

DOKUZ EYLUL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

**MODELING AND IMPROVEMENT OF THE
PRODUCTION SYSTEM OF A COMPANY IN THE
AUTOMOTIVE INDUSTRY WITH SIMULATION**

by

Aysu UĞRAŞ

January, 2025

IZMIR

MODELING AND IMPROVEMENT OF THE PRODUCTION SYSTEM OF A COMPANY IN THE AUTOMOTIVE INDUSTRY WITH SIMULATION

**A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Master of Science in Industrial
Engineering, Industrial Engineering Program**

**by
Aysu UĞRAŞ**

January, 2025

İZMİR

M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled “**MODELING AND IMPROVEMENT OF THE PRODUCTION SYSTEM OF A COMPANY IN THE AUTOMOTIVE INDUSTRY WITH SIMULATION**” completed by **AYSU UGRAS** under supervision of **ASSOC.PROF.DR. SEREN OZMEHMET TAŞAN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of. Master of Science.

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AYSU UĞRAŞ

MODELING AND IMPROVEMENT OF THE PRODUCTION SYSTEM OF A COMPANY IN THE AUTOMOTIVE INDUSTRY WITH SIMULATION

ABSTRACT

This thesis presents a comprehensive study on the optimization of production systems in the automotive industry, with a focus on reducing backorders and improving supply chain efficiency. The research employs a methodological framework that integrates advanced simulation modeling techniques with Industry 4.0 principles. The study is structured in four phases: Problem contextualization, process mapping, simulation model development, and output analysis. A case study in an automotive manufacturing plant demonstrates the application of this framework. The research utilizes ARENA simulation software to model the current system, develop alternative scenarios, and design an optimized system. The study incorporates statistical analysis, process optimization, and economic comparisons to evaluate system performance. Key findings reveal significant improvements in system efficiency and backorder reduction through strategic reconfiguration of production processes and resource allocation. The research contributes to both theoretical understanding and practical application of simulation-based optimization in supply chain management, offering valuable insights for industry practitioners and researchers in the field of operational excellence.

Keywords: Simulation modeling, penalty cost, supply chain, backorder

OTOMOTİV SEKTÖRÜNDEKİ BİR FİRMANIN ÜRETİM SİSTEMİNİN SİMÜLASYON İLE MODELLENMESİ VE İYİLEŞTİRİLMESİ

ÖZ

Bu tez, otomotiv endüstrisinde üretim sistemlerinin optimizasyonu üzerine kapsamlı bir çalışma sunmaktadır. Araştırma, özellikle ürün teslimindeki gecikmeleri (backorder) azaltmaya ve tedarik zinciri verimliliğini artırmaya odaklanmaktadır. Çalışmada, ileri simülasyon modelleme tekniklerini Endüstri 4.0 prensipleriyle bütünleştiren yenilikçi bir metodolojik çerçeve kullanılmıştır. Araştırma dört aşamada yapılandırılmıştır: Problem belirleme, süreç haritalama, simülasyon modeli geliştirme ve çıktı analizi. Bir otomotiv üretim tesisinde gerçekleştirilen vaka çalışması, bu çerçevenin uygulamasını göstermektedir. Araştırmada, mevcut sistemi modellemek, alternatif senaryolar geliştirmek ve optimize edilmiş bir sistem tasarlamak için ARENA simülasyon yazılımı kullanılmıştır. Çalışma, sistem performansını değerlendirmek amacıyla istatistiksel analiz, süreç optimizasyonu ve tasarımı ve ekonomik karşılaştırmalar içermektedir. Temel bulgular, üretim süreçlerinin ve kaynak planlamanın stratejik olarak yeniden yapılandırılması yoluyla sistem verimliliğinde önemli iyileştirmeler ve gecikmelerde azalma olduğunu ortaya koymaktadır. Bu araştırma, tedarik zinciri yönetiminde simülasyon tabanlı optimizasyonun hem teorik anlaşılmasına hem de pratik uygulamasına katkıda bulunmakta, operasyonel mükemmellik alanındaki endüstri uygulayıcıları ve araştırmacılar için değerli içgörüler sunmaktadır.

Anahtar Kelimeler: Simülasyon modelleme, ceza maliyeti, tedarik zinciri, sipariş gecikmeleri

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ABBREVIATIONS

SCM :	Supply Chain Management
KPI :	Key Performance Indicator
IoT :	Internet of Things
NR :	Number in Resource
NQ :	Number in Queue
ROI :	Return on Investment



CHAPTER ONE

INTRODUCTION AND RESEARCH CONTEXT

The 21st century has seen the emergence of ever-increasing consumer demand, the production of more products from limited and diminishing resources, complexity of processes, and the digital transformation of the business world, commonly referred to as Industry 4.0 (Ghobakhloo, 2020). As a result of the exponential acceleration of technological development with Industry 4.0, many companies have entered the digitalization process. Digital transformation is essential for companies to compete in a rapidly changing environment. This transformation has led to businesses to maximize their profitability and adopt the goal of operational excellence by reducing waste. The ability to objectively solve highly complex problems and its speed is one of the key benefits of digital transformation. There is considerable scope for creative solutions in Industry 4.0 solutions, large-scale simulations, and artificial intelligence (AI) applications. (Malega et al., 2022). As a result of the increasingly competitive environment created by the global economy, in order to be competitive, companies have focused on increasing their profitability by minimizing their production inputs. Digital transformation should not only be seen as a tool to increase the profitability of companies, but organizations should be treated holistically, as it implies a permanent change that can affect different aspects of the business. Sustainability, corporate culture, and the quality of the data collected are just some of the aspects affected. (Wolf et al., 2018). This study aims to optimize operational efficiency and boost profitability for the subject company through a comprehensive analysis of its production processes.

A powerful method for modelling complex systems is simulation that is used to understand the behavior and performance of a system and to evaluate the outputs of different scenarios. A design-size system that has not yet been realized can be modeled or used to improve existing systems. In this way, before the investment is made, information about the system behavior and outputs can be obtained and a feasibility analysis can be made. This can be a huge advantage in terms of the costs involved. Furthermore, recurring problems, bottlenecks, and areas for improvement in existing systems can be easily identified and the system improved. (Altıok, 2010).

Especially since the problems caused by stochastic systems cannot be predicted in advance, the ability to model different scenarios in a computer environment, to perform analyses in design

scenarios and to take actions in accordance with these results makes it possible to solve many problems before they occur. The interpretation derived from this; simulation modelling is useful for companies that need a feasibility study prior to making an investment.

Operational inefficiencies of companies cause results such as not meeting customer demand on time (losing customers in the long run), incurring penalty costs due to exceeding the committed time, and reducing the profitability of the company. Since the penalty costs paid by the company are considered to be high, this study considers the company as a case study and aims to optimize it in order to increase its profitability.

1.1 Economic Impact of Backorders on Companies

Companies prefer to allow backorders depending on the industry's conditions, company strategies and goals. When forecasting the buying behavior of customers, it is found that consumers prefer to have their demands placed on backorder when there is a shortage of stock. (Hajek et al., 2020) Nowadays companies that can provide the product in the shortest time dominate the market and have the highest market share. Especially in industries such as the automotive industry, where minutes are of great importance in material supply, companies need to allow an optimum level of backorder to reach their sales targets. In case customers are willing to wait, although there is a penalty cost for delay, companies maintain their sales and increase their profitability with an effective backorder management. Implementing a detailed backorder management system can help companies secure future sales and ensure efficient inventory replenishment.

For instance, companies that work on a project basis and have high inventory investment costs prefer allowing backorder because it can provide space saving, reduce holding cost, and ensure itself for situations such as customer's order cancellation. Particularly in these days when there is a liquidity problem, the fact that a large amount of money is not tied to stock provides a huge advantage for companies.

Backorder has some advantages for companies as well as some disadvantages that it brings with it. One of the most critical and risky disadvantages of backorder is the penalties paid due to timeout, and it causes heavy fines, and it directly affect to project profit. In Beaumart (2014), The

Berlin Airport project was planned to be opened in 2011 with a cost of 2.5 billion euros, when the project was postponed to 2017, the cost was calculated as approximately 8 billion euros. Considering that the airport was opened in 2020, a cost beyond what was calculated occurred. In the same study, the contract signed in 2010 for the construction of the concert hall called Elbphilharmonie in Hamburg, the project cost increased from 114 million euros to 575 million euros in 2014. Considering that the project was completed in 2017, it can be interpreted that this cost is also higher than calculated in 2014. Stuttgart 21 is a railway stop between Stuttgart and Augsburg. The project cost, which was determined as 2.5 billion euros in 1995, was calculated as 6.5 billion euros in 2013. The cost of the project, which is planned to be completed in 2025, is expected to exceed the estimated cost.

The concept of backorders, while potentially beneficial, carries significant risks and challenges, especially in large-scale projects. The examples from major German infrastructure projects—the Berlin Airport, Elbphilharmonie concert hall, and Stuttgart 21 railway project—vividly illustrate the severe financial consequences of delays and mismanagement. These cases demonstrate dramatic cost escalations, significant time overruns, and consistent underestimation of project complexity. The pattern of underestimating both time and cost requirements point to systemic issues in project planning and risk assessment. These examples underscore the critical importance of accurate project planning, robust risk management, and effective backorder management. They highlight the need for more conservative initial estimates, built-in contingencies, regular reassessments, and improved mechanisms for managing delays. In the context of backorder management, these cases serve as cautionary tales, emphasizing the need for businesses to carefully balance the potential benefits of backorders against the risks of delayed delivery and associated penalties. Effective backorder strategies must include realistic timelines, clear communication with stakeholders, and agile processes to adapt to unforeseen challenges.

1.2 Research Aim and Scope

The aim of this study is maximizing the profitability of a company operating in automotive sector to be more competitive in global market and therefore increase its sales volume and market share. Delays in material supply pose a high risk, as line downtimes in the automotive sector cause very high costs. Especially in project timeout, high penalty costs are paid and the effect of penalty

costs on project profitability is quite high. The goal is to increase operational excellence by minimizing the bottlenecks experienced in the material supply and production processes to minimize the penalty costs. In line with this goal, the production line of the machining workshop was simulated using ARENA simulation software to identify and eliminate bottlenecks and to increase resource utilization rate and efficiency throughout the entire supply chain.

Since the automation factory works on a project basis, the arrival date of the projects is unpredictable and stochastic, and for this reason, situations that are very difficult to manage are encountered. Observing the system behavior with different scenarios and analyzing what constitutes a constraint will greatly support the company in taking the necessary actions in advance. One of the main problems is product cycle times can be very long due to the problems occurred in the supply of materials from the workshop.

1.3 Research Objectives and Questions

This research endeavor was undertaken with three primary objectives, as delineated in Figure 1.1. Objectives 1 and 3 can be categorized as strategic imperatives for the organization, with their successful attainment potentially yielding long-term enhancements to the company's financial performance. Conversely, Objective 2 focuses on operational excellence and can thus be classified as a tactical goal. The impact of Objective 2 is quantifiable in terms of process efficiency improvements in the short to medium term. These objectives collectively address both strategic and operational aspects of the organization, with the potential to yield substantial improvements in overall performance and competitive positioning.

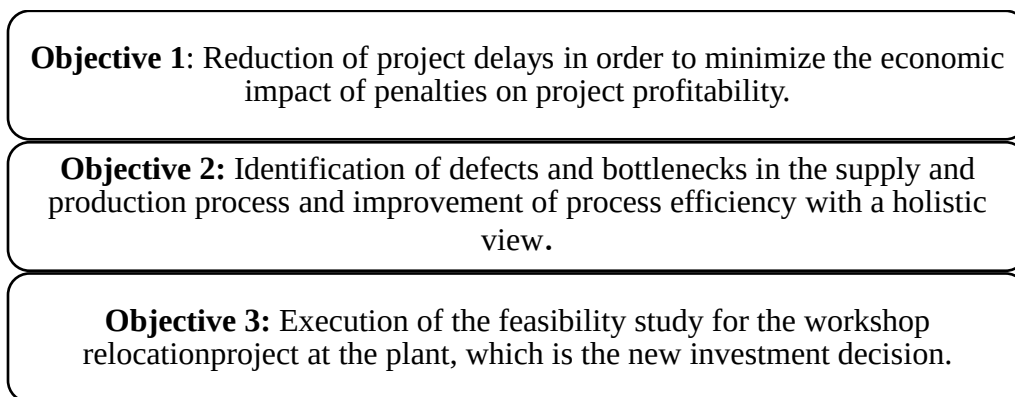


Figure 1.1 Objectives of Thesis

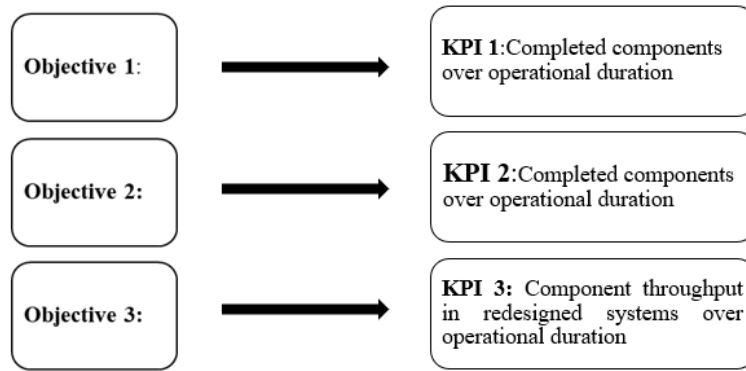


Figure 1.2 Objective-Aligned Key Performance Indicator Formulations

Figure 1.1 delineates the thesis objectives, while Figure 1.2 presents the key performance indicators (KPIs) that facilitate the analysis of objective attainment. The KPIs depicted herein are predominantly quantifiable through mathematical means; however, it is noteworthy that there exist additional performance metrics classified as non-tangible.

Sustainability emerges as one of the paramount objectives among these non-tangible metrics. The equilibration of workload intensity for personnel holds significant importance in mitigating the risk of over-exertion. Furthermore, the strategic design of positions to incorporate redundancy through backup measures represents a crucial long-term initiative for corporate entities.

The juxtaposition of tangible and intangible performance indicators provides a comprehensive framework for assessing organizational efficacy. This multifaceted approach to performance evaluation aligns with contemporary management theories that emphasize holistic organizational health beyond mere quantitative benchmarks. The inclusion of sustainability as a key non-tangible metric reflects the growing recognition of its importance in modern corporate strategy. This aligns with the triple bottom line concept, which posits that organizational success should be measured not only by financial performance but also by social and environmental impacts. The emphasis on workload balancing and position redundancy underscores the significance of human resource management in achieving long-term organizational resilience. These strategies are congruent with current research on organizational behavior and human capital management, which highlight the

importance of employee well-being and institutional knowledge preservation for sustained corporate success.

The primary objective of this research is to provide a comprehensive and quantifiable definition of the problem by calculating the monetary equivalence of penalty costs. Subsequently, the study aims to analyze the causal factors contributing to these penalty costs. The final phase involves developing a strategic roadmap outlining the necessary steps for mitigating these identified causes.

The secondary objective focuses conducting a holistic analysis of the root causes underlying inefficiencies across various departmental processes. This analysis will inform the development of alternative solutions designed to either eliminate or significantly reduce the impact of the most critical causal factors.

