of two elements:
 - Availability at time t : The production system availability overtime. The state of the system is observed on daily basis .The system can have different value of availability every day (depending on the actual working time and the down time). The availability denoted as $A_t \dots, A_n$.
 - System quality rate at time t , denoted as $Q_t \dots, Q_n$. By defining the quality rate as a state variable, we capture the level of conformance of the produced item to specified standards.
3. The action space (z): Each day, the decision-maker relies upon the system state vector (A_t, Q_t) at the onset of day t . In light of the state information, the decision-maker undertakes the appropriate maintenance action (b) and produc-

tion quantity per day or production speed action (a). The maintenance actions in our model are :

- Do nothing (b1): There is no any type of maintenance actions will happened because the machine work in a good condition.
- Do maintenance (b2) which include two types of maintenance, preventive maintenance which is performed proactively to prevent equipment failure or degradation. It involves routine inspections, servicing, adjustments, and replacements based on predetermined schedules or condition-based monitoring and the second type of maintenance is the corrective maintenance action is carried out in response to a malfunction, failure, or breakdown of equipment. It aims to restore the equipment to its normal operating condition and may involve troubleshooting, repairs, or component replacements.

The production actions in our model are selecting the production quantity for every day ,so it demonstrated as $a_1, a_2, a_3, \dots, a_i$.

Consequently, the system transitions to state $S(t + 1)$, and the corresponding reward is obtained. The subsequent point will elucidate the computation of this reward.

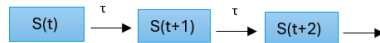


Figure 4.1: Systems transitions

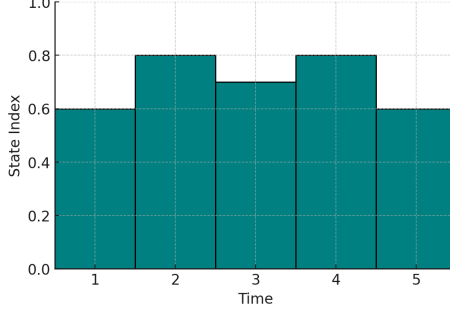


Figure 4.2: Systems transitions

4. Transition probabilities, P : whenever the system moves from time t to time point $t + 1$, the system moves probabilistically to a new state function of the current state, the action taken. This is expressed as $Prob(A_{t+1}^i, Q_{t+1}^j | A_t^i, Q_t^j, a_{t+1}, b_{t+1})$. note that A_t^i and Q_t^j represent the availability and the discretized quality rate values. Fig (4.1) and (4.2) illustrate the system transition when taking action from state $s(t)$ to state $s(t+1)$ and this change happens daily based on the action taken

5. Reward criteria, $R_t(S_t, a_{t+1}, b_{t+1}, S_{t+1})$: Our proposed model operates within a finite discrete state space in which the quality is discretized within the interval $[0, 1]$. This discretization of continuous state elements is a common practice in numerous research studies, as it strikes a delicate balance between model accuracy and computational complexity.

The model's reward depends on several factors, including the current system state (S_t), the actions initiated at the beginning of time epoch t (a_{t+1} and b_{t+1}), and the subsequent system state (S_{t+1}). These elements play a pivotal role in the determination of the Overall Equipment Effectiveness (OEE_t), which, in

turn, serves as the reward for the current time period (t).

The expected system reward during the time interval t is denoted as $R(S_t, a_{t+1}, b_{t+1}, S_{t+1})$. The reward criteria in our model are Overall Equipment Effectiveness (OEE) which refers to the continuous improvement process aimed at optimizing the effectiveness of equipment or machinery in a manufacturing or production, with take in consideration the three factors: availability, process rate, and quality.

The overall equipment effectiveness take all the previous factors in consideration and it is calculated by using the following equation :

$$OEE = A * P * Q$$

By continuously monitoring and improving availability, process rate, and quality, organizations can increase their OEE, which translates to improved productivity, reduced costs, increased throughput, and ultimately, enhanced profitability. OEE maximization is a key aspect of lean manufacturing and operational excellence initiatives and is computed as follows:

$$\begin{aligned} R(S_t, a_{t+1}, b_{t+1}, S_{t+1}) &= R(A_t, Q_t, a_{t+1}, b_{t+1}, A_{t+1}, Q_{t+1}) = OEE_t = \\ &\sum_i \sum_j (A_{t+1}^i \times M_{t+1} \times Q_{t+1}^j \times \text{Prob}(A_{t+1}^i, Q_{t+1}^j \mid A_t^i, Q_t^j, a_{t+1}, b_{t+1})) \end{aligned} \quad (4.1)$$

After defining the MDP elements, the model's expected optimal value func-

tion ($V(S_t)$) over the planning horizon (T) can be calculated using Bellman's equation as follows:

$$a_{t+1}^*, b_{t+1}^* = \operatorname{argmax}_{a_{t+1}, b_{t+1}} \{V(S_t)\}$$

4.3 Case Study: A Food Factory

The study used data from a food factory over the course of three years of operation. System availability, process rate, quality rate, maintenance time and overall equipment effectiveness are reflected in the data as daily instances of system . Data cleaning and preprocessing was performed to ensure uniformity and correctness. addressing missing values and outliers as necessary. To make an integrated study and build a Markov model, the required historical data must be collected and analyzed to define the different states of the system. In practice, the quantities are defined based on production line availability, quality rate of products, customer's demand, and inventory level.

4.3.1 Availability

Availability is the percentage of time that the machines are available for scheduled production compared with the amount of time they were producing. Scheduled maintenance, planned downtime events, or equipment

trials are not considered to be part of the time that machines are available for production. This allows a plant manager to readily identify whether machine downtime issues are part of a known calendar or if there is a more serious problem.

$$\text{Availability}(\%) = \left(\frac{\text{Up Time}}{\text{Total Time}} \right) \times 100$$

Where: Up Time = Actual Operating Time
Total Time = Up Time + Down Time

4.3.2 Quality Rate

Quality rate is the percentage of items that pass the quality inspection. This allows a plant manager to compare consistency between individual machines and in turn allows for comparisons between different manufacturers as well as machine specifications and others. Quality rate is defined as:

$$\text{Quality Rate} = \frac{\text{Good Products}}{\text{Total Products}}$$

4.4 MDP Model to Maximize Overall Equipment Effectiveness (OEE)

This section presents an MDP model to maximize the overall equipment's effectiveness. Furthermore, we demonstrate the model elements by using the case presented in Section I.