The tertiary aim of this study is to evaluate the feasibility of relocating the workshop, currently situated in a separate facility, to within the main factory premises. The proposed simulation modeling methodology will be employed to simulate the potential impact of this investment decision on overall processes. Should the projected productivity increase prove sufficient, the study will provide actionable feedback to the organization regarding implementation strategies.

A comprehensive literature review has been conducted to support this research. Initially, seminal studies in simulation modeling were examined to elucidate the types of problems amenable to this methodology. Subsequently, research investigating and applying process analysis techniques for developing valid and effective simulation models was reviewed. Finally, an in-depth analysis was performed on papers utilizing simulation-based optimization approaches for enhancing production efficiency across various domains. This analysis was crucial in determining the most appropriate methodological approach given the specific characteristics of the problem at hand.

1.4 Thesis Structure and Chapter Overview

This study is structured in a systematic manner, comprising eight distinct chapters that collectively address the research objectives and contribute to the field of study. The thesis commences with Chapter 1: Introduction and Research Context, which establishes the foundation

for the subsequent discourse. This is followed by Chapter 2: Supply Chain Management Focusing on Backorders, which provides essential background information for the study. The literature review is divided into five sections in Chapter 3: Literature Review on Simulation Modelling and Optimization of Production Systems to cover the literature all the necessary steps of proposed methodology. Chapter 4: Principles and Applications of Simulation Modeling. This chapter allows for a comprehensive examination of both theoretical and practical aspects of the subject matter. Chapter 5: The Proposed Methodological Framework introduces the approach developed in this research. Subsequently, Chapter 6: Application of Proposed Methodology in an Automotive Industry Case Study. Finally, Chapter 8: Conclusions synthesizes the findings and outlines potential avenues for further investigation. This structure facilitates a logical progression from theoretical foundations to practical application, culminating in a comprehensive analysis of the research outcomes and their implications for both academia and industry.

The following provides a concise synopsis of the content addressed within each chapter of this thesis.

Chapter one sets the stage for the thesis by providing an overview of the research topic. It introduces the concept of Industry 4.0 and the pivotal role of simulation modeling within this context. The chapter outlines the thesis's objectives, research questions, and the significance of the study. It also presents the methodology and structure of the thesis, offering the reader a roadmap of what to expect in the subsequent chapters.

Chapter two provides comprehensive examination of supply chain management (SCM), laying the foundation for understanding its role and significance in modern industry. The chapter begins by defining SCM and discussing its evolution from traditional logistics focus to a complex, strategic framework integral to organizational success. It emphasizes the importance of SCM in creating customer value and achieving a sustainable competitive advantage. The chapter then systematically breaks down the components of SCM a complex, strategic framework integral to organizational success. It emphasizes the importance of SCM in creating customer value and achieving a sustainable competitive advantage. The chapter then systematically breaks down the components of SCM.

Chapter three delves into the core principles of simulation modeling, offering readers a comprehensive introduction to the subject. It discusses the various domains where simulation modeling is applied, highlighting its versatility and importance across different industries. The chapter also addresses the challenges encountered in the application of simulation modeling, such as computational complexity and model validation. The stages of developing a simulation model, from conceptualization to implementation, are outlined in detail. Furthermore, a classification of different types of simulation—such as discrete-event, agent-based, and Monte Carlo simulations—is provided to give readers a clear understanding of the field's breadth.

In chapter four, an extensive literature review is presented, focusing on the intersection of simulation modeling and production optimization. The chapter evaluates current research and methodologies, identifying gaps that the thesis aims to address. It also reviews various optimization techniques that have been integrated with simulation models to enhance production processes, discussing their strengths and limitations.

Chapter five offers a detailed description of the specific problem faced by the company in question. It articulates the operational inefficiencies or challenges that necessitate the adoption of simulation modeling and optimization techniques. The chapter then proposes a solution method, justifying its potential effectiveness in addressing the company's issues. This proposed method is contextualized within the framework of Industry 4.0, emphasizing its relevance and timeliness.

In chapter six, the thesis provides an overview of the company's profile, including its history, mission, products, and market position. This background information is crucial for understanding the significance and impact of the operational problem discussed in the previous chapter. The chapter illustrates how the problem affects the company's performance and the potential benefits of solving it through the proposed method.

Chapter seven is dedicated to the practical application of the proposed solution method within the company. It describes the step-by-step process, starting from data collection and model building to the execution of the simulation and analysis of results. The chapter details the implementation challenges and how they were overcome, as well as the adjustments made to tailor the solution to the company's specific needs.

The final chapter presents the results of the thesis, analyzing the outcomes of the applied solution method. It discusses the implications of the findings for the company, including the improvements in production efficiency and cost-effectiveness. The chapter concludes with recommendations for the company based on the results, suggesting how the method can be refined and potentially applied to other areas of operation. It also outlines future research directions, building on the insights gained from the thesis.

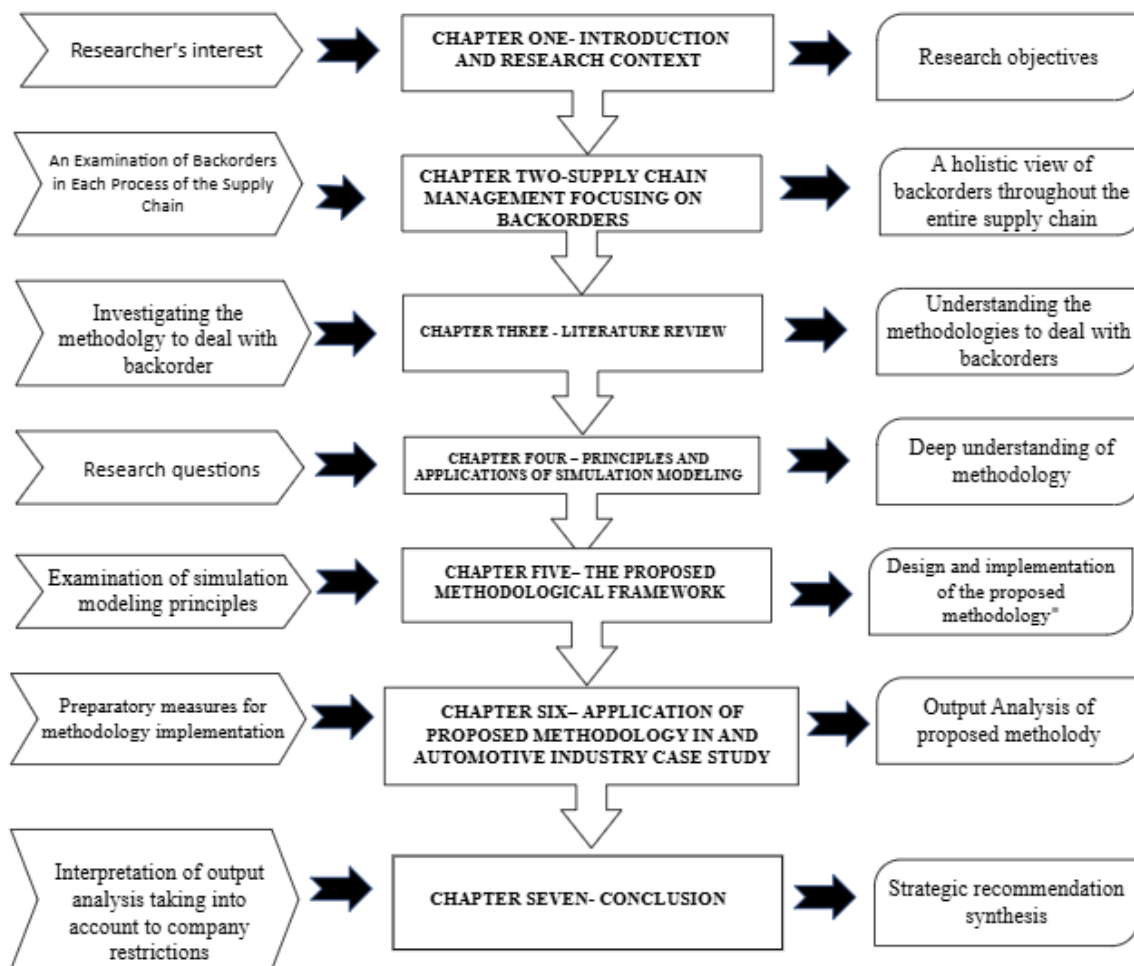


Figure 1.3 Structural Framework of the study

CHAPTER TWO

SUPPLY CHAIN MANAGEMENT FOCUSING ON BACKORDERS

SCM is a multifaceted discipline that orchestrates the movement of goods, the flow of data, and the management of financial transactions across the entire lifecycle of a product (Lu, H. et al, 2024). From the initial acquisition of raw materials to the final delivery of the product to the consumer, SCM seeks to optimize and streamline operations to enhance efficiency and customer satisfaction. Figure 2.1, as referenced below, visually encapsulates this intricate network, illustrating the interconnectedness of various SCM components. The complexity of SCM is further underscored by its integration of multiple business functions, including procurement, manufacturing, logistics, and distribution. Each of these functions plays a crucial role in ensuring the smooth flow of products and information throughout the supply chain. For instance, procurement focuses on sourcing raw materials and components, while manufacturing transforms these inputs into finished goods. Logistics then manages the storage and transportation of these goods, and distribution ensures they reach the end consumers efficiently.

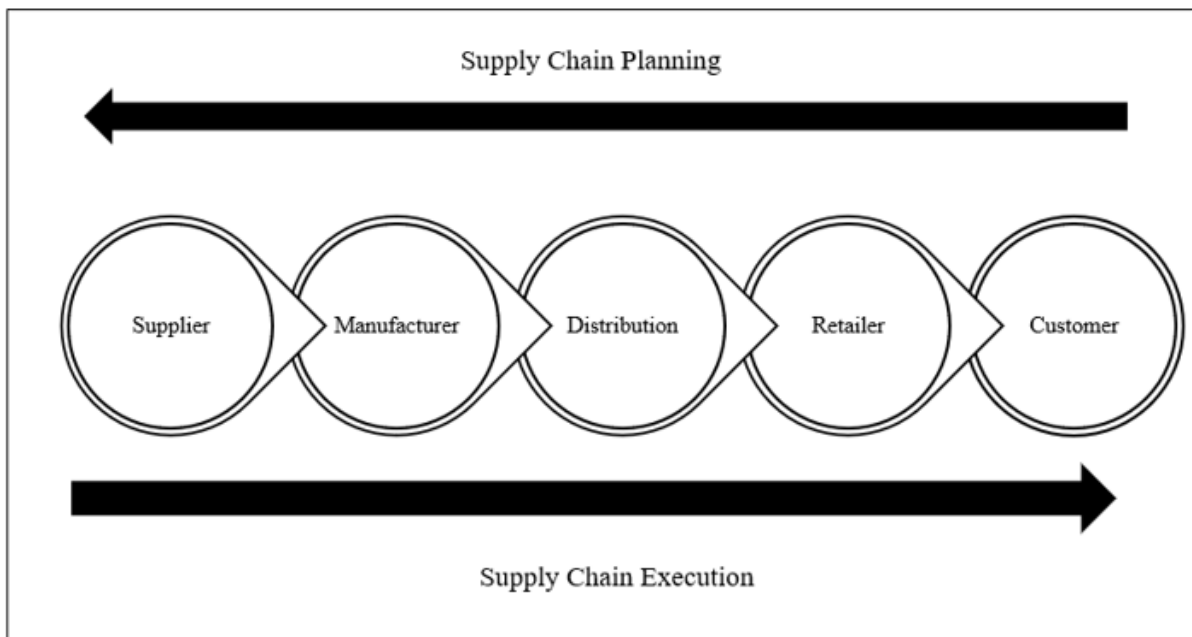


Figure 2.1 Illustration of supply chain process

2.1 Industry 4.0 and Supply Chain Management: Leveraging Digitalization for Operational Excellence and Backorder Reduction

The advent of Industry 4.0 has ushered in a new era of digital transformation in manufacturing and supply chain management (Lasi et al., 2014). This paradigm shift, characterized by the integration of cyber-physical systems, Internet of Things (IoT), and cloud computing, has profound implications for supply chain operations and performance optimization (Xu et al., 2018).

The convergence of Industry 4.0 technologies and supply chain management offers unprecedented opportunities to address longstanding challenges in supply chain operations (Tjahjono et al., 2017). One of the most significant impacts is the potential to minimize bottlenecks through enhanced visibility, real-time data analytics, and predictive capabilities (Ivanov et al., 2019). The digital thread that runs through an Industry 4.0-enabled supply chain allows for seamless information flow, enabling organizations to identify and mitigate bottlenecks proactively (Buer et al., 2018).

A key area where Industry 4.0 demonstrates substantial promise is in the reduction of backorders and associated penalty costs (Dolgui et al., 2020). Backorders, which occur when demand exceeds available inventory, can lead to significant financial implications through penalty costs and lost sales (Chen et al., 2017). The digitalization brought about by Industry 4.0 offers several mechanisms to address this issue across various aspects of supply chain management (Hofmann & Rüsch, 2017):

- Strategic Planning in Supply Chain Operations (Referred to in Chapter 2.2)
- Procurement Strategies and Their Impact on Backorder (Referred to in Chapter 2.3)
- Production Planning and Scheduling Methodologies (Referred to in Chapter 2.4)
- Inventory Management Systems and Backorder Mitigation (Referred to in Chapter 2.5)
- Warehousing Optimization for Backorder Mitigation (Referred to in Chapter 2.6)
- Logistics and Distribution in Backorder Management (Referred to in Chapter 2.7)

2.2 Strategic Planning in Supply Chain Operations

Each organization needs to manage its own resources to maximize benefits. The planning process identifies the customer's demand, and the sources of supply required to meet the demand. Supply chain teams are accountable for organizing supply sources in a timely manner and making them available to begin production to ensure that all required element is available. Enhancing relationships with sellers is also vital. As part of the planning process, several departments are co-operating to provide forecasts to suppliers

Organizations are tasked with the critical responsibility of managing their resources effectively to maximize benefits. This encompasses a strategic allocation of financial, human, and material resources to ensure that the organization's operations are streamlined and that it maintains a competitive edge in the marketplace. The planning process is central to this resource management, serving as the blueprint for aligning the organization's capabilities with market demands. The planning process begins with a thorough analysis of customer demand. This involves collecting and interpreting data from various sources, including market trends, historical sales figures, and customer feedback, to predict future demand accurately. Understanding what customers will need—and when they will need it—allows the organization to tailor its supply chain activities accordingly.

Once demand is identified, the next step is to determine the sources of supply that can satisfy this demand. This could involve engaging with existing suppliers, developing new supply sources, or even considering changes to in-house production capabilities. Supply chain teams are then responsible for the timely organization of these supply sources, ensuring that materials and products are available when production is scheduled to start. This synchronization is crucial to prevent bottlenecks and delays in the supply chain. A key aspect of the planning process is the development and enhancement of relationships with suppliers, also known as vendors or sellers. Strong supplier relationships are instrumental for achieving a responsive and flexible supply chain. By working closely with suppliers and engaging in collaborative planning, organizations can ensure a more reliable flow of materials and potentially benefit from innovations and efficiencies that suppliers bring to the table.

The planning process is not confined to a single department within an organization. It requires a cross-functional effort where various departments such as procurement, operations, sales, and finance collaborate. This collaboration is essential for creating accurate and comprehensive forecasts that can be communicated to suppliers. These forecasts are critical for suppliers to plan their production and logistics to meet the organization's needs. Providing suppliers with forecasts is a proactive measure that allows them to adjust their operations to meet the upcoming demand. This can involve sharing projections of order volumes, delivery schedules, and even changes to product specifications. By giving suppliers visibility into future requirements, organizations can mitigate the risk of supply disruptions and ensure that all elements required for production are available when needed.

In summary, the planning process in supply chain management is a multifaceted and dynamic task that requires careful resource management, demand planning, supplier relationship management, and cross-departmental collaboration. It is a forward-thinking approach that prepares the organization to meet customer demand efficiently and effectively, ensuring that all elements of the supply chain are synchronized, and that the organization is poised to deliver value to its customers.

2.3 Procurement Strategies and Their Impact on Backorder

It is important to make a distinction between procurement and sourcing. Sourcing is part of the procurement, and it's the whole process that leads to successful supply chain management. Procurement is the acquisition of all equipment, materials used to achieve the target in terms of production outputs. In other words, ensure all necessary inputs are available to produce final product. Figure 2.2 illustrates the stages of the procurement process.

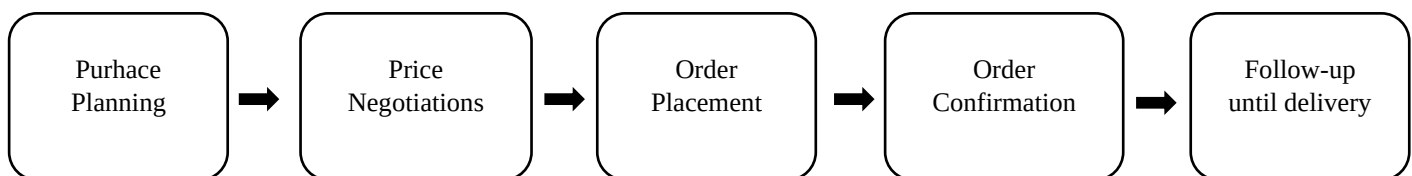


Figure 2.2. Stages of Procurement Process

The primary objective of sourcing is cost-effectiveness and quality standards. The sourcing process includes the control and verification of the quality of the goods, the analysis of the feasibility of the suppliers in terms of capability analysis, reliability, and financial and operational risks.

2.4 Production Planning and Scheduling Methodologies

Production planning consists of drawing up a plan to make the most of the available resources to be faithful to the time requested by the customer. In other words, production planning in accordance with the time commitment of the sales department or the project timeline. Since this thesis is based on data from a real company working on a project basis, it can be considered as the project deadline. Typically, organizations must produce multiple products in the same plant and provide a variety of customers. As a result, it is essential to prioritize production based on timelines and production capacity. An appropriate allocation of resources for each production line is crucial to ensure quality standards.

2.5 Inventory Management Systems and Backorder Mitigation

Inventory management allows companies to find the optimum number of raw materials needed to meet future orders. Shortage of raw materials can result in delivery delays, leaving customers with a negative impression. It is also critical to maintain the optimal level of finished products to manage the expected orders or unexpected order known as safety stock. In addition, effective inventory management avoids the risk of excessive inventory levels and excess inventory in the long run.

Inventory management is critical for businesses of all sizes, as it helps ensure that customers always have access to the products they need, while also helping to keep costs low and profits high. Inventory management helps businesses track when products need to be restocked, when to order new products, and how to store and manage their inventory efficiently. It also helps businesses better forecast and plan for future purchases and manage their cash flow more

effectively. By having an effective inventory management system in place, businesses are able to run more efficiently and increase their profits.

2.6 Warehousing Optimization for Backorder Mitigation

Warehousing is the practice of storing goods in a secure facility for the purpose of distribution and inventory management. Warehousing is an integral part of the supply chain and is a critical element of logistics. Warehousing is important for companies because it provides a secure place to store goods until they are needed, and it allows for efficient and cost-effective distribution of goods to customers. Warehousing also helps to reduce the risk of product damage and loss, and it enables companies to optimize inventory control to ensure the right goods are available when and where they are needed.

Warehousing is where they store goods for a variety of purposes. Such products may be in the form of raw materials, finished or semi-finished products. However, the primary objective of a warehouse is to minimize freight costs as much as possible. The management of warehouses at different sites reduces the overall costs of delivering products to customers in this region. Warehouses may hold the goods for an extended period to benefit from higher prices. Companies also save the raw material to be used in scarcity days.

2.7 Logistics and Distribution in Backorder Management

Logistic is a branch of applied mathematics and operations research that deals with the optimization of complex processes or systems. It is used for planning, implementing, and controlling processes that involve the flow of goods and services. Logistic also involves the management of resources such as personnel, materials, vehicles, and information.

Additionally, it is used to optimize the delivery of goods and services from the point of production to the point of consumption. Logistics is an important part of any company's operations. It ensures that goods are delivered on time and in the right quantities to the right customers and locations. Logistics helps companies save money by reducing inventory costs and increasing efficiency. It also helps them to better manage their resources, maximize profits, and improve

customer satisfaction. Logistics can also be used to improve service levels and reduce delivery times.

Effective supply chain management offers numerous benefits, both directly and indirectly, as main advantages outlined below.

- Timely and undamaged deliveries increase customer satisfaction and continuity.
- Effective supply chain management lowers operating costs and generates savings.
- It allows to respond promptly to any requests and prevent losses in case of unforeseen circumstances.
- It enables to be prepared for sudden market changes known as agility and flexibility.
- It ensures the minimization of production, inventory, and logistics and penalty costs with proper inventory management.
- It provides shorter lead times and product life cycle.

Through the development of Industry 4.0, companies have become more competitive for their place in the global economy. To compete in challenging competitive conditions, the Operational Excellence approach emerged with a focus on issues such as fastest delivery, sales growth, and increased profitability. Industry 4.0 has enabled the management of smart processes and has provided a new paradigm for the management of industry (Moeuf et al., 2017).

Given that one of the key objectives in this study is to minimize the cost of penalties resulting from project delays, process improvements to reduce cycle time and expedite delivery are being considered. To ensure the shortest cycle time all processes from the sourcing of raw materials to the delivery of products, must be considered and improved in their entirety. As stated in the introduction, the most efficient way to reduce the cost of penalties is through efficient supply chain management. When we examine best practices in supply chain management, we find many different software. The purpose of the software which brings additional sophistication to the supply chain management system used is to automate and digitize the parts that need to be improved once bottlenecks are detected. However, detecting bottlenecks are predecessor of improvements, simulation is a very handy and beneficial method.

CHAPTER THREE

LITERATURE REVIEW ON SIMULATION MODELLING AND OPTIMIZATION OF PRODUCTION SYSTEMS

3.1 Research on Backorders in Supply Chain

The economic implications of backorders in supply chain management have garnered significant attention in recent years, particularly as businesses navigate increasingly complex multi-channel environments. This phenomenon has spurred a wealth of research examining various facets of backorder impacts on supply chain performance and strategy.

In the context of dual-channel supply chains, Gao et al. (2019) provide a comprehensive analysis of how backorders influence pricing strategies, channel selection, and overall profitability. Their findings underscore the critical role of backorders in shaping optimal strategies within these complex ecosystems. This research is particularly pertinent given the growing prevalence of omnichannel retail strategies; a trend further explored by Chen et al. (2017) in their examination of supply chains featuring manufacturer-owned online channels. Their work illuminates the intricate interplay between backorders, price competition, and channel performance in modern retail landscapes.

The uncertainty inherent in market demand adds another layer of complexity to backorder management. Chen and Wang (2016) delve into this issue, investigating pricing and inventory decisions under conditions of uncertain demand and partial backordering. Their research highlights the significant impact of backorder rates on supply chain performance, emphasizing the need for flexible and adaptive strategies in inventory management and pricing.

Financial considerations also play a crucial role in backorder dynamics. Tiwari et al. (2016) explore this dimension, examining supply chain coordination under trade credit conditions and partially backordered shortages. Their work provides a more holistic view of backorder impacts, integrating financial aspects with traditional inventory management concerns.

Operational strategies to mitigate backorder costs have also been a focus of recent research. Paterson et al. (2018) offers a comprehensive review of lateral transshipment models, synthesizing recent developments in using inter-location stock transfers to reduce the negative impacts of

stockouts and backorders. This approach represents an important tactical tool in modern supply chain management.

The relationship between production quality, backorders, and overall supply chain performance is explored by Sarkar and Saren (2016). Their investigation into economic production quantity models in imperfect production systems, incorporating backorders and inspection errors, reveals the complex interrelationships between quality control, production planning, and backorder management.

Collectively, these studies paint a picture of backorder management as a multifaceted challenge requiring a comprehensive approach. Effective strategies must consider pricing dynamics, channel management, inventory policies, financial implications, and quality control measures. As supply chains continue to evolve in complexity and global reach, understanding and mitigating the economic effects of backorders remains a critical area of focus for both academics and practitioners in the field of supply chain management.

This integrated body of research underscores the need for adaptive, holistic approaches to backorder management that can respond to the dynamic nature of modern supply chains. The complexity of contemporary supply networks, characterized by global reach, intricate interdependencies, and heightened customer expectations, necessitates a multifaceted strategy for mitigating backorders. Such strategies must not only address immediate inventory shortfalls but also anticipate potential disruptions and optimize overall supply chain performance. Future research directions may include exploring the impact of emerging technologies, such as artificial intelligence and blockchain, on backorder management. Artificial intelligence, for instance, could revolutionize demand forecasting and inventory optimization, potentially reducing the occurrence of backorders through more accurate predictions and real-time adjustments.

Table 3.1 categorizes the methods and tools employed for managing backorders in the supply chain, based on a comprehensive review of the literature. This categorization serves as a valuable reference point for both practitioners and researchers, offering a structured overview of the diverse approaches available for addressing the persistent challenge of backorders in modern supply chains

Table 3.1 Literature Review Categorization Based on Methods and Tools

Study	Authors	Year	Methods Used	Tools Used
The Impact of Backorders on Dual-Channel Supply Chains	Gao, Y., Wen, X., & Ding, X.	2019	- Mathematical modeling - Game theory analysis - Numerical simulations	- Numerical computing environment - Statistical software
Pricing and inventory decisions in a supply chain with uncertain demand and partial backordering	Chen, X., & Wang, X.	2016	- Stochastic programming - Sensitivity analysis - Numerical examples	- Optimization software - Monte Carlo simulation tools
Coordinating a supply chain with a manufacturer-owned online channel	Chen, J., Zhang, H., & Sun, Y.	2017	- Game-theoretic models - Nash equilibrium analysis - Comparative statics	- Game theory software - Mathematical modeling software
Impact of trade credit and inflation on retailer's ordering policies	Tiwari, S., Cárdenas-Barrón, L. E., Khanna, A., & Jaggi, C. K.	2016	- Mathematical modeling - Optimization techniques - Sensitivity analysis	- Optimization software - Spreadsheet tools
Inventory models with lateral transshipments: A review	Paterson, C., Kiesmüller, G., Teunter, R., & Glazebrook, K.	2018	- Systematic literature review - Meta-analysis - Conceptual modeling	- Reference management software - Qualitative data analysis software
Product inspection policy for an imperfect production system	Sarkar, B., & Saren, S.	2016	- Mathematical modeling - Optimization techniques - Numerical examples	- Optimization software - Statistical software

3.2 Research on Simulation Optimization Methodologies

There is various categorization in simulation optimization methods in literature as explained below. In this study, the simulation-based optimization approach was separated into two main categories according to the result obtained: Global optimization solution methods and local (near) optimum solution methods. Which approach to use depends on the type of problem being solved. Review papers were examined to better understand and internalize the literature on simulation optimization approaches.

In Tekin and Sabuncuoglu (2004), simulation optimization techniques were categorized as given in Figure 1 according to characteristics of the problem such as the shape of the response surface, objective functions, parameter spaces. Furthermore, the advantages and disadvantages of techniques were analyzed elaborately. Since the various structures of the problems, it is not possible to solve all problems with a single method. Therefore, it was tried to solve the problems that spread over a wider area with more powerful methods. Most robust simulation software works with meta-heuristics. It was stated that the best results were obtained by using metaheuristics and traditional methods (RSM, gradient-based) together, and more hybrid methods would be used in the future.

Ammeri et al. (2010), gave a comprehensive literature view with different categories such as response surface (global or local optimization), objective functions (single or multiple objectives), and parameter spaces (discrete or continuous parameters) in simulation approach optimization.

Figure 3.1 presents a hierarchical classification of optimization problems and their associated solution methodologies. At the apex, optimization problems are bifurcated into two primary categories: Local Optimization and Global Optimization. Local Optimization is further delineated into two subcategories: Discrete Decision Space and Continuous Decision Space. The Discrete Decision Space encompasses methods such as Ranking and Selection, Multiple Comparison, Ordinal Optimization, and Random Search. It also includes more sophisticated approaches like Simplex/Compelx Search, Single Factor Method, and Hooke-Jeeves Pattern Search. Under the Continuous Decision Space, we find techniques including Response Surface Methodology, Finite Difference Estimates, and Perturbation Analysis. Additionally, this category incorporates

Frequency Domain Analysis and Likelihood Ratio Estimates. Global Optimization, on the other hand, is subdivided into Evolutionary Algorithms and Bayesian/Sampling Algorithms. The former includes methods like Tabu Search and Simulated Annealing, while the latter features the Gradient Surface Method and Stochastic Approximation. This comprehensive taxonomy illustrates the diverse array of methodologies available for addressing various optimization challenges, ranging from localized problem-solving approaches to techniques designed for global optimization scenarios. The classification provides a structured overview of the field, facilitating understanding of the relationships between different optimization strategies and their applicability to specific problem domains.