- S_t : System state at time t where $S_t \in \{S_0, S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{10}, S_{11}\}$
- $P[S_t, a_{t+1}, b_{t+1}, S_{t+1}]$: Transition probability from state S_t to S_{t+1} .
- b_i : Maintenance action (b_1 (Do nothing), b_2 (Do maintenance))
- a_i : Production quantity action (a_1, a_2, a_3, a_4)
- Q_t : System quality rate at time t where $Q_t \in \{Q_1, Q_2, Q_3\}$
- A_t : System availability at time t where $A_t \in \{A_1, A_2, A_3, A_4\}$
- $S(A_t, Q_t)$: System state at time t (quality level and availability)

Maximizing the OEE depends on three factors; we will take the most important two factors, which are the availability and quality rate of the products.

If the system availability is low, that means we cannot produce a high quantity, and we need to perform maintenance activities to increase the system availability and products' quality. Both factors should be taken care of together because in some cases, the system availability may be high, and all machines work, but most of the products are defective. On the other side, the quality rate may be high, but the system availability is low, and

the system just operated for two hours. So, taking the decision variables (production quantity, production quality level, and maintenance time) will be based on the current system's state and will affect the system state in the future. For example, if the system availability is low and quality is high, and the decision maker chooses to produce a high quantity and reduce maintenance time, that will lead to a further reduction in system availability and a lower quality rate. Conversely, if the decision maker decides to produce a lower quantity while performing maintenance activities, it will lead to enhanced quality and system availability.

The system states at any point of time $S(t)$ will be defined by specific quality rate, availability, and process rate (A_t, Q_t) and specific level of OEE. Based on the decision variables taken by the manager (production quantity, quality, and maintenance time), the state of the system will change to $S(t + 1)$ with a new value for OEE.

4.4.1 States Spaces

The system states are defined based on the combination of quality and availability, considering all possible states that systems can be in.

Availability States

The state space for the availability (A) factor in the production line is defined as follows:

- **State A1:** Availability rate (A) ≥ 0.9 which represent maintenance time (0-2.4h).
- **State A2:** $0.8 \leq$ Availability rate (A) < 0.9 which represent maintenance time (2.5-4.8h).
- **State A3:** $0.7 \leq$ Availability rate (A) < 0.8 which represent maintenance time (4.9-7.2h).
- **State A4:** Availability rate (A) < 0.70 which represent maintenance time (> 7.2 h).

Quality States

The state space for the quality (Q) factor in the production line is defined as follows:

- **State Q1:** Quality rate (Q) ≥ 0.95 .
- **State Q2:** $0.9 \leq$ Quality rate (Q) < 0.95 .
- **State Q3:** Quality rate (Q) < 0.90 .

At any point in time, a production line will have an indicator for both the quality factor and availability. The system state at any time will be one of 12 possible states based on the combination of these factors: A1Q1, A1Q2, A1Q3, A2Q1, A2Q2, A2Q3, A3Q1, A3Q2, A3Q3, A4Q1, A4Q2, A4Q3. We simplify these states using the symbols $S_0, S_1, \dots, S_{11}$.

The time for maintenance used to represent the availability rate in the transition metrics and the quality rate to make it more easier to understand for the decision-

maker who will make the maintenance planning and scheduling . The increase in maintenance time will decrease the availability of system and decreasing the maintenance time lead to system deterioration , so it is important to make balance and select the optimal maintenance time .

4.4.2 Actions Space

There are two action spaces in the system. The first action space is for maintenance decisions:

- b_1 : Do nothing.
- b_2 : Do maintenance.

The second action space relates to production quantity:

- a_1 : Production quantity > 6500 cartons per day.
- a_2 : $5500 \leq$ Production quantity < 6500 cartons per day.
- a_3 : $4500 \leq$ Production quantity < 5500 cartons per day.
- a_4 : Production quantity < 4500 cartons per day.

Combining these factors results in 8 actions:

$z_0 : a_1b_1$ (Production > 6500 cartons/day, no maintenance)

$z_1 : a_2b_1$ (Production $5500 \leq Quantity < 6500$ cartons/day, no maintenance)

$z_2 : a_3b_1$ (Production $4500 \leq Quantity < 5500$ cartons/day, no maintenance)

$z_3 : a_4b_1$ (Production < 4500 cartons/day, no maintenance)

$z_4 : a_1b_2$ (Production > 6500 cartons/day, perform maintenance)

$z_5 : a_2b_2$ (Production $5500 \leq Quantity < 6500$ cartons/day, perform maintenance)

$z_6 : a_3b_2$ (Production $4500 \leq Quantity < 5500$ cartons/day, perform maintenance)

$z_7 : a_4b_2$ (Production < 4500 cartons/day, perform maintenance)

4.4.3 Transition Matrices

In the context of a food factory, a transition matrix can be used to model the relationship between quality rate, availability, production rate, maintenance actions, and overall equipment effectiveness (OEE). The reward in this model is the overall equipment effectiveness (OEE), a key process rate indicator that combines quality, process rate, and availability into a single metric. OEE is maximized when the production rate is optimized, quality defects are minimized, and machinery downtime is reduced. The transition matrices in this MDP model are obtained using probabilities of moving from system state $S(A_t, Q_t)$ at time (t) with availability A_t and Quality rate Q_t to another state $S(A_{t+1}, Q_{t+1})$ with availability A_{t+1} and Quality rate Q_{t+1} given certain actions (selected production quantity and maintenance action). These

probabilities calculated from daily historical data of three year reflecting the behavior of the system of a food factory over time. Such data will include system availability, quality rates, and the impact of different production speed (process rate) and maintenance decisions. Most values in the transition matrices are zero, reflecting the low probability of certain transitions, which simplifies the model by focusing only on the most significant state changes. These sparse transition matrices simplify a model by taking into consideration only the most common state changes. They do suffer, however, from a number of limitations; they may miss infrequent events. Despite this, they balance simplicity with practical decision-making in environments dominated by frequent transitions. The transition matrices for the possible actions with system state are in the following.