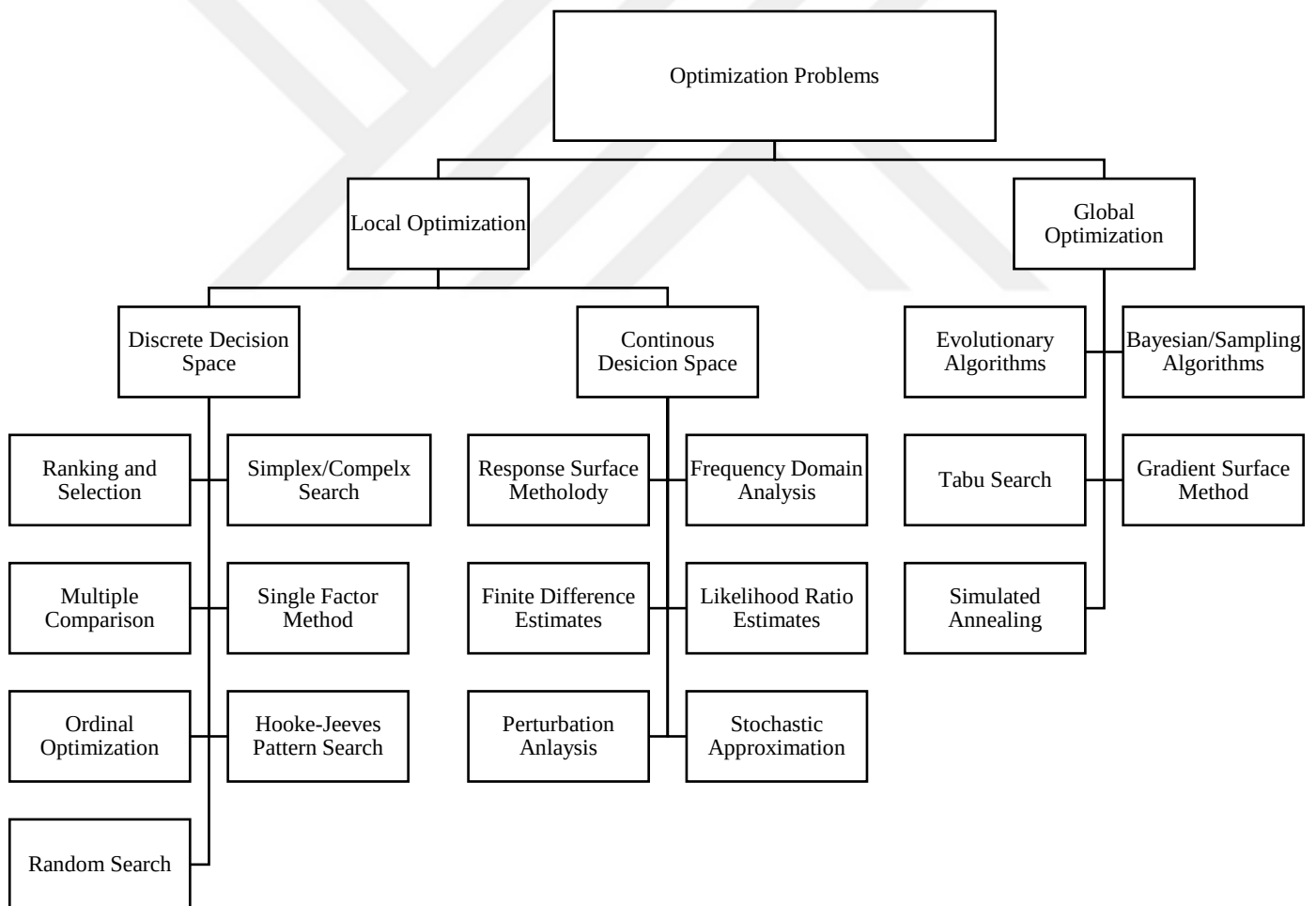


Figure 3.1 Categorization of Optimization Problems (Tekin and Sabuncuoglu (2004))

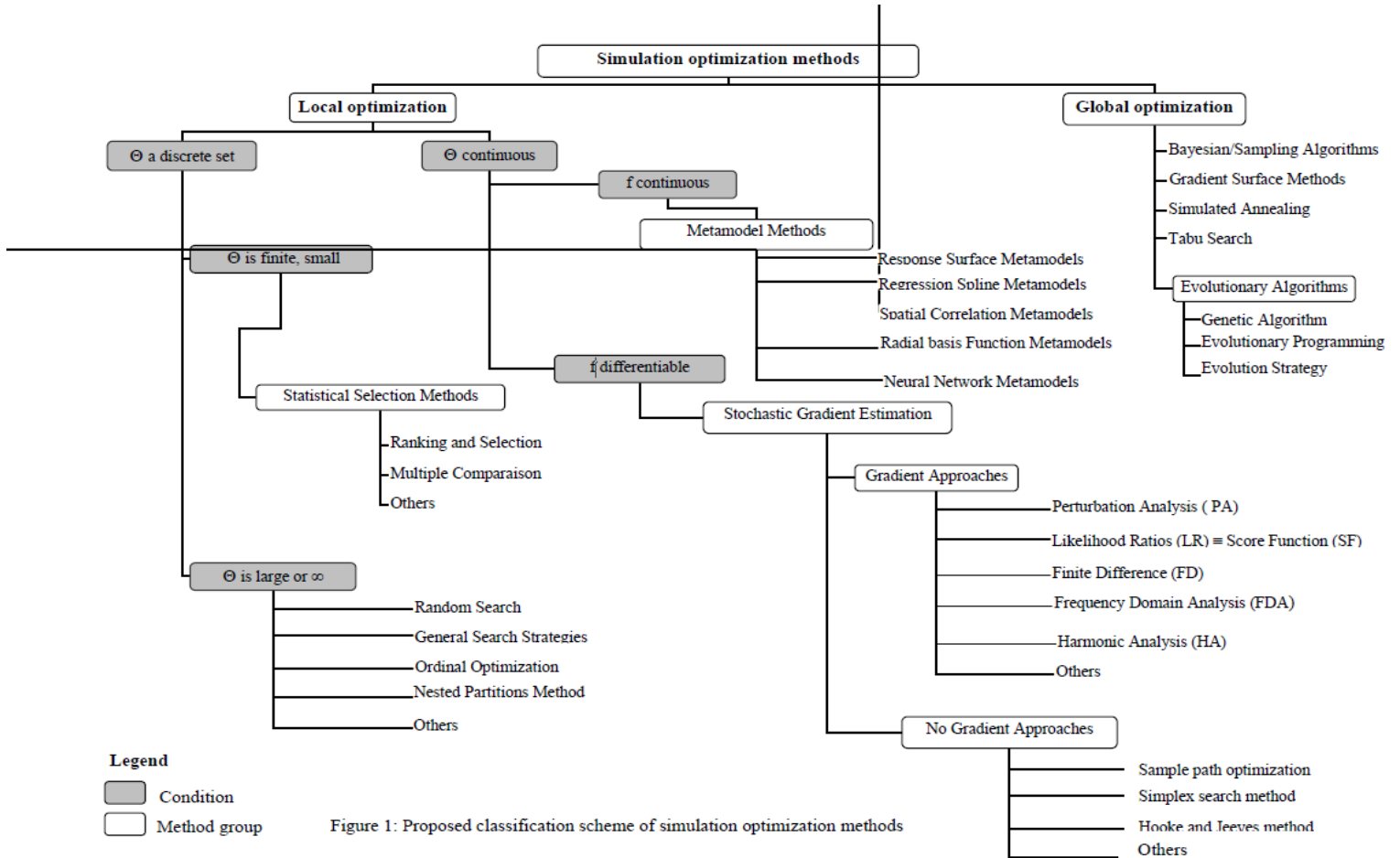


Figure 1: Proposed classification scheme of simulation optimization methods

Figure 3.2 Classification of simulation optimization methodologies

Figure 3.2 presents a comprehensive classification scheme for simulation optimization methods. The diagram delineates these methods into two primary categories: local optimization and global optimization, each with its distinct subcategories and approaches. This taxonomic structure offers a systematic overview of the field, encompassing a wide array of techniques ranging from statistical selection methods and gradient-based approaches in local optimization to evolutionary algorithms and Bayesian sampling methods in global optimization, thus providing a valuable framework for understanding and applying various simulation optimization strategies. Liu et al. (2018), studied simulation optimization method, which are used to eliminate the uncertainty and decision-making difficulties created by stochasticity in problems, were examined in detail. In these studies, a comprehensive overview was given on simulation optimization

approaches in specially manufacturing. The categorization of optimization problems was the same as given in Tekin and Sabuncuoglu (2004). The advantages and disadvantages of these approaches were discussed. Lugaresi and Matta (2018), examined real-time discrete simulation studies in detail. For a successful simulation, important points to be considered about all stages from data collection to validation were stated. Successful applications and methods were explained elaborately. With all the developments experienced, the necessity of more applications and literature studies were emphasized.

3.3 Research on Process Mapping Techniques

To solve real-life problems with simulation and tackle the low computational efficiency, processes must be analyzed very well. Therefore, process flows should be mapped in detail using the appropriate technique. Value Stream Mapping (VSM) is one the most efficient technique that gives a chance to observe bottlenecks in the whole process and it allows us to discover areas that are open to improvement. To establish an accurate simulation model, studies using the VSM method were examined.

In Bait et al. (2020) process simulation with Extended Value Stream Mapping (X-VSM) was used to minimize wastes and eliminate activities that did not add value to the process. Data acquisition, process analyzing, and validation of the model are fundamental for a sustainable simulation-optimization approach. Therefore, VSM and simulation model was combined to achieve a waste reduction in the production process. As a result, what-if scenarios were applied on the parameters and the system that gave the best result was selected.

After a year, Malega et al. (2021) a simulation-based approach was proposed to increase production efficiency due to a high number of model parameters and variability of the environment. Computer-aided Tecnomatix software was used to demonstrate that this approach improves production performance with the Plant Simulation tool. Layout optimization was done by grouping stations working together. A higher utilization rate was achieved by the relocation of the machines and the production amount was increased by reducing the production time. Statistical results of the comparison of the existing system and the improved system are given in the article. A large-scale experiment was conducted, and promising results were shown.

3.4 Research on Global Optimum Solution Methods

In this part studies on metaheuristic approach-based simulation optimization were viewed. Various metaheuristic methods can achieve a global optimal solution. Dengiz and Alabas (2000) proposed to use simulation optimization to analyze complicated systems with stochastic characteristics to increase the performance of the production system. Tabu Search Algorithm (TS) was implemented to find the optimum number of Kanban. TS and Random Search Algorithm (RS) were applied to the same problem to find the method that gave the best result. As a result of these study, it was recommended to use TS, which performs better than RS.

Spieckermann et al. (2000) presented a simulation-based approach which is a combination of meta-heuristics such as Genetic Algorithm (GA) and Simulated Annealing (SA) to solve body shop design problems including layout filling. A real case study was conducted at a German car manufacturer to test the suggested approach. In conclusion, the GA provided desired planning of the body shop process and was expected to be used more in the future.

Azadeh and Maghsoudi (2010) suggested using TS and Design of Experiment (DoE) to optimize the performance of the steelmaking process. Firstly, the process in detail was simulated by using Visual SLAM software, and the model was verified and validated. Moreover, RSM implemented to optimize decision variables and local optimum was achieved. However, DoE and TS methods combined and successfully applied to reach the global optimum.

Neubert et al. (2010) proposed to use TS to optimize the production process by determining hidden costs and eliminating wastes. The objective function includes multiple criteria however, the result of the simulation approach revealed that the best solution cannot be achieved with these targets. Therefore, the goal was achieved with a convenient solution. It is highly recommended using VSM to observe the whole process and ascertain the hidden costs and be able to waste them through VSM.

Koulouriotis et al. (2010) suggested using a GA to evaluate the manufacturing process for each assembly line by using discrete event simulation. Six types of pull control policies were compared, and the one giving the best results was found. In the article, it is stated that studies in this field will increase to solve the problems that come by stochasticity and Artificial Intelligence (AI) will contribute to this field.

Kuo and Yang (2011) suggested using Particle Swarm Optimization (PSO) with a similarity mutation algorithm to increase efficiency in assemble line design. A different algorithm such as PSO, Particle Swarm Optimization with Map Structure (PSOMS), two types of GAs (Type 1 and Type 2) was implemented successfully. Through the result of statistical tests demonstrates suggested algorithm (PSO) is way better than the other implemented algorithms.

Varthanan et al. (2012) proposed to use discrete particle swarm optimization (DPSO) to provide a trade-off between backorder and holding cost in production-distribution planning decision points. To determine the validity of the applied method, two different data sets were also applied, and the results were found to be quite successful.

Grasas et al. (2016) proposed to use iterated located search (ILS) to tackle complex combinatorial optimization problems (COPs). The hybrid model consisting of simulation and local search operations (ILS), called SimILS, successfully applied to different problems and reached near-optimal solutions.

Naderi et al. (2020) suggested using a combination of meta-heuristics which are the Bat Algorithm (BA) and Quasi-Newton method to eliminate uncertainties in production to maximize profit. The method was successfully applied, and results revealed that the profit increased between 2.35% and 9.27%.

3.5 Research on Local Optimum Solution Methods

In Park et al. (2001), DoE, regression analysis, and compromise programming methods were presented to identify design and control parameters of flexible manufacturing systems (FMS) which is stochastic with complex structure. The strict constraint multi-objective problem was optimized using the hybrid model and it was suggested that future researchers use this model from an economic point of view.

Kenne and Gharbi (2001) suggested using a combination of DoE and RSM to be able to control complex production system and minimize cost. The suggested model was validated and implemented successfully.

Lai (2005) proposed to use Surrogate Search to optimize large-scale production systems in his Ph.D. thesis. Like other papers examined in this study, this method was highly recommended to use DoE to identify the system parameters and using simulation to observe system behavior. A method performed well and suggested using simulation-optimization for especially large-scale manufacturing stochastic systems.

Azadeh et al. (2009) presented to implement RSM to decrease queues and the method implemented successfully. GUI Software used in study includes different optimization algorithms such as RSM and TS. For future researchers, GUI Software was recommended because it has open-source and can be easily applied to other cases.

Kabirian and Ólafsson (2011) suggested using Golden Region Search (GRS) to increase the efficiency of simulation optimization methods. This method proposes to combine different search techniques to achieve the best result. GRS tested statistically and found it more efficient than the other compared methods. All in all, the theoretical structure was developed to compare simulation optimization methods.

In Dengiz et al. (2016) it was aimed to redesign complex production systems and increase the daily production amount and control the system by using hybrid simulation optimization, which is a combination of mathematical and simulation models. DoE was used to analyze the parameters affecting the outputs and to examine the relationship between them. A meta-model was developed as an objective function to optimize the process by considering system boundaries which include economical and physical restrictions. By successful implementation of a hybrid model, the daily production amount was increased by 15% and this model increased the flexibility of decision making by giving the chance to try the scenarios that may occur in the future. Monazzam et al. (2021) proposed a simulation-optimization approach to optimize production consisting of different departments such as logistics, production planning, and the flow of materials. After constructing a simulation model using Enterprise Dynamics (ED), DoE was used for designing scenarios. For better analysis of decision and response variables, the step-weight assessment ratio (SWARA) method was used to prioritize and weight inputs and outputs of a system. Finally, the Fuzzy RED Method was used to evaluate the performance of production scenarios. Chen et al. (2021) presented a meta-model-based global simulation-optimization approach to increase effective usage of AGV

(Automated Guided Vehicles) in manufacturing systems. The system is divided into two parts as a design and operational status. (Two-stage optimization). Real case study was conducted. Current and optimized system results were compared statistically, and the desired goal was achieved with the suggested model.

Table 3.2 Classification of thesis based on solution approach and software

No	Author	Software	Solution Approach
	Malega, P., Gazda, V., & Rudy, V. (2021).	Tecnomatix	Genetic Algorithm
	Dengiz, B., İç, Y. T., & Belgin, O. (2016).	ARENA	Hybrid simulation optimization (Regression meta-model simulation optimization)
	Monazzam, N., Alinezhad, A., & Adibi, M. A. (2021).	Enterprise Dynamics (ED)	Simulation-optimization design of experiment (DoE), step-weight assessment ratio (SWARA), Fuzzy RED Method
	Bait, S., Di Pietro, A., & Schiraldi, M. M. (2020).	Not given in the article	Extended Value Stream Mapping (X-VSM)
	Zahraee, S. M., Rohani, J. M., & Wong, K. Y. (2018).	ARENA	Response Surface Methodology (RSM) and Design of Experiments (DOE)
	Naderi, M., Khamsehchi, E., & Karimi, B. (2020).	Eclipse compositional simulator	Quasi-Newton method (Broyden Fletcher–Goldfarb–Shanno), Bat Algorithm (BA)
No	Author	Software	Solution Approach
	Park, T., Lee, H., & Lee, H. (2001).	SIMAN/CINEMA	Design of experiment (DoE)
	Spieckermann, S., Gutenschwager, K., Heinzl, H., & Voß, S. (2000).	SIMPLE++, Witness	Queuing theory, Genetic algorithms, simulated annealing
	Feyzioğlu, O., Pierreval, H., & Deflandre, D. (2005).	GAMS- SBB Solver. Promodel 4.2	Bootstrap method, regression meta-modelling
	Dengiz, B., & Alabas, C. (2000)	PASCAL, Arena	Tabu Search (TS)
	Tekin, E., & Sabuncuoglu, I. (2004).	Not given in the article	Response surface methodology, Gradient-based methods, Stochastic approximation, Evolutionary algorithms, Simulated annealing, Tabu search, Bayesian/sampling algorithm, Gradient surface method

Table 3.2 (continued)

Grasas, A., Juan, A. A., & Lourenço, H. R. (2016).	Not given in the article	Iterated Local Search (ILS)
Kuo, R. J., & Yang, C. Y. (2011).	Flexsim software	PSO algorithm, PSOMS, Genetic Algorithm-(Type 1 and Type 2)
Liu, R., Xie, X., Yu, K., & Hu, Q. (2018).		Review on simulation optimization methods for production system operations
Azadeh, A., & Maghsoudi, A. (2010).	Visual SLAM	Design of experiment (DOE), Tabu search (TS).
Ammeri, A., Chabchoub, H., Hachicha, W., & Masmoudi, F. (2010, May).		Review on simulation optimization methods
G., Savino, M. M., & Pedicini, C. (2010).	Witness	Tabu Search (TS)
Koulouriotis, D. E., Xanthopoulos, A. S., & Tourassis, V. D. (2010).	Not given in the article	Genetic Algorithm (GA)
Kabirian, A., & Ólafsson, S. (2011).	Not given in the article	Golden Region Search (GRS)
Lai, J. P. (2005).	ARENA	Surrogate Search (Multiple linear regression, various search methodologies.)
Azadeh, A., Tabatabaee, M., & Maghsoudi, A. (2009).	ARENA	Response Surface Methodology
Varthan, P. A., Murugan, N., & Kumar, G. M. (2012).	LINGO, JMP-SAS	Discrete Particle Swarm Algorithm (DPSA)
Lugaresi, G., & Matta, A. (2018, December).		Review on simulation optimization challenges
Chen, J. C., Chen, T. L., & Teng, Y. C. (2021).	Minitab, FlexSim	Meta-modeling
Kenne, J. P., & Gharbi, A. (2001).		Response Surface Methodology, Design of experiment (DoE)

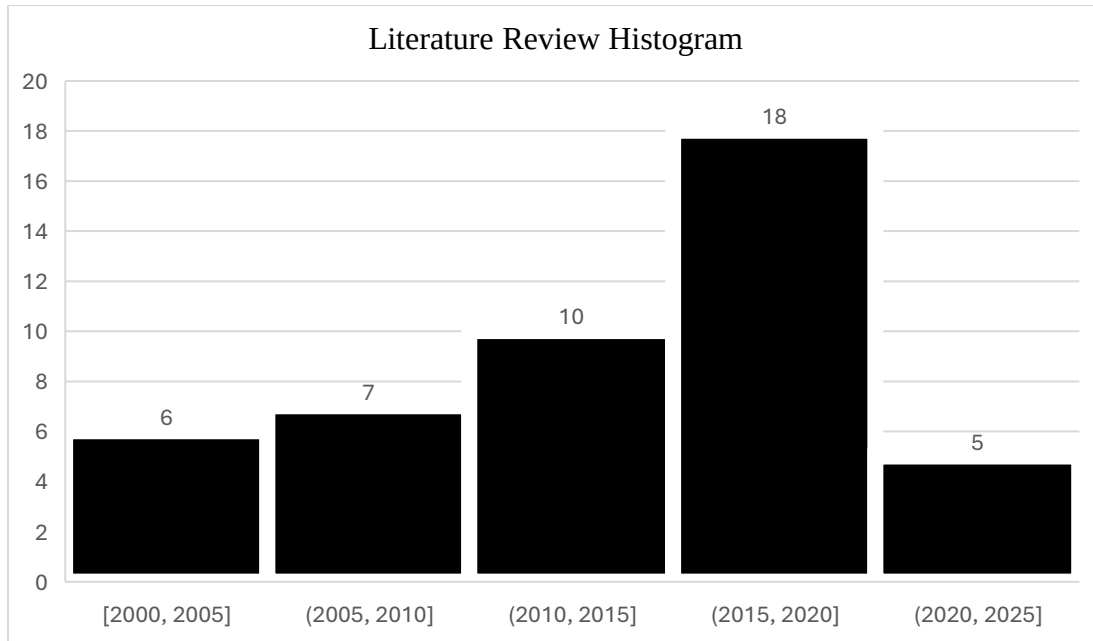


Figure 3.1 Literature Review Histogram Graph

The histogram presents a chronological distribution of the literature reviewed for this thesis, spanning from 2000 to 2025. The data is segmented into five-year intervals, revealing the following trends:

The period from 2015 to 2020 exhibits the highest concentration of relevant literature, with 18 sources identified. This suggests a significant surge in research activity pertinent to the thesis topic during this quinquennium.

The preceding interval (2010-2015) shows the second-highest frequency, with 11 sources, indicating a sustained research interest in the field.

Earlier periods demonstrate a relatively consistent level of scholarly output: 10 sources for 2000-2005 and 9 for 2005-2010, implying a stable foundation of research in the early 2000s.

The most recent period (2020-2025) accounts for 8 sources. While this figure is lower than the peak, it represents ongoing research relevance, considering that this interval is not yet complete and may include predictive or prospective studies.

This temporal distribution of sources underscores the evolving nature of the research field, with a notable intensification of scholarly interest in the latter half of the 2010s. The inclusion of recent literature (2020-2025) ensures that the thesis incorporates cutting-edge research while maintaining a comprehensive historical perspective spanning over two decades.

When delving into the existing literature, it becomes evident that studies which meticulously map the flow of processes prior to engaging in simulation modeling tend to yield more realistic and meaningful solutions. The accurate representation of the underlying system is paramount in ensuring that the results derived from simulation modeling are not only realistic but also significant in their implications. Furthermore, it is important to recognize that simulation modeling is a specialized endeavor, and individuals well-versed in the intricacies of the system, but lacking expertise in simulation modeling, may encounter challenges when it comes to validating the system. Therefore, the synergy between those who construct the model and those intimately familiar with the system forms the bedrock of the study.

Consequently, it is imperative to consider process mapping as the initial step in simulation modeling to guarantee that the digital replica of the system faithfully mirrors its real-world counterpart. By doing so, the foundation for establishing the most appropriate model is laid, and the subsequent development of scenarios with a holistic approach is substantiated.

Simulation modeling serves as an effective tool for addressing inefficiencies within businesses. However, owing to the substantial levels of uncertainty and the multitude of parameters involved, attaining the 'best' global solution is not always feasible. Therefore, focusing on local optimum scenarios, often referred to as 'possible good' scenarios, can be advantageous. Crafting virtual representations of real systems within a digital environment is a complex and specialized undertaking. Process mapping emerges as a pivotal step in mitigating the challenges associated with simulation modeling. Notably, an in-depth exploration of the literature underscores that studies which diligently undertake process mapping tend to yield more realistic results, a notion reinforced by model verification and validation.

Hence, reiterating the significance of process mapping as the primary phase of simulation modeling is crucial to ensure the faithful emulation of the real system within its digital counterpart.

This approach not only establishes the foundation for constructing the most suitable model but also bolsters the development of scenarios with a comprehensive and holistic perspective.

3.6 Discussion

The selection of simulation methodology for process improvement in the automation factory was deemed the most appropriate approach, given the complexity of the system and the project-based nature of operations. A comprehensive review of relevant literature reveals a diverse array of methodologies employed in similar studies, each with its own merits and limitations in addressing supply chain and production challenges.

Gao et al. (2019) utilized mathematical modeling and game theory analysis to investigate the impact of backorders in dual-channel supply chains. While this approach offers valuable insights into strategic decision-making, it may not fully capture the dynamic and stochastic nature of project-based manufacturing environments. Similarly, Chen and Wang (2016) employed stochastic programming and sensitivity analysis to examine pricing and inventory decisions under uncertain demand and partial backordering. Although these methods provide robust analytical solutions, they may fall short in accommodating the high variability and unique characteristics inherent in customized automation projects.

The game-theoretic models and Nash equilibrium analysis applied by Chen et al. (2017) in coordinating supply chains with manufacturer-owned online channels demonstrate the power of strategic modeling. However, such approaches may not adequately represent the intricate interdependencies and temporal aspects of complex manufacturing processes. Tiwari et al. (2016) leveraged mathematical modeling and optimization techniques to study the impact of trade credit and inflation on retailer's ordering policies. While these methods excel in optimizing specific parameters, they may struggle to encompass the multifaceted nature of project-based manufacturing systems.

Paterson et al. (2018) conducted a systematic literature review and meta-analysis of inventory models with lateral transshipments, providing valuable insights into broader trends and theoretical frameworks. However, this approach, while comprehensive in scope, lacks the granularity required for analyzing specific operational nuances in a customized automation environment. Sarkar and

Saren (2016) developed mathematical models and optimization techniques for product inspection policies in imperfect production systems. Although these methods offer precise solutions under certain assumptions, they may not fully account for the real-world complexities and uncertainties prevalent in project-based manufacturing.

In contrast, simulation methodology, particularly through the use of advanced software like Arena, offers several distinct advantages in the context of this study. Firstly, it allows for a more realistic modeling of the dynamic system behavior, capturing the intricate interactions between various processes and resources. Secondly, simulation enables risk-free experimentation with different scenarios, a crucial factor when dealing with high-stakes automation projects where real-world trials could be prohibitively expensive or disruptive.

Moreover, simulation provides a data-driven approach to decision-making, allowing for the quantitative comparison of multiple process improvement strategies. This is particularly valuable in a project-based environment where standardization is challenging, and each project may present unique constraints and opportunities. The flexibility of simulation models also facilitates the incorporation of stochastic elements, such as variable processing times and unpredictable delays, which are common in complex manufacturing settings.

Furthermore, the visual nature of simulation tools like Arena enhances stakeholder communication and understanding, fostering a more collaborative approach to process improvement. This is especially beneficial in cross-functional projects where alignment among diverse teams is crucial.

In conclusion, while various analytical and mathematical methods offer valuable insights into specific aspects of supply chain and production management, the simulation approach was selected as the most comprehensive and adaptable methodology for addressing the unique challenges posed by the automation factory's project-based structure and the critical issue of backorder-related penalty costs. This choice aligns with the need for a holistic, flexible, and risk-averse strategy in optimizing complex manufacturing processes in a highly dynamic and customized production environment.

CHAPTER FOUR

PRINCIPLES AND APPLICATIONS OF SIMULATION MODELING

Simulation modeling, as defined by Altiook and Melamed (2010), represents a paradigm specifically crafted to unravel the intricate behaviors of complex systems. This approach involves the creation of a virtual representation of the system under scrutiny, allowing for a comprehensive statistical analysis of its behavior. By harnessing this virtual environment, simulation modeling offers a multitude of advantages, including enhanced system design, the ability to carry out cost-benefit analysis, explained in detail in 3.1. section and the evaluation of the sensitivity of various design parameters.

As downtime in industrial systems such as production systems, supply chain and transport systems are costly, identifying the areas for improvement in the digital environment and applying it once the decision has been made reduces the cost loss. Another advantage is that a system that does not exist yet can be designed digitally and built-in line with the system outputs, which supports the establishment of the best system. Simulation modeling allows us to avoid unpalatable efforts.

4.1 Advantages of Simulation

Uncertainty, complexity, and variability are quite high in real-time cases. For that reason, mathematical modeling is difficult to use for real-time systems. However, with simulation modeling real-life systems can be modeled using statistical distributions and solutions to real-life problems can be presented.

The use of simulation in project management is an aid to the development of new ways of thinking about the progress of the process (El Khatib, 2022). Different scenarios such as what-if scenarios can be studied easily by changing the parameters in simulation modeling, and this flexibility feature provides the opportunity to observe many scenarios, choose the option that gives the best output, and create an agile solution approach in the face of changes. In addition, simulation modeling enables to measure how important the inputs are for performance measurement criteria such as utilization, efficiency and so on with sensitivity analysis.

One of the major advantages of simulation modeling is the feasibility analysis of the project can be carried out by applying the scenarios that will create high costs, such as re-designing system, re-configuration the layout, as well as parameter changes, in digital environment without incurring project implementation costs. The ability to get immediate feedback on performance is also one of the most important aspects of using project simulation in management (Schwalbe, 2015). Since line shutdowns in industrial systems such as production systems, supply chain, transportation systems cause high costs, determining the areas to be improved in the digital and applying it after the decision is made reduce the cost.

Another advantage is that a system that does not exist yet can be designed digitally and built-in line with the system outputs, which supports the establishment of the best system. It can be interpreted that simulation modeling allows us to avoid unpalatable efforts.

4.2 Methodological Challenges in Simulation Modeling

Although successful project management can have positive outcomes, simulations also have drawbacks and can result in unfavorable situations within a project. Rosemann and vom Brocke (2015) suggest that simulations may never fully replicate real-life conditions as envisioned during the project planning phase.

Simulation modeling challenges are given below.

- Since data collection is one of the most important steps, insufficient data will cause inaccurate reflection of the real-life problem. (Referred to in Chapter 6.3.1)
- Before starting the simulation modeling, the system flow to be modeled must be analyzed and mapped in detail with the appropriate mapping methods. Otherwise, a completely different system will be modeled, and it will lead to an incorrect decision. (Referred to in Chapter 6.2)
- The global optimum solution cannot be reached using only simulation modeling. For this reason, it is tried to be strengthened by combining different methods.
- Simulation model cannot be used for different systems as each system is unique.

4.3 Application Areas of Simulation

The usage area of simulation modeling is quite wide, and it is used in many areas from traffic models to logistics-supply models, from military systems to health systems.

Simulation modeling can be used in projects with high application costs in the real world and if a new system that has not been designed before will be installed and if it is dangerous to try and in situations that require high effort to solve manually due to complexity. The application areas of simulation are better understood with origin story of the Monte Carlo simulation. The Monte Carlo

Simulation model was developed as a quantitative technique by the mathematician John von Neumann during World War II. While working with neutrons at the Los Alamos Science Laboratory, Neuman used the simulation method to solve physics problems that are very complex and costly to solve manually. Simulation modeling can offer solutions to the following issues in detail.

- Production and assembly line balancing works can be performed.
- Six-Sigma proposals can be tested.
- The whole system can be examined with a holistic review, improved areas can be detected, and alternatives can be compared.
- Complex scheduling and planning problems can be solved.
- With the sensitivity analysis, the importance of the parameters for the system can be determined.
- It can be used in military logistics and operational planning.

4.4 Systematic Approach to Simulation Model Development

Simulation modeling stages are given in Figure 4.1 and each step is explained in detail below this section. This figure provides a structured approach to the simulation modeling process, outlining the key phases from problem formulation to model implementation and analysis. The

stages typically include problem definition, conceptual model development, data collection, model translation, verification and validation, experimentation, and results analysis.