Transition Matrix for Action a_1b_1 (Production greater than 6500 cartons/day, no maintenance)

	(0 - 2.4, 0.95 - 1)	(0 - 2.4, 0.90 - 0.95)	(0 - 2.4, < 0.90)	(2.5 - 4.8, 0.95 - 1)	(2.5 - 4.8, 0.90 - 0.95)	(2.5 - 4.8, < 0.9)	(4.9 - 7.2, 0.95 - 1)	(4.9 - 7.2, 0.90 - 0.95)	(4.9 - 7.2, < 0.90)	(> 7.3, 0.95 - 1)	(> 7.3, 0.90 - 0.95)	(> 7.3, < 0.90)
(0 - 2.4, 0.95 - 1)	0.667	0.333	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(0 - 2.4, 0.90 - 0.95)	0.143	0.714	0.143	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(0 - 2.4, < 0.90)	0.091	0.091	0.818	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2.5 - 4.8, 0.95 - 1)	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2.5 - 4.8, 0.90 - 0.95)	0.000	0.750	0.250	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2.5 - 4.8, < 0.9)	0.000	0.143	0.857	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(4.9 - 7.2, 0.95 - 1)	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(4.9 - 7.2, 0.90 - 0.95)	0.000	0.333	0.667	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(4.9 - 7.2, < 0.90)	0.667	0.000	0.333	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, 0.95 - 1)	0.500	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, 0.90 - 0.95)	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, < 0.90)	0.000	0.250	0.750	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Transition Matrix for Action a_1b_2 (Production greater than 6500 cartons/day, with maintenance)

	(0 - 2.4, 0.95 - 1)	(0 - 2.4, 0.90 - 0.95)	(0 - 2.4, < 0.90)	(2.5 - 4.8, 0.95 - 1)	(2.5 - 4.8, 0.90 - 0.95)	(2.5 - 4.8, < 0.9)	(4.9 - 7.2, 0.95 - 1)	(4.9 - 7.2, 0.90 - 0.95)	(4.9 - 7.2, < 0.90)	(> 7.3, 0.95 - 1)	(> 7.3, 0.90 - 0.95)	(> 7.3, < 0.90)
(0 - 2.4, 0.95 - 1)	0.063	0.000	0.313	0.250	0.188	0.000	0.125	0.063	0.000	0.000	0.000	0.000
(0 - 2.4, 0.90 - 0.95)	0.024	0.286	0.143	0.024	0.262	0.095	0.024	0.143	0.000	0.000	0.000	0.000
(0 - 2.4, < 0.90)	0.038	0.096	0.192	0.019	0.115	0.404	0.000	0.000	0.115	0.019	0.000	0.000
(2.5 - 4.8, 0.95 - 1)	0.100	0.000	0.100	0.100	0.200	0.100	0.200	0.100	0.000	0.000	0.100	0.000
(2.5 - 4.8, 0.90 - 0.95)	0.059	0.235	0.176	0.000	0.176	0.059	0.000	0.176	0.118	0.000	0.000	0.000
(2.5 - 4.8, < 0.9)	0.000	0.083	0.167	0.000	0.042	0.208	0.083	0.042	0.375	0.000	0.000	0.000
(4.9 - 7.2, 0.95 - 1)	0.000	0.000	0.000	0.000	0.500	0.000	0.000	0.500	0.000	0.000	0.000	0.000
(4.9 - 7.2, 0.90 - 0.95)	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000
(4.9 - 7.2, < 0.90)	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, 0.95 - 1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, 0.90 - 0.95)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, < 0.90)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Transition Matrix for Action a_2b_1 (Production 5500-6500 cartons/day, no maintenance)

	(0 - 2.4, 0.95 - 1)	(0 - 2.4, 0.90 - 0.95)	(0 - 2.4, < 0.90)	(2.5 - 4.8, 0.95 - 1)	(2.5 - 4.8, 0.90 - 0.95)	(2.5 - 4.8, < 0.9)	(4.9 - 7.2, 0.95 - 1)	(4.9 - 7.2, 0.90 - 0.95)	(4.9 - 7.2, < 0.90)	(> 7.3, 0.95 - 1)	(> 7.3, 0.90 - 0.95)	(> 7.3, < 0.90)
(0 - 2.4, 0.95 - 1)	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(0 - 2.4, 0.90 - 0.95)	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(0 - 2.4, < 0.90)	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2.5 - 4.8, 0.95 - 1)	0.500	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2.5 - 4.8, 0.90 - 0.95)	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(2.5 - 4.8, < 0.9)	0.000	0.500	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(4.9 - 7.2, 0.95 - 1)	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(4.9 - 7.2, 0.90 - 0.95)	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(4.9 - 7.2, < 0.90)	0.333	0.000	0.667	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, 0.95 - 1)	0.000	0.333	0.667	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, 0.90 - 0.95)	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(> 7.3, < 0.90)	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Transition Matrix for Action a_2b_2 (Production 5500-6500 cartons/day, with maintenance)

	(0 - 2.4, 0.95 - 1)	(0 - 2.4, 0.90 - 0.95)	(0 - 2.4, < 0.90)	(2.5 - 4.8, 0.95 - 1)	(2.5 - 4.8, 0.90 - 0.95)	(2.5 - 4.8, < 0.9)	(4.9 - 7.2, 0.95 - 1)	(4.9 - 7.2, 0.90 - 0.95)	(4.9 - 7.2, < 0.90)	(> 7.3, 0.95 - 1)	(> 7.3, 0.90 - 0.95)	(> 7.3, < 0.90)
(0 - 2.4, 0.95 - 1)	0.000	0.000	0.286	0.000	0.143	0.286	0.143	0.000	0.143	0.000	0.000	0.000
(0 - 2.4, 0.90 - 0.95)	0.000	0.143	0.286	0.000	0.000	0.143	0.000	0.286	0.143	0.000	0.000	0.000
(0 - 2.4, < 0.90)	0.000	0.000	0.167	0.000	0.083	0.500	0.000	0.083	0.167	0.000	0.000	0.000
(2.5 - 4.8, 0.95 - 1)	0.056	0.056	0.000	0.333	0.111	0.056	0.111	0.167	0.056	0.056	0.000	0.000
(2.5 - 4.8, 0.90 - 0.95)	0.000	0.113	0.048	0.048	0.403	0.016	0.065	0.242	0.016	0.000	0.032	0.016
(2.5 - 4.8, < 0.9)	0.000	0.064	0.064	0.128	0.064	0.298	0.000	0.106	0.191	0.021	0.021	0.043
(4.9 - 7.2, 0.95 - 1)	0.087	0.000	0.000	0.261	0.174	0.043	0.087	0.043	0.174	0.043	0.000	0.087
(4.9 - 7.2, 0.90 - 0.95)	0.011	0.044	0.000	0.033	0.209	0.022	0.055	0.407	0.088	0.000	0.110	0.022
(4.9 - 7.2, < 0.90)	0.014	0.000	0.043	0.014	0.014	0.275	0.014	0.087	0.435	0.000	0.029	0.072
(> 7.3, 0.95 - 1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.500	0.000	0.000	0.000
(> 7.3, 0.90 - 0.95)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.500	0.000	0.000	0.000
(> 7.3, < 0.90)	0.000	0.000	0.000	0.000	0.333	0.000	0.000	0.667	0.000	0.000	0.000	0.000