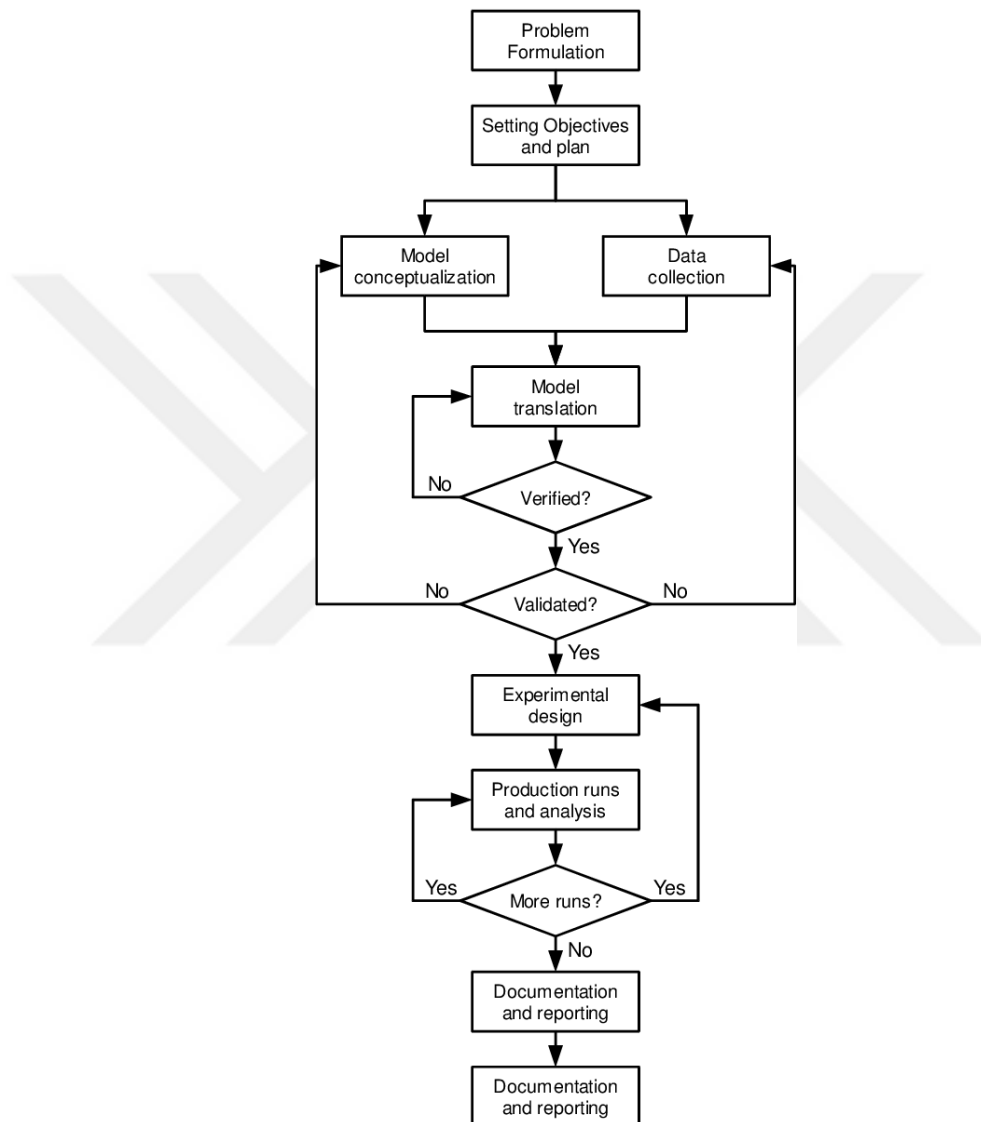


Figure 4.1 Simulation Model Development Process (Marzolla, M. (2005))

4.4.1 Problem Analysis and Information Acquisition

Simulation modeling is seldom used for its own sake. Rather, modeling is conducted to find a solution for a system-oriented problem. The first step of simulation modeling is to analyze the problem by making a clear problem definition and collecting structural information about the

system. It comprises inputs and outputs, performance criteria of interest, and correlation among flows and components. Problem definition must be specific and measurable as far as possible for a better understanding of the problem and facilitate the solution. It is useful to represent it using methods such as flowcharts, hierarchy trees, logic flow, visual mapping, and so on for demonstration. Afterward, the point to be reached with the output of the study which is called objectives should be determined clearly.

4.4.1.1. Data Gathering & Statistical Input Analysis

Data gathering is the process of collecting the numerical data of the system to be modeled and its components. There are various ways to gather data such as historical data, system records, direct observations (time studies, etc.)

It is used to formulate assumptions about the distribution of random variables to reflect the real system and for simulation model validation which will be explained in its section. Since number of data to be collected has crucial for accurate reflection of the model, enough observation must take as many as possible.

If the data about the events in the system are deterministic, it is easy to examine these structures. Since there is no obligation to fit the data into a distribution. However, if the data about the events are random, that is, if there are stochastic data, it is necessary to collect a significant amount of data. To make stochastic data meaningful and use it in the simulation model, the data are fitted to probability distributions. The data set is very important since statistical analyzes will be conduct according to the distribution of the collected data and data will be produced according to the selected probability distribution. The process of testing the independence of the data, fitting, and testing the appropriate distribution is called input analysis. The steps of input analysis are given below in detail.

4.4.1.2 Assessing Data Independency

As the first step of the input analysis, the data independence test is performed to understand whether the data are related to each other, in other words, whether a data influences the data formed immediately after it. The dependence of the data causes the wrong probability distribution to be chosen, and this causes variance between the modeled system and the real system, briefly a successful simulation study cannot be performed.

4.4.1.3. Probability Distribution Fitting Techniques

Data distributions are required for describing emerging data in real systems. Since the data is not static in actual systems and the system can be affected by random parameters the data set is defined by fitting the one closest to the distributions which has the certain characteristics with the help of statistical techniques. In other words, the distribution of probabilities allows consideration of a wide range of scenarios to address uncertainty. There are a lot of specialty software can be used for probability distribution adjustment.

4.4.1.4 Goodness of Fit Statistical Tests

Once the distributions have been adjusted, it is necessary to determine how closely the distributions you have selected match your data. This can be done using specific fit tests or visually by comparing empirical (based on sample data) versus theoretical (adjusted) distribution graphs. The tests applied to check whether the distribution of a sample is compatible with a theoretical distribution or whether the sample comes from a predicted theoretical distribution are called goodness-of-fit tests. Some of the most used goodness-of-fit tests are determined below.

- Chi-Square Test
- Kolmogorov-Smirnov Test
- Lilliefors Test
- Shapiro-Wilk Test

4.4.2 Conceptual and Computational Model Construction

The simulation model is constructed by an analyst after thoroughly comprehending the process and problem under study and collecting sufficient data. This approach aligns with the methodology outlined by Law and Kelton (2000), who emphasize the importance of a systematic approach to simulation modeling. Banks et al. (2010) further stress that the quality of the simulation model is directly related to the depth of understanding of the system being modeled and the accuracy of the data collected. There are several simulation modeling software packages available, each with its own strengths and applications. Some of the widely used platforms include:

Arena: Known for its versatility in discrete-event simulation (Kelton et al., 2015)

Witness: Particularly strong in manufacturing and supply chain simulations (Robinson, 2004)

Flexsim: Offers 3D visualization capabilities for complex systems (Nordgren, 2003)

Enterprise Dynamics: Suitable for large-scale enterprise simulations (Boer and Bruin, 2002)

Promodel: Focused on production systems and operational analysis (Harrell et al., 2011)

GPSS (General Purpose Simulation System): One of the oldest simulation languages, still used for its simplicity (Ståhl et al., 2011)

While these specialized software packages offer user-friendly interfaces and built-in functionalities, simulation models can also be constructed using general-purpose programming languages such as C++ or Visual Basic. This approach, as noted by Pidd (2004), offers greater flexibility and control over the model's structure and behavior, albeit at the cost of increased development time and complexity. The choice between specialized simulation software and general-purpose programming languages often depends on factors such as the complexity of the system being modeled, the required level of customization, and the expertise of the modeler (Rossetti, 2015). Regardless of the tool chosen, the fundamental principles of simulation modeling, including verification and validation as described by Sargent (2013), remain crucial for ensuring the accuracy and reliability of the simulation results

4.4.3 Model Verification and Validation Protocols

Model verification is conducted to compare the model code with the conceptual model and test whether the model is set up correctly. It is aimed to reflect the real system in the most accurate way by debugging the model from frictions. There are various verification methods such as reviewing the model code, output analysis, using trace and debugging processes. Model verification is one of the most important steps, and as seen in figure 1, if a conflict is encountered, the model must be rebuilt.

The fact that a simulation model works and produces results does not guarantee that it is an accurate representative of the modeled system and that the results it produces are correct. Model verification is the process of determining that the model is working as intended. In that process the answer to the question that **Is it true?** is searched. (Law, 2022)

Validation is the process of achieving a level of confidence and accepting that the outcomes of the model are correct and representative, applicable to the actual system. While verification is performed to see if the model set-up correctly (the relationship between the simulation model and the conceptual model), validation is the process of determining whether we have set-up the right model (the simulation model and the real system).

Sokolowski and Banks (2011) stated that verification and validation are done as part of a simulation project, not in isolation. In the article, over 90 different verification and validation methods are grouped into four categories (informal, static, dynamic, and formal) and each is explained in detail. Consequently, based on the simulation type and purpose, the most appropriate verification and validation method can be selected.

Collier and Lambert (2019), defined model validation as it is a set of techniques and procedures used to measure the performance of a model and determine how well the model works with real-world data. These techniques are used for purposes such as ensuring that the model is not overfitting, testing the generalizability of the model and adjusting the parameters used to improve the accuracy of the model.

Model validation is an important step to improve the reliability of machine learning mod. Validation must and can be performed for all models, regardless of whether the system concerned is already in existence in some form or will be built in the future. (Law, 2022)

The purpose of validation is to check whether the correct model has been established. When a model of an existing system or similar is built, the model behavior can be compared to the actual system. In the case of designing a new system, the data should accurately reflect the design features of the system, and the model should be carefully validated, as there is no pre-established performance data. If the model works as expected, it can be said that the model is valid.

In other words, validation is the inductive process whereby the modeler can draw conclusions about model accuracy based on available data. Since the differences between the actual system and the simulated system are examined, people familiar with the system should be included in the validation phase. The validation of existing systems and the validation of newly installed systems will certainly not be the same.

Under the current system validation approach, the performance indicators of the real system and the simulated system are compared using real data and if they are compatible, the model is interpreted as valid. In case of significant difference, the simulated system must be checked again.

In the first model validation approach, as there is no historical data, the hypothetical hypothesis-based system should be used. The following methods are used.

- Subsystem Validity
- Internal Validity
- Sensitivity Analysis
- Face Validity

4.4.4 Output Analysis and Recommendations

Output analysis is a model stage that used to examine and analyses the performance of simulation model with various statistical techniques. In numerous simulation studies, significant resources are allocated to model development and programming, while insufficient attention is given to thoroughly analyzing the output data generated by the simulation. As simulation models rely on random samples, resulting estimates are specific realizations with potentially large variances, leading to errors. (Law, 2020)

Three significant challenges in output-data analysis are given Law's study:

- Neglecting to establish a warmup period for steady state analyses.
- Analyzing simulation output data from a single run using independence-assuming formulas, potentially leading to underestimated variances and overly optimistic confidence intervals.
- Overlooking the statistical precision of simulation output statistics through confidence intervals, achievable via the replication approach.

Given that the inputs of the simulation model are random, the outputs are also random. Random data sets reflect how real systems operate so that the best actions can be taken given the many situations that can occur in real systems. For this reason, statistical analysis is the most important element in the output analysis. Performing the simulation several times also supports this, the more the system is executed, the greater the chances of observing. The following criteria are examples of major indicators used in output analysis.

- Average processing time,
- Average time spent in the system,
- Average queuing time,
- Average queue length
- Utilization rate of resources (worker, machine, etc.)

4.5 Simulation Model Classification

The classification of models based on their distinct characteristics serves as a fundamental framework for comprehending the underlying assumptions and intricacies inherent in each model. This systematic categorization facilitates a nuanced understanding of the strengths and limitations associated with different model types, thereby enabling the selection of the most suitable model for a given dataset or analytical context. Models are typically categorized along three primary dimensions: temporal characteristics, probabilistic nature, and continuity over time, yielding the classifications of Dynamic-Static, Deterministic-Stochastic, and Discrete-Continuous.

4.5.1. Dynamic-Static Simulation Models

A deterministic simulation model is characterized by the absence of random variables, with events occurring at predetermined times. This deterministic framework entails a clear and unequivocal specification of the timing of events, devoid of any stochastic or probabilistic elements. In contrast, a stochastic simulation model incorporates one or more random variables as inputs, reflecting the inherent uncertainty and variability present in real-world phenomena. Given the inherent unpredictability of numerous real-world events, stochastic models are indispensable for capturing the complex and uncertain nature of various systems and phenomena.

In practical applications, stochastic models are often favored due to the inherent limitations in predicting every event with absolute precision. The inclusion of random variables in stochastic models enables the incorporation of uncertainty and variability, thereby offering a more realistic representation of real-world systems. Examples of deterministic models encompass well-defined mathematical formulations such as linear and nonlinear equations, as well as linear and nonlinear programming, which are governed by precise and deterministic relationships. Conversely, stochastic models encompass a diverse array of methodologies, including Markov chains, Monte Carlo simulations, and Brownian motion models, which are adept at encapsulating the probabilistic and uncertain nature of real-world systems and phenomena.

4.5.2. Deterministic-Stochastic Simulation Models

Deterministic simulation models are characterized by the absence of random variables, and the precise timing of events is predetermined. This deterministic framework entails a clear and unequivocal specification of the timing of events, devoid of any stochastic or probabilistic elements. In contrast, a stochastic simulation model incorporates one or more random variables as inputs, reflecting the inherent uncertainty and variability present in real-world phenomena. Given the inherent unpredictability of numerous real-world events, stochastic models are indispensable for capturing the complex and uncertain nature of various systems and phenomena.

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The utilization of stochastic models in real-life issues and systems is underpinned by the recognition that perfect prediction of every event is unattainable due to the inherent complexity and variability of real-world phenomena. By embracing stochastic modeling approaches, practitioners can effectively capture the inherent uncertainty and variability, thereby yielding more robust and realistic insights into the behavior and dynamics of complex systems.

4.5.3. Discrete-Continuous simulation Models

Discrete simulation models are characterized by state variables that undergo changes only at specific points in time, corresponding to the occurrences or alterations of events. In this context, the temporal dynamics of the system are delineated by discrete time intervals, with state transitions occurring at these distinct time points. For instance, consider the scenario of a bank, where the number of customers fluctuates over discrete time intervals within the bank's operating hours. Each discrete time unit represents a distinct state of the system, and the changes in the number of customers are observed at these discrete time points, reflecting the discrete nature of the simulation model.

On the other hand, continuous simulation models are distinguished by state variables that change continuously over time, without abrupt transitions. In contrast to discrete models, continuous simulation models capture the evolution of system states in a seamless and uninterrupted manner, mirroring real-world processes that exhibit continuous changes. This continuous evolution of state variables reflects a more fluid and uninterrupted representation of the system's behavior, in contrast to the discrete and punctuated nature of state transitions in discrete simulation models.