Transition Matrix for Action a_3b_1 (Production 4500-5500 cars/day, no maintenance)

	$(0-2.4, 0.95-1)$	$(0-2.4, 0.90-0.95)$	$(0-2.4, <0.90)$	$(2.5-4.8, 0.95-1)$	$(2.5-4.8, 0.90-0.95)$	$(2.5-4.8, <0.9)$	$(4.9-7.2, 0.95-1)$	$(4.9-7.2, 0.90-0.95)$	$(4.9-7.2, <0.90)$	$(>7.3, 0.95-1)$	$(>7.3, 0.90-0.95)$	$(>7.3, <0.90)$
$(0-2.4, 0.95-1)$	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(0-2.4, 0.90-0.95)$	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(0-2.4, <0.90)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(2.5-4.8, 0.95-1)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(2.5-4.8, 0.90-0.95)$	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(2.5-4.8, <0.9)$	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(4.9-7.2, 0.95-1)$	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(4.9-7.2, 0.90-0.95)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(4.9-7.2, <0.90)$	0.500	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(>7.3, 0.95-1)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(>7.3, 0.90-0.95)$	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(>7.3, <0.90)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Transition Matrix for Action a_3b_2 (Production 4500-5500 cars/day, with maintenance)

	$(0-2.4, 0.95-1)$	$(0-2.4, 0.90-0.95)$	$(0-2.4, <0.90)$	$(2.5-4.8, 0.95-1)$	$(2.5-4.8, 0.90-0.95)$	$(2.5-4.8, <0.9)$	$(4.9-7.2, 0.95-1)$	$(4.9-7.2, 0.90-0.95)$	$(4.9-7.2, <0.90)$	$(>7.3, 0.95-1)$	$(>7.3, 0.90-0.95)$	$(>7.3, <0.90)$
$(0-2.4, 0.95-1)$	0.000	0.000	0.000	0.000	0.000	0.000	0.250	0.000	0.750	0.000	0.000	0.000
$(0-2.4, 0.90-0.95)$	0.000	0.300	0.000	0.000	0.100	0.100	0.200	0.100	0.200	0.000	0.000	0.000
$(0-2.4, <0.90)$	0.000	0.000	0.143	0.143	0.071	0.286	0.000	0.071	0.143	0.071	0.000	0.071
$(2.5-4.8, 0.95-1)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
$(2.5-4.8, 0.90-0.95)$	0.000	0.500	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(2.5-4.8, <0.9)$	0.000	0.000	0.400	0.000	0.000	0.400	0.000	0.000	0.000	0.000	0.200	0.000
$(4.9-7.2, 0.95-1)$	0.000	0.000	0.000	0.429	0.000	0.000	0.429	0.000	0.143	0.000	0.000	0.000
$(4.9-7.2, 0.90-0.95)$	0.000	0.059	0.000	0.000	0.118	0.176	0.059	0.353	0.000	0.000	0.176	0.059
$(4.9-7.2, <0.90)$	0.000	0.042	0.083	0.042	0.000	0.167	0.042	0.083	0.333	0.042	0.000	0.167
$(>7.3, 0.95-1)$	0.000	0.000	0.000	0.000	0.000	0.000	0.167	0.167	0.000	0.333	0.167	0.167
$(>7.3, 0.90-0.95)$	0.000	0.000	0.000	0.000	0.000	0.000	0.429	0.071	0.071	0.286	0.143	0.143
$(>7.3, <0.90)$	0.000	0.059	0.059	0.000	0.000	0.000	0.059	0.059	0.235	0.059	0.176	0.294

Transition Matrix for Action a_4b_1 (Production < 4500 cars/day, no maintenance)

	$(0-2.4, 0.95-1)$	$(0-2.4, 0.90-0.95)$	$(0-2.4, <0.90)$	$(2.5-4.8, 0.95-1)$	$(2.5-4.8, 0.90-0.95)$	$(2.5-4.8, <0.9)$	$(4.9-7.2, 0.95-1)$	$(4.9-7.2, 0.90-0.95)$	$(4.9-7.2, <0.90)$	$(>7.3, 0.95-1)$	$(>7.3, 0.90-0.95)$	$(>7.3, <0.90)$
$(0-2.4, 0.95-1)$	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(0-2.4, 0.90-0.95)$	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(0-2.4, <0.90)$	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(2.5-4.8, 0.95-1)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(2.5-4.8, 0.90-0.95)$	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(2.5-4.8, <0.9)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(4.9-7.2, 0.95-1)$	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(4.9-7.2, 0.90-0.95)$	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(4.9-7.2, <0.90)$	0.500	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(>7.3, 0.95-1)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(>7.3, 0.90-0.95)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$(>7.3, <0.90)$	0.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Transition Matrix for Action a_4b_2 (Production < 4500 car- tons/day, with maintenance)

	(0 - 2.4, 0.95 - 1)	(0 - 2.4, 0.90 - 0.95)	(0 - 2.4, < 0.90)	(2.5 - 4.8, 0.95 - 1)	(2.5 - 4.8, 0.90 - 0.95)	(2.5 - 4.8, < 0.9)	(4.9 - 7.2, 0.95 - 1)	(4.9 - 7.2, 0.90 - 0.95)	(4.9 - 7.2, < 0.90)	(> 7.3, 0.95 - 1)	(> 7.3, 0.90 - 0.95)	(> 7.3, < 0.90)
(0 - 2.4, 0.95 - 1)	0.500	0.000	0.000	0.000	0.000	0.500	0.000	0.000	0.000	0.000	0.000	0.000
(0 - 2.4, 0.90 - 0.95)	0.000	0.273	0.000	0.000	0.273	0.091	0.000	0.091	0.000	0.091	0.000	0.182
(0 - 2.4, < 0.90)	0.000	0.000	0.077	0.077	0.077	0.462	0.000	0.154	0.077	0.000	0.000	0.077
(2.5 - 4.8, 0.95 - 1)	0.000	0.000	0.000	0.000	0.286	0.286	0.143	0.143	0.143	0.000	0.000	0.000
(2.5 - 4.8, 0.90 - 0.95)	0.000	0.133	0.100	0.033	0.367	0.033	0.000	0.290	0.067	0.000	0.067	0.000
(2.5 - 4.8, < 0.9)	0.032	0.000	0.097	0.000	0.129	0.258	0.000	0.065	0.290	0.000	0.000	0.129
(4.9 - 7.2, 0.95 - 1)	0.000	0.000	0.000	0.250	0.250	0.000	0.250	0.250	0.000	0.000	0.000	0.000
(4.9 - 7.2, 0.90 - 0.95)	0.000	0.059	0.000	0.000	0.118	0.176	0.059	0.353	0.000	0.000	0.176	0.059
(4.9 - 7.2, < 0.90)	0.000	0.042	0.083	0.042	0.000	0.167	0.042	0.083	0.333	0.042	0.000	0.167
(> 7.3, 0.95 - 1)	0.000	0.000	0.000	0.000	0.000	0.000	0.167	0.167	0.000	0.333	0.167	0.167
(> 7.3, 0.90 - 0.95)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.429	0.071	0.071	0.296	0.143
(> 7.3, < 0.90)	0.000	0.059	0.059	0.000	0.000	0.000	0.059	0.059	0.235	0.059	0.176	0.294

4.4.4 Reward Matrix

In the context of optimizing a food factory's operations, the reward matrix can be leveraged independently from the steps of a Markov Decision Process (MDP) to evaluate the impact of various production and maintenance actions on overall equipment effectiveness (OEE). This approach focuses on the immediate outcomes of actions without explicitly considering the sequential decision-making framework inherent to MDPs.

The reward matrix is designed to map the relationships between the production line state defined by quality rate, availability, and the actions taken, which include in production speed (process rate) and maintenance action. The reward is measured in terms of OEE which reflects the actions effectiveness in maintaining the equipment in high availability ,process rate and quality rate.

The reward for our case study will be calculated:

$$R(S_t, a_{t+1}, b_{t+1}, S_{t+1}) = R(A_t, Q_t, a_{t+1}, b_{t+1}, A_{t+1}, Q_{t+1}) = OEE_t = \sum_i \sum_j A_{t+1}^i \times M_{t+1} \times Q_{t+1}^j \times \text{Prob}(A_{t+1}^i, Q_{t+1}^j | A_t^i, Q_t^j, a_{t+1}, b_{t+1})$$

The calculated reward matrix in the following matrix:

State/Action	(P $\geq$ 6500, No)	(6499-5500, No)	(5499-4500, No)	(P $\leq$ 4499, No)	(P $\geq$ 6500, Do)	(6499-5500, Do)	(5499-4500, Do)	(P $\leq$ 4499, Do)
(0-2.4,0.95-1)	0.753	0.683	0.618	0.463	0.775	0.698	0.601	0.399
(0-2.4,0.90-0.95)	0.756	0.647	0.586	0.463	0.765	0.700	0.607	0.391
(0-2.4,<0.90)	0.726	0.647	0.554	0.439	0.712	0.737	0.585	0.385
(2.5-4.8,0.95-1)	0.715	0.702	0.554	0.416	0.721	0.736	0.584	0.397
(2.5-4.8,0.90-0.95)	0.746	0.683	0.586	0.439	0.760	0.720	0.602	0.397
(2.5-4.8,<0.9)	0.721	0.665	0.618	0.416	0.740	0.700	0.570	0.385
(4.9-7.2,0.95-1)	0.715	0.647	0.586	0.439	0.763	0.722	0.632	0.416
(4.9-7.2,0.90-0.95)	0.728	0.720	0.554	0.463	0.721	0.719	0.598	0.396
(4.9-7.2,<0.90)	0.769	0.671	0.586	0.439	0.804	0.691	0.577	0.389
(>7.3,0.95-1)	0.776	0.659	0.554	0.416	0.000	0.716	0.614	0.398
(>7.3,0.90-0.95)	0.715	0.647	0.618	0.416	0.000	0.716	0.602	0.394
(>7.3,<0.90)	0.725	0.683	0.554	0.416	0.000	0.749	0.571	0.385

4.5 Solving MDP Using Policy Iteration

The policy iteration can effectively be used to solve the Markov Decision Process that is employed in modeling various operational decisions regarding the food factory production line. In this respect, the aims focused on optimisation of the level of production speed, quality rate, availability, and maintenance actions with a view to maximising overall equipment effectiveness.

Policy iteration is used to solve for the optimal policy regarding production, quality, and maintenance. The two phases in finding an optimal policy are outlined as follows:

Policy Evaluation: The value function $V(s)$ is computed iteratively for a given policy. This step solves the Bellman expectation equation to estimate the expected OEE for each state given the current policy. This ensures that the value for each state in the value function V reflects the cumulative reward, OEE, of following the current policy from that state.

Computing the value function V^π for the current policy π . which involves solving the system linear equations. For each state s_i (where i ranges from 1 to 12) the value function $V^\pi(s_i)$.

Policy Improvement: The policy is updated by selecting actions that maximize the expected return based on the current value function. This is done by evaluating the potential rewards of different actions and choosing the one that leads to the highest expected OEE. The policy improvement step ensures that the actions taken in each state are optimal given the current understanding of the value function. Improve the policy by choosing actions that maximize the expected value at each state:

Compute for all actions in each state to choose the best action for each state. By applying and solving the MDP using policy iteration, we get the optimal policy and value function, which are:

Optimal Policy and Value Function

Optimal Policy:

[4, 0, 5, 5, 4, 4, 4, 1, 4, 0, 5, 5]

Value Function:

[75.579, 75.585, 75.543, 75.564, 75.5748, 75.565, 75.566, 75.543, 75.614, 75.602, 75.539, 75.547]

This means:

- If the system is in state $S(0)$, take action (z_4) , which includes producing more than 6500 cartons and performing maintenance activity. The expected reward (OEE) is 75.579.
- If the system is in state $S(1)$, take action (z_0) , which includes producing more

than 6500 cartons without performing any maintenance activity. The expected reward (OEE) is 75.585.