CHAPTER FIVE

THE PROPOSED METHODOLOGICAL FRAMEWORK

This study proposes a comprehensive methodology comprising four distinct phases, each further delineated into sub-components to establish a systematic, traceable, and implementable approach. The subsequent sections of this research provide detailed explanations on the practical application of each main phase. The methodology emphasizes the critical importance of adhering to the prescribed sequence of phases, as bypassing any phase could significantly complicate the simulation modeling process and challenge the model's alignment with the real-world system. A thorough examination of the literature review reveals that the omission of certain phases in previous studies has been identified as a significant limitation, highlighting areas for improvement.

The proposed four-phase methodology is designed to overcome these limitations, offering several key advantages. It provides a structured framework for researchers and practitioners, ensures better tracking of the research process, and accommodates various types of automation systems and project-based manufacturing environments. By incorporating lessons learned from the literature review, this methodology addresses gaps identified in previous studies, providing a more holistic approach to simulation-based process improvement. The emphasis on following the prescribed sequence acts as a built-in quality control mechanism, reducing the risk of errors and inconsistencies in the simulation model.

The structured approach allows for iterative refinement at each phase, enhancing the validity and reliability of the simulation models and leading to more credible and actionable results. Furthermore, the clear structure and detailed explanations of each phase facilitate better knowledge transfer, making it easier for other researchers or practitioners to apply this methodology in different contexts. In conclusion, the proposed four-phase methodology represents a significant advancement in the field of simulation-based process improvement for automation factories and project-based manufacturing environments, aiming to enhance the effectiveness and reliability of simulation studies in complex manufacturing settings.

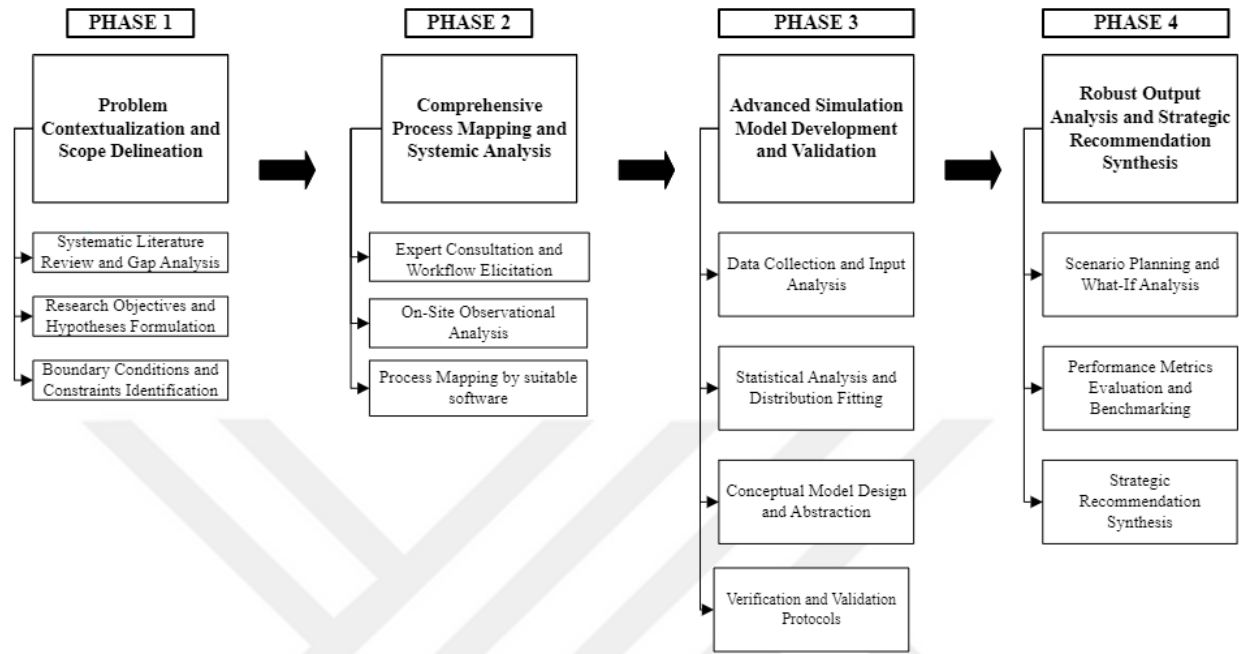


Figure 5.1 Proposed Methodology Visual Framework

Figure 5.1 presents a visual representation of the methodological framework proposed in this thesis. The study comprises four primary phases, each with its respective sub-components.

Phase 1 encompasses Problem Conceptualization and Scope Delineation, establishing the foundational context for the research. Phase 2 focuses on Comprehensive Process Mapping and Systemic Analysis, providing a detailed examination of the subject matter. Phase 3 involves Advanced Simulation Model Development and Validation, employing sophisticated modeling techniques to simulate the system under study. The final stage, Phase 4, consists of Robust Output Analysis and Strategic Recommendation Synthesis, where the results are rigorously analyzed and translated into actionable insights.

This structured approach ensures a systematic progression from problem identification through to the formulation of evidence-based recommendations, underpinning the scientific rigor of the study.

5.1 Phase 1: Problem Contextualization and Scope Delineation

This section of the study elucidates the initial phase of the proposed method, which involves the detailed articulation of the problem context and scope. The thorough determination and analysis of the problem context is of paramount importance for effective problem resolution.

Brown (2019) emphasizes the critical significance of problem formulation as a fundamental constituent of the scientific methodology. The author conducts a comprehensive examination of how precise problem delineation influences subsequent stages of research, including hypothesis generation, data acquisition, and analytical procedures. The manuscript elucidates the cascading effects of a well-articulated research question on the entire investigative process, demonstrating its pivotal role in shaping the trajectory of scientific inquiry.

Lee and Park (2021) corroborate this perspective in their comprehensive study, asserting that "well-defined problem statements are fundamental to shaping robust research designs and ensuring the reliability of outcomes" (p. 80). Their analysis elucidates the intricate relationship between precise problem articulation and the subsequent phases of research methodology.

The ability to analyze both the primary causes and sub-causes of a problem is crucial. Various techniques can be employed for this purpose, with the selection of these techniques' contingent upon both the problem type and the competency of the individual employing the technique. As Lee and Park (2021) note, "the quality of problem formulation is directly proportional to the overall rigor and relevance of the research" (p. 88), highlighting the far-reaching implications of this initial step in the research process.

It is noteworthy that apparent causes may sometimes be consequences of the problem. Therefore, the application of problem-solving techniques facilitates the rapid identification of effective solutions. These techniques and tools aim to uncover the root causes of problems through targeted questioning, thereby eliminating them in a manner that precludes recurrence. In environments characterized by high inter-departmental conflict and project-related stress, objective problem identification can be particularly challenging. Long-term employees who lack a solution-oriented mindset often attribute problems to external factors. Consequently, it is essential to approach problems from multiple perspectives and invest time in operational analysis.

The process of mapping workflows from inception to completion aids in identifying bottlenecks and objectively prioritizing issues for resolution. The subsequent section provides a detailed exposition of process mapping methodologies.

5.2 Phase 2: Comprehensive Process Mapping and Systemic Analysis

Upon completion of Phase 1, which entails the rational and specific determination of the problem and objective—a crucial initial step in the proposed study—the research progresses to Phase 2. This subsequent phase encompasses Comprehensive Process Mapping and Systemic Analysis. Within this segment of the study, the significance of process mapping is elucidated in detail, along with a thorough exposition of its methodological implementation.

The transition from problem identification to process analysis represents a critical juncture in the research framework. Process mapping, as a fundamental tool in organizational analysis, serves to visually represent the intricate workflows and interdependencies within a system. This phase not only highlights the importance of process mapping in understanding complex organizational structures but also provides a methodical approach to its execution.

The detailed explication of process mapping techniques in this phase underscores its pivotal role in identifying inefficiencies, bottlenecks, and potential areas for improvement within organizational processes. Furthermore, the integration of systemic analysis complements the process mapping exercise, offering a holistic perspective on the interrelationships between various organizational components.

This comprehensive approach in Phase 2 lays the groundwork for subsequent phases of the study, ensuring a thorough understanding of the current state of processes before proceeding to intervention design and implementation.

Process mapping has emerged as a crucial tool for enhancing organizational performance across various sectors. A comprehensive systematic literature review conducted by Dumas et al. (2018) elucidates the significant impact of process mapping on key organizational metrics. Their study demonstrates that the implementation of process mapping techniques leads to substantial improvements in operational efficiency, cost reduction, and customer satisfaction levels. Furthermore, Dumas et al. (2018) identify specific industries where process mapping proves most

effective and delineate optimal methodologies for its application. This research underscores the strategic importance of process mapping in driving organizational excellence and provides valuable insights for practitioners and researchers alike in the field of business process management.

In their seminal work, Pereira et al. (2020) propose an innovative framework that integrates process mapping with discrete event simulation to enhance business process improvement initiatives. This comprehensive approach offers a robust methodology for optimizing operational efficiency across various organizational contexts. The authors elucidate the practical application of their framework through a case study conducted in a manufacturing company, demonstrating its efficacy in real-world scenarios. The results of their study reveal that this integrated approach leads to significant improvements in process efficiency. Pereira et al. (2020) provide compelling evidence for the synergistic benefits of combining these two powerful tools, offering valuable insights for practitioners and researchers in the field of performance management and process optimization.

Process mapping is a complex process, particularly for smaller companies that do not have standardized processes. Oftentimes the work that must be done by more than one station is done at one station. This causes increased cycle-times due to the not-specialized employees and the emerged set-up times. Despite these difficulties, if the flow is analyzed and mapped correctly, the places where the most time is lost in the process, namely the bottlenecks, can be determined and necessary studies can be carried out to eliminate them. Process mapping is an effective way to identify and optimize process that enable to decrease movement between station, transportation times, material movement, and time-wasting activities. It is very effective at looking at the big picture from a holistic perspective, particularly for activities that take place in more than one facility.

Optimizing layouts is critical to maximizing productivity, but many businesses do not consider it at the time of setup. For businesses that value operational excellence, layouts are reorganized to increase productivity after the process mapping phase. There is no possibility of optimizing the layout during the production process. It is very costly and there is a demand to be met. For this reason, bringing about the desired changes in digital environments such as simulation and analysis of results is an advantage in terms of the feasibility of the study. New investments can also be

considered within the same scope, for example, the effect of buying a new machine on production is analyzed using simulation and it is decided whether it gives the desired results or not.

5.2.1 Expert Consultation and Workflow Elicitation

Initially, detailed workflow analyses were conducted in collaboration with technical experts from each facility. This step was crucial in ensuring the accuracy and comprehensiveness of the process mapping exercise. The involvement of domain specialists provided invaluable insights into the nuances of operations that might not be immediately apparent to external observers. This expert consultation phase involved:

- **Structured interviews with domain specialists**

These interviews were instrumental in capturing tacit knowledge and experiential insights often absent from formal documentation. Experts highlighted critical areas of concern, potential bottlenecks, and informal workarounds that had developed over time. The structured nature of these interviews ensured systematic coverage of all process aspects while allowing flexibility for unexpected revelations, thereby providing a comprehensive understanding of the operational landscape.

- **Documentation review of existing process guidelines**

Expert guidance was crucial in interpreting formal documentation, providing context and explaining how written procedures translate into actual practice. This review process helped identify discrepancies between documented processes and real-world implementation, a vital step in process improvement. By reconciling official guidelines with practical application, areas for potential optimization and standardization were identified.

- **Identification of key process nodes and decision points**

Leveraging their deep understanding of the processes, experts pinpointed critical junctures where decisions significantly impact outcomes. This expert-driven identification ensured that subsequent analysis and improvement efforts were focused on the most impactful areas of the process. By highlighting these key nodes, the team could prioritize resources and attention on areas with the greatest potential for enhancing overall process efficiency and effectiveness.

➤ **Delineation of inter-departmental process flows**

Expert input was vital in mapping the complex interactions between different departments and teams. Their insights helped in understanding informal communication channels and collaborative practices that often play a crucial role in smooth operations. This comprehensive view of inter-departmental dynamics revealed opportunities for improved coordination and streamlined workflows across organizational boundaries.

5.2.2. On-Site Observational Analysis

Following the expert consultation phase, a comprehensive program of field observations was meticulously executed to validate and refine the initial process maps. This empirical approach served to bridge any potential gaps between reported processes and actual operational practices. The field observation phase consisted of the following key components:

- **Systematic on-site observations:** Trained researchers conduct structured observations across all relevant operational areas. These observations were carefully timed to capture process variations across different shifts, days of the week, and operational conditions.
- **Time-motion studies:** Detailed time-motion analyses were performed on critical process steps identified during the expert consultation phase. These studies provided quantitative data on process durations, variability, and resource utilization rates.
- **Informal staff interviews:** Brief, opportunistic interviews with frontline staff were conducted during observation sessions. These conversations often revealed valuable insights into informal practices, workarounds, and practical challenges not captured in formal documentation or management-level interviews.

5.2.3. Process Mapping by Suitable Software

This section of the study delineates the process mapping phase, which follows the acquisition of detailed information from experts and the determination of workflows. It elucidates the step of mapping processes using appropriate software and expounds on the advantages of this procedure. Additionally, due to the benefits afforded by Visio, a component of Microsoft Office 365, this tool

is recommended for process mapping implementation. The utilization of Microsoft Visio in this process mapping exercise offered several advantages:

- **Standardized Notation:** Visio's built-in shapes and symbols for flowcharting ensured consistency across all process representations.
- **Hierarchical Modeling:** The software facilitated the creation of multi-level process maps, allowing for both high-level overviews and detailed subprocess breakdowns.
- **Dynamic Linking:** Interconnected processes could be linked across different sheets, providing a cohesive view of the entire operational ecosystem.
- **Collaborative Editing:** Visio's sharing capabilities enabled real-time collaboration with stakeholders, ensuring accuracy and comprehensiveness of the process maps.

The resulting process map serves as a foundational document, offering a holistic view of the organization's operational landscape. It not only captures the current state of processes but also serves as a valuable tool for:

- Identifying process inefficiencies and bottlenecks
- Facilitating cross-functional communication and understanding
- Providing a baseline for future process improvement initiatives
- Supporting the development of accurate simulation models

This comprehensive approach to process mapping, combining expert knowledge with empirical observation and leveraging advanced visualization tools, ensures a robust foundation for subsequent phases of the research, particularly in the context of simulation modeling and system optimization.

This expanded version provides a more detailed, academic treatment of the process mapping procedure, emphasizing the methodological approach and the use of Visio as a key tool in the process. It also highlights the broader implications and utility of the resulting process map.

5.3 Phase 3: Advanced Simulation Model Development and Validation

Following the process mapping and conceptual model development, the study proposes the implementation of Phase 3, which encompasses Advanced Simulation Model Development and Validation. This phase is a critical progression in the proposed methodology, building upon the foundational work established in the preceding stages. As Law (2015) emphasizes, "simulation modeling is an indispensable problem-solving methodology for the solution of many real-world problems".

In this segment of the research, a comprehensive elucidation is provided on the methodologies for constructing and validating a robust simulation model. The study meticulously delineates the intricate steps involved in developing a successful and valid simulation model, emphasizing the importance of accuracy and reliability in representing the complex systems under investigation. This approach aligns with Sargent's (2013) assertion that "model validation is crucial and is a key part of the model development process if models are to be accepted and used to support decision-making".