- If the system is in state $S(2)$, then take action (z5) which includes producing between 5500 to 6500 cartons with maintenance activity to get an expected reward (OEE) is 75.543.
- If the system is in state $S(3)$, then take action (z5) which includes producing between 5500 to 6500 cartons with maintenance activity . The expected reward (OEE) is 75.564.
- If the system is in state $S(4)$, then take the action (z4) which includes producing over 6500 cartons and proceed with the maintenance activity. The expected reward (OEE) is 75.5748.
- If the system is in the state $S(5)$, then take the action (z4) which includes producing over 6500 cartons and proceed with the maintenance activity. The expected reward (OEE) will be 75.565.
- If the system is in state $S(6)$, then take the action (z4) which include producing over 6500 cartons and proceed with the maintenance activity, The expected reward (OEE) is 75.566.
- If the system is in state $S(7)$, then take action (z1): which includes producing between 5500 to 6500 cartons without doing any maintenance activity. The expected reward in terms of OEE is 75.543.
- If the system is in state $S(8)$, then take action (z4) which include producing over 6500 cartons and proceed with the maintenance activity. The expected reward

(OEE) is 75.614.

- If the system is in state $S(9)$, take the action (z0), which include producing more than 6500 cartons with no maintenance activity. The expected reward (OEE) is 75.602.
- If the system is in state $S(10)$, take action (z5), which include producing within a range of 5500 to 6500 cartons with maintenance activity. The expected reward (OEE) is 75.539.
- If the system is in state $S(11)$, take action (z5), which include producing within a range of 5500 to 6500 cartons with maintenance activity. The expected reward (OEE) is 75.549.

Evaluating the Policy

By taking data from the food factory to evaluate the model and comparing the current policy with the policy produced from the MDP and the value iteration, the result is shown in the following table:

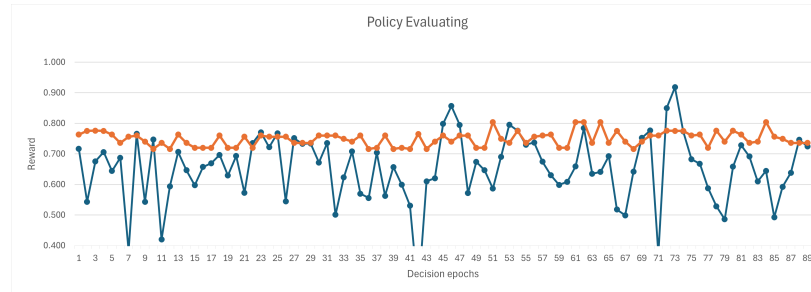


Figure 4.3: Comparison of OEE(Traditional) and Reward OEE (MDP)

Table 4.2: MDP OEE Analysis Table

Day	OEE (Traditional)	State	Action	Reward (OEE)	Difference
1	0.717	S6	4	0.763	0.046
2	0.543	S0	4	0.775	0.232
3	0.675	S9	0	0.776	0.101
4	0.706	S0	4	0.775	0.069
5	0.644	S6	4	0.763	0.119
6	0.687	S3	5	0.736	0.049
7	0.383	S1	0	0.756	0.373
8	0.766	S4	4	0.760	-0.006
9	0.543	S5	4	0.740	0.197
10	0.747	S10	5	0.716	-0.031
11	0.420	S3	5	0.736	0.316
12	0.593	S10	5	0.716	0.123
13	0.706	S6	4	0.763	0.057
14	0.646	S3	5	0.736	0.090
15	0.597	S7	1	0.720	0.123
16	0.657	S7	1	0.720	0.063
17	0.669	S7	1	0.720	0.051
18	0.696	S4	4	0.760	0.064
19	0.629	S7	1	0.720	0.091
20	0.693	S7	1	0.720	0.027

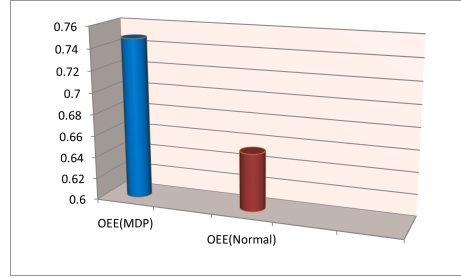


Figure 4.4: Comparison of Average OEE(Traditional) and Reward OEE (MDP)

4.6 Result and Discussion

The observed Overall Equipment Effectiveness (OEE) in fig(1) under normal conditions is 65.3%, whereas the OEE under the Modified Design Parameters (MDP) demonstrates a significant improvement, reaching 75.5%. This comparison highlights a notable enhancement in operational efficiency with the application of MDP, indicating a 10.2% increase in OEE.

The line chart comparison between the OEE Normal and OEE MDP methods in fig(2) demonstrates a clear distinction in process rate and consistency. Over the 90-day period, the OEE MDP method consistently shows higher OEE values com-

pared to the OEE Normal method. The OEE MDP values generally remain stable, predominantly ranging from 0.753 to 0.758, highlighting its reliability and robustness in maintaining high equipment effectiveness. In contrast, the OEE Normal method exhibits notable variability, with OEE values fluctuating between 0.30 and 0.90. The variability here indicates that the OEE Normal method is less stable and highly susceptible to inconsistencies because of process variation. Hence, the OEE MDP method tends to be better in sustaining high OEE process rate and therefore is more effective in terms of strategy to achieve and sustain optimal equipment effectiveness.

4.7 Conclusion

This study introduces a Markov Decision Process (MDP) model to optimize Overall Equipment Effectiveness in the production process. It takes in consideration all OEE parameters availability and quality rate in state space and process rate with the availability in the actions. In this approach of MDP, the OEE is continually increased along with the optimization of maintenance and production schedules, providing stable range of OEE between 0.72 and 0.775 as compared to the traditional methods used, which it is ranged between 0.30 and 0.90. The policy iteration implementation allows the select the optimal actions in different states to maximize OEE, as was shown in a case study in a food factory. This MDP model is not only effective for optimizing productivity and cost; it is also an effective strategic tool for managing complex production systems. The adaptability of the MDP model offers promising areas for future research, where it can be extended to multi-stage systems, allowing for a more

comprehensive optimization across the entire production line. The second direction is integrating with the reinforcement learning to further adapt the MDP model. another direction for future research is to expand the state spaces and the set of actions to cover all system conditions and possible decisions by using new methodology that use the artificial intelligent and machine learning algorithm to solve the MDP models and find the optimal solution.

CHAPTER 5

MAXIMIZING AVAILABILITY WITH BUDGET CONSTRAINTS USING MDP MODEL

5.1 Introduction

Industrial operations need very high levels of system availability to maintain efficient. High system availability ensures dependability and operational reliability, which are the key concerns in manufacturing and production industries. However, such availability requires an optimal methodology that balances frequent uptime with budgetary limitations. Inadequate budget allocations for maintenance lead to considerable losses due to downtimes, while excessively high budgets have led to inefficient use of resources. Maintenance operations should therefore be optimized in such a way that it results in maximum availability of the system within the budgetary limits.

This chapter will develop optimum maintenance strategies that would enhance system availability and ensure financial sustainability in an industrially demanding environment. The purpose is to present an MDP model and apply it in order to determine the optimum maintenance plan. More specifically, in this work, the research will investigate the optimal maintenance decision that maximum system availability through different states .

5.2 MDP Model

This section presents a novel MDP model to maximize system availability subject to budget constraints. An MDP is defined by the tuple $\langle S, A, P, R, T \rangle$, where:

- T denotes the planning horizon, which can be either finite or infinite and encompasses time epochs t .
- S represents the set of potential system states.
- A is the set of actions available to the decision maker at discrete time points within T .
- P represents the collection of Markovian transition probability matrices that correspond to different actions.
- R indicates the reward obtained from taking action a at time t when the system is in state s . The reward may depend on the initial and/or future system states and can be either deterministic or stochastic.

The MDP model for maximizing system availability for a single machine is formulated as follows:

5.2.1 Decision/Time Epochs ($t \in T$)

Our analysis assumes an infinite time planning horizon T . In this paper, without loss of generality, a day is the time epoch.

5.2.2 State Space (S_t)

At each decision epoch, the system is fully described by its state S . The state of the system represents different levels of the machine's deterioration:

- S_1 : As good as new (high availability level)
- S_2 : Slightly deteriorated (moderate availability level)
- S_3 : High deterioration level (low availability level)
- S_4 : Failed/Down (system is down)

The state space S is represented as:

$$S = \{S_1, S_2, S_3, S_4\}$$

These states represent different conditions of the machine, which are inversely proportional to the machine availability.

5.2.3 Action Space (A)

Each day, the decision-maker relies upon the system state vector S at the beginning of day t . In light of the state information, the decision-maker undertakes the appropriate

maintenance action. The maintenance actions in our model are:

$$A = \{a_0, a_1, a_2\}$$

Where:

- a_0 : Do nothing
- a_1 : Minimal repair
- a_2 : Major repair (restores the system to S_1 and is only applicable in S_4)

5.2.4 Transition Probabilities $P(s'|s, a)$

The system's transitions from one state to another are dependent on both the state and the action taken. Specifically, $P(s'|s, a)$ defines the probability that the system moves to state s' given that it was in state s and action a was taken. These transition probabilities, for action a , can be represented in matrix form as P_a .

5.2.5 Reward Criteria $R(S)$ and $C(s, a)$

The decision-maker aims to maintain the machine in its optimal state to maximize availability. Since different machine states correspond to varying levels of degradation, availability decreases as the machine's condition deteriorates. Therefore, not all operational states equally contribute to the machine's availability. This relationship is represented by $R(S)$, where the availability reward is assumed to depend on the machine state.

In addition to the state-dependent reward, maintenance incurs a cost, representing

a secondary objective for the decision-maker. Thus, we define a state-action dependent cost, denoted by $C(s, a)$, which captures the cost of taking action a in state s . To achieve the secondary objective, we assume that costs must not exceed a given budget. Since the planning horizon is infinite, the budget is defined as the cost rate in our model.

5.3 Numerical Analysis

This section presents a numerical example that illustrates the model developed earlier in Section 5.2.

5.3.1 Demonstrative Example

Consider a machine that can exist in various states. State 1 represents a new system, while State 4 represents a failed system. The intermediate states correspond to different levels of deterioration. Three maintenance actions are considered:

- **Do Nothing** (a_0): This action maintains the system in its current state or allows it to transition to a worse state.
- **Minimal Repair** (a_1): This action either preserves the current state or improves the machine's condition.
- **Major Repair** (a_2): This action is only applicable when the machine is in State 4, i.e., failed or down, and it restores the machine to an "as good as new" state.

The transition matrices for these actions are given next:

$$P_{a_0} = \begin{bmatrix} 0.9 & 0.1 & 0.0 & 0.0 \\ 0.0 & 0.8 & 0.2 & 0.0 \\ 0.0 & 0.0 & 0.7 & 0.3 \\ 0.0 & 0.0 & 0.0 & 1.0 \end{bmatrix}, \quad P_{a_1} = \begin{bmatrix} 0.9 & 0.1 & 0.0 & 0.0 \\ 0.2 & 0.7 & 0.1 & 0.0 \\ 0.0 & 0.3 & 0.6 & 0.1 \\ 0.0 & 0.0 & 0.4 & 0.6 \end{bmatrix}, \quad P_{a_2} = \begin{bmatrix} 1.0 & 0.0 & 0.0 & 0.0 \end{bmatrix}$$

At discrete points in time, the decision-maker must select one of the maintenance actions to maximize the expected availability. Additionally, the average maintenance cost should not exceed a predefined budget. Since maximizing availability is the primary objective, the budget will be treated as a constraint. The expected availability levels and maintenance costs are presented as follows:

$$R(S_1) = 100\%, \quad R(S_2) = 75\%, \quad R(S_3) = 50\%, \quad R(S_4) = 0\%$$

$$C(S_1, a_0) = 0, \quad C(S_1, a_1) = 1000, \quad C(S_1, a_2) = \text{N/A}$$

$$C(S_2, a_0) = 0, \quad C(S_2, a_1) = 2000, \quad C(S_2, a_2) = \text{N/A}$$

$$C(S_3, a_0) = 0, \quad C(S_3, a_1) = 3000, \quad C(S_3, a_2) = \text{N/A}$$

$$C(S_4, a_0) = 0, \quad C(S_4, a_1) = \text{N/A}, \quad C(S_4, a_2) = 8000$$

5.3.2 Methodology

In this section, linear programming is employed to determine the optimal policy for the infinite horizon MDP example provided in Section 5.3.1. This method is particularly effective for constrained MDPs where safety or reliability constraints are considered Zadorojniy et al.(2006), Zhao et al.(2021). To solve the model, we define the decision

variable y_i^k , which represents the probability of taking decision k in state i . The LP is formulated as follows:

Objective Function

$$\text{Maximize: } Z = 100 \sum_{k=1}^2 y_1^k + 75 \sum_{k=1}^2 y_2^k + 50 \sum_{k=1}^2 y_3^k$$

This function aims to maximize the expected reward by prioritizing decisions that keep the higher reward states.

Constraints

Normalization Constraint:

$$\sum_k \sum_i y_i^k = 1$$

Budget Constraint:

$$1000y_1^2 + 2000y_2^2 + 3000y_3^2 + 8000y_4^2 \leq 1000$$

State Transition Constraints:

$$\begin{aligned}
\text{State 1: } & \sum_{k=1}^2 y_1^k - \sum_{i=1}^4 \sum_{k=1}^2 y_i^k P_{i1}^k = 0 \\
\text{State 2: } & \sum_{k=1}^2 y_2^k - \sum_{i=1}^4 \sum_{k=1}^2 y_i^k P_{i2}^k = 0 \\
\text{State 3: } & \sum_{k=1}^2 y_3^k - \sum_{i=1}^4 \sum_{k=1}^2 y_i^k P_{i3}^k = 0 \\
\text{State 4: } & \sum_{k=1}^2 y_4^k - \sum_{i=1}^4 \sum_{k=1}^2 y_i^k P_{i4}^k = 0
\end{aligned}$$

Nonnegativity:

$$y_{ik} \geq 0 \quad \text{for } i = 0 \dots M; k = 1, 2, \dots K$$

5.4 Results and Discussion

Excel Solver was used to solve the model in Section 4.2, yielding the results shown in Table 5.1.

Table 5.1: Solution of the MDP Model

State i	Decision k	Optimal y_i^k	Optimal Action
1	Do nothing (1)	0.638	1
1	Minimal repair (2)	0	0
2	Do nothing (1)	0	0
2	Minimal repair (2)	0.284	1
3	Do nothing (1)	0	0
3	Minimal repair (2)	0.071	1
4	Do nothing (1)	0	0
4	Major repair (3)	0.007	1

The implementation of the MDP model using linear programming successfully

identifies the optimal maintenance policy for maximizing system availability. Table 5.1 The results show that the best policy gives high priority to actions maintaining the system in high-availability states when a minimal repair policy can be implemented. That is confirmed by Table (5.1), when the system in high-availability state (S1), the optimal decision rule would be to keep availability as high as possible without taking unnecessary interventions by choosing the action "do nothing," since it minimizes the cost of maintenance. In the S2 state, when it is slightly deteriorated, minimal repairs should be performed, and they can be refined to assure cost-effectiveness. When deterioration has worsened—that is, in the S3 state—minimal repairs are also quite critical to prevent the system from failing. Major repair is required once it reaches the state of failure, S4, to get the system up again at full efficiency.

5.5 Conclusion

The study presents an integrative method to optimize maintenance scheduling in the MDP model for industrial systems under budget constraints and proposes an effective maintenance policy that balances system availability against budget limits under uncertainty. Because the model adapts to changes in the system, it minimizes the occurrence of financial risks due to over-maintenance or under-maintenance. Hence, it has practical applicability in real-world maintenance decision-making.

CHAPTER 6

CONCLUSION

6.1 Conclusion

This study introduces a Markov Decision Process (MDP) model to optimize Overall Equipment Effectiveness (OEE) in the production process. It takes into consideration all OEE parameters, including availability, quality rate in the state space, and process rate in the actions. The study started by analyzing the OEE parameters. The analysis showed the correlation between the OEE at time (T) and the availability, process rate and quality rate at time ($T - 1$). Availability is the highest correlated parameter to OEE, so it has been studied with more details and modeled using ARIMA.

Based on the data analysis, correlation, the need to dynamic model that capture all the states and satisfy the changeable production environment of the system the MDP model was selected. The MDP model proves highly effective in optimizing maintenance and production schedules, delivering a stable OEE reward range between 0.72 - 0.78 with average 0.755, as demonstrated in a case study. This contrasts with traditional methods used in the same case study, where OEE fluctuated significantly

between 0.40 - 0.90 and with average 0.65. The MDP approach provides a more consistent and optimized outcome, showcasing its potential for improving production stability and overall effectiveness. The policy iteration implementation allows for the selection of optimal actions in different states to maximize OEE.

There is a need to develop new model for OEE to put new constraints like budget on OEE, to apply that new model build in chapter 5, the model use the availability parameter. The study presents an integrative method to optimize maintenance scheduling in the MDP model for industrial systems under budget constraints and proposes an effective maintenance policy that balances system availability against budget limits under uncertainty. Because the model adapts to changes in the system, it minimizes the occurrence of financial risks due to over-maintenance or under-maintenance. Hence, it has practical applicability in real-world maintenance decision-making.

6.2 Future work

The adaptability of the MDP model offers promising avenues for future research. It can be extended to multi-stage systems or applied with increased granularity by considering the availability of different stages or individual elements of the production line. This would allow for more precise and comprehensive optimization across the entire production process, addressing specific bottlenecks and improving overall system process rate.

In the Model with budget the primary issue here is that it is quite hard to correctly estimate the transition probabilities between system states, and for that purpose, lots

of data are to be collected. Besides, it is assumed that the budget is fixed, while under normal conditions, production equipment is exposed to an increased failure rate with time. These two challenges indicate the directions for further research.

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