The advanced simulation model serves as a powerful tool for analyzing and predicting system behavior under various conditions. Banks et al. (2010) note that "simulation enables the study of, and experimentation with, the internal interactions of a complex system or of a subsystem within a complex system" (p. 3). This phase underscores the significance of rigorous validation procedures to ensure the model's fidelity to real-world processes. As Kleijnen (1995) argues, "validation of simulation models is a crucial issue in the practice of simulation" (p. 145).

By focusing on the nuances of simulation model development and validation, this phase establishes a crucial link between theoretical conceptualization and practical application, setting the stage for subsequent phases of analysis and optimization in the overall research methodology. This approach is consistent with Robinson's (2014) view that "the purpose of simulation is to aid understanding, to predict performance, and to identify improvements" (p. 3).

As stated in the preceding section, it is not possible to make certain changes in terms of time, money, and feasibility in real-world systems. For this reason, it is highly beneficial to create a digital twin of the real system and test various scenarios through simulation. This approach aligns

with the concept of digital twins, which Tao et al. (2018) define as "a virtual representation of a physical object or system across its lifecycle, using real-time data to enable understanding, learning and reasoning" .

The flow must be meticulously mapped to establish a precise simulation model. This will facilitate the validation of the model, a crucial step in ensuring the model's accuracy and reliability. As Sargent (2013) emphasizes, "model validation is substantiating that the model, within its domain of applicability, behaves with satisfactory accuracy consistent with the study objectives".

The simulation model can be implemented with various software programs, each offering unique features and capabilities. Some of these include:

1. Enterprise Dynamics (ED)
2. ARENA
3. Tecnomatix
4. Visual SLAM
5. Simple++
6. Witness
7. SIMAN/CINEMA
8. GAMS
9. ProModel

Jahangirian et al. (2010) conducted a comprehensive review of simulation in manufacturing and business, noting that "ARENA, ProModel, and Witness are among the most popular commercial simulation packages" (p. 86). However, they also highlight that the choice of software depends on various factors, including the specific requirements of the project and the user's expertise.

As each software has some advantages and disadvantages, it is advisable to choose the one that is most suitable given the ease of application and the specific needs of the project. Mourtzis et al. (2014) suggest that "the selection of the appropriate simulation software tool is a critical decision that affects the overall effectiveness of the simulation project" (p. 213).

In recent years, there has been a growing interest in agent-based simulation models. Macal and North (2010) argue that "agent-based modeling and simulation (ABMS) is an approach to modeling systems comprised of autonomous, interacting agents" (p. 151), which can be particularly useful for complex systems with many interacting components.

Furthermore, the integration of simulation with other technologies, such as artificial intelligence and machine learning, is opening new possibilities. As noted by Negahban and Smith (2014), "the integration of simulation with optimization, data mining, and other analytical tools has led to more powerful decision-support systems" (p. 86).

In conclusion, while the choice of simulation software is important, the key to successful simulation modeling lies in the accurate representation of the system, rigorous validation, and the ability to interpret and apply the results effectively to real-world decision-making processes.

5.4 Phase 4: Robust Output Analysis and Strategic Recommendation Synthesis

The final stage of the proposed methodology encompasses comprehensive analysis of simulation results and development of strategic recommendations based on these analyses. This phase establishes a critical link between simulation outputs and real-world decision-making processes.

The analysis of simulation output data is a fundamental step for the success of the study (Montevechi et al., 2018). This process employs statistical techniques to ensure accurate interpretation of results. To enhance the reliability of the analysis, the model is tested under various scenarios. Guo et al. (2017) propose a robust optimization framework that addresses uncertainties in simulation models.

The appropriate selection and evaluation of performance metrics determine the effectiveness of the simulation study (Pires et al., 2016). These metrics provide measurable indicators of system performance and identify areas for improvement. Comparison of different scenarios enables the identification of optimal solutions. Oliveira et al. (2019) emphasize the importance of "what-if" analysis in simulation studies.

Based on the insights gained from these analyses, actionable strategic recommendations are developed. Goodarzi et al. (2020) stress the necessity of translating simulation results into practical recommendations. The effective presentation of results and the formulation of an implementation plan are complementary steps in this phase. Xu et al. (2016) highlight the significance of visualization techniques in communicating simulation results to decision-makers.

In conclusion, Phase 4 ensures that the simulation study provides tangible benefits to the organization. As Barlas and Heavey (2016) state, the ultimate goal of simulation is not only to model systems but to improve them. In this context, this phase maximizes the value of the simulation study and facilitates the effective application of the knowledge gained.

This structured approach ensured that the simulation model was both valid and reliable, thereby providing a robust foundation for the thesis research. The step-by-step processes of validation and verification are detailed below:

CHAPTER SIX

APPLICATION OF PROPOSED METHODOLOGY IN AUTOMOTIVE INDUSTRY

CASE STUDY

Chapter 6 presents an application of the proposed methodology within an automotive industry firm, adhering to the framework delineated in Chapter 5. This implementation serves to validate the methodology's efficacy and practical applicability in a real-world industrial context. The application process was structured into four distinct phases, beginning with the problem contextualization and scope. In this initial phase, the problem scope and strategic objectives were meticulously defined, considering the specific constraints and operational parameters of the automotive firm. This critical step ensured that the simulation study was closely aligned with the organization's strategic imperatives and operational realities. The second phase focused on comprehensive process mapping, identified as a crucial precursor to successful simulation. This step involved a detailed analysis and documentation of the firm's operational processes, workflows, and interdependencies, laying a solid foundation for the subsequent simulation model development. In the third chapter of the study, an advanced simulation model was developed based on the process maps and data was collected. Verification and validation tests were conducted to ensure the model's consistency and accuracy in representing real-world operations, establishing the credibility and reliability of the simulation model. The final phase encompassed a thorough statistical analysis of the simulation outputs. Based on these analyses, alternative scenarios were generated and evaluated against the company's investment objectives and operational constraints.

The outcomes were synthesized into a set of strategic recommendations tailored to the automotive firm's specific context, providing actionable insights for operational improvements and strategic investments. This practical application demonstrates the methodology's versatility and effectiveness in addressing complex industrial challenges. By systematically progressing through each phase, the study not only provided valuable insights into the automotive firm's operations but also generated actionable strategies for improvement. The successful implementation underscores the methodology's potential as a powerful tool for decision-making and strategic planning in the automotive industry and potentially in other manufacturing sectors.

6.1 Phase 1: Problem Contextualization and Scope Delineation

This section describes the implementation of Phase 1, "Problem Contextualization and Scope Delineation," in the study. The process began with an examination of the company's organizational profile and context to establish the problem's scope. Subsequently, the Ishikawa (Fishbone) Diagram was employed to conduct a detailed analysis of the problem, identifying primary and secondary causal factors. This analysis was supported by empirical data collected from the company (Referred to in Chapter 6.3.1.), ensuring a comprehensive and evidence-based approach to problem definition. The methodology provided a thorough understanding of the organizational context and root causes, laying a strong foundation for developing targeted solutions in later phases of the study.

The multinational automotive enterprise under examination presents a compelling case study in global manufacturing strategy and operational excellence. This organization has established a formidable presence in the automotive supply chain, with production facilities strategically distributed across six countries: Turkey, Brazil, Italy, China, and the United States, with one additional location unspecified. This geographical diversification not only allows the company to optimize its supply chain logistics but also positions it to respond effectively to regional market demands and regulatory environments. The centralization of research and development activities at the company's headquarters represents a deliberate strategy to consolidate innovation efforts, potentially fostering a more cohesive and efficient approach to product development and technological advancement.

In addition to its manufacturing footprint, the company has judiciously established a network of technical and commercial offices throughout various European locations. This strategic deployment of resources underscores the organization's commitment to maintaining proximity to key markets and clients, facilitating responsive customer service and enabling agile adaptation to market trends. The company's significant market penetration is evidenced by the incorporation of its products in over 300 million vehicles globally, a testament to its quality, reliability, and widespread acceptance within the automotive industry. Supporting this extensive operational network is a global workforce exceeding 3,000 individuals, highlighting the substantial human capital investment required to sustain such a complex, multinational enterprise.

The company's operational philosophy is characterized by a keen awareness of industry developments and a demonstrated ability to swiftly adapt its production systems to align with emerging trends. This adaptability is exemplified by the organization's strategic pivot from manufacturing television components to focusing on electric vehicle parts, a transition that reflects both market foresight and operational agility. In pursuit of operational excellence, the company has set an ambitious quality target of 9-sigma, a standard that surpasses the widely recognized 6-sigma benchmark and underscores an uncompromising commitment to product quality and process optimization.

The strategic focus of the enterprise is multifaceted, encompassing four key areas that are at the forefront of automotive innovation: components for electric vehicles, smart materials, clean energy solutions, and zero-defect products. This strategic orientation not only aligns with current industry trends towards electrification and sustainability but also positions the company as a potential leader in the ongoing transformation of the automotive sector. The emphasis on smart materials and zero-defect manufacturing further demonstrates a forward-thinking approach that anticipates future market demands and regulatory requirements.

The company's Turkish operations serve as a microcosm of its global manufacturing strategy, comprising four specialized factories that form an integrated production ecosystem. The first facility focuses on the production of plastic components, a critical element in modern automotive design that contributes to vehicle weight reduction and fuel efficiency. The second factory, dedicated to ignition coil production, underscores the company's continued involvement in traditional internal combustion engine technologies while potentially adapting these components for hybrid vehicle applications. The third facility, producing ancillary parts that enable electrification, directly supports the company's strategic shift towards electric vehicle technologies. Finally, the fourth factory, referred to as the "automation factory," produces production lines, indicating a significant level of vertical integration and suggesting a capacity for continuous process improvement and customization of manufacturing processes.

The material flow between these Turkish facilities, as indicated by arrows in the referenced Figure 1, implies a highly coordinated and efficient production network. This integrated approach likely facilitates just-in-time manufacturing practices, reduces transportation costs, and enhances quality control measures across the production chain. Moreover, the presence of an in-house

automation factory suggests that the company possesses the capability to rapidly adapt and optimize its production processes in response to changing market demands or technological advancements.

In conclusion, this multinational automotive enterprise exemplifies the complexities and strategic considerations inherent in global manufacturing operations within the rapidly evolving automotive industry. Its geographical diversification, centralized R&D approach, market responsiveness, and commitment to cutting-edge technologies position it favorably to navigate the challenges and opportunities presented by the ongoing transition to electric and smart vehicle technologies. The company's integrated production ecosystem in Turkey, coupled with its ambitious quality targets and focus on innovation, underscores a comprehensive strategy aimed at achieving and maintaining a leadership position in the competitive automotive supply chain landscape.

The company starts by signing numerous different projects at the same time within very short delivery times to meet sales targets, increase sales volume and customer portfolio. There is a risk of not being able to complete the project on time and it causes with high penalty costs, particularly in very dynamic areas such as the automotive industry. However, as mentioned in first chapter of the thesis where the economic effect of backorder is examined in detail, backorders are allowed within certain tolerance limits in line with the strategic goals of the companies. The allowance of backorders by companies can be attributed to several key factors. These include demand management, customer retention, production efficiency, inventory management, and market competition. Each of these factors plays a significant role in shaping the strategic decision-making process behind the acceptance of backorders within the business context.

The projects on which the company is working are categorized into line projects and modifications which have been illustrated in Figure 6.1. In line projects, the whole production line is built from the ground up to produce the new product and the cost is high. However, in line modifications, only the necessary modifications and adjustments to the line are required and the line is less costly than line projects.

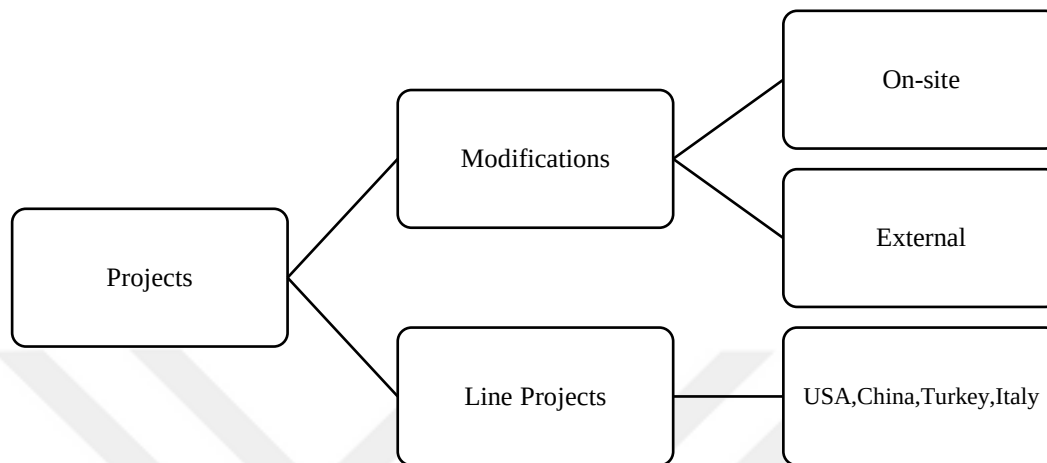


Figure 6.1 Classification of projects

Table 6.1 below offers a detailed and all-encompassing view of the delay costs, project values, and penalty cost effects across a range of projects. This comprehensive dataset provides valuable insights into the financial consequences of delays and penalties within each distinct project category. It is clear that project delays carry substantial implications for both the financial performance and the reputation of the business, ultimately exerting a profound influence on long-term sales and overall profitability.

The notable diversity in the impact of delays and penalties across the spectrum of projects underscores the strategic necessity of implementing a comprehensive approach to address and mitigate the effects of project delays. This underscores the critical importance of proactive management and mitigation strategies to minimize the adverse financial and operational impacts of delays, thereby safeguarding the overall success and sustainability of the business.

Table 6.1 Project Penalty Costs

Project Name	Delay (Day)	Delay Cost/Day	Delay Cost Total	Project Value	Penalty Cost Effect
Sub-project 1	40	\$5,200	\$208,000	\$5,200,000	4%
Sub-project 2	35	\$3,500	\$122,500	\$3,500,000	4%
Sub-project 3	22	\$1,800	\$39,600	\$1,800,000	2%
Sub-project 4	50	\$7,500	\$375,000	\$7,500,000	5%
Sub-project 5	15	\$2,000	\$30,000	\$2,000,000	2%
Line Project 1			\$775,100	\$20,000,000	4%
Sub-project 1	45	\$9,000	\$405,000	\$9,000,000	5%
Sub-project 2	30	\$7,000	\$210,000	\$7,000,000	3%
Sub-project 3	50	\$4,000	\$200,000	\$4,000,000	5%
Sub-project 4	15	\$4,000	\$60,000	\$4,000,000	2%
Sub-project 5	15	\$2,500	\$37,500	\$2,500,000	2%
Line Project 2			\$912,500	\$26,500,000	3%
Modification Project 1	12	\$8,000	\$96,000	\$500,000	19%
Modification Project 2	18	\$12,800	\$230,400	\$800,000	29%
Modification Project 3	16	\$5,600	\$89,600	\$350,000	26%
Modification Project 4	5	\$5,600	\$28,000	\$350,000	8%
Modification Project 5	9	\$15,520	\$139,680	\$970,000	14%
Modification Project 6	13	\$10,400	\$135,200	\$650,000	21%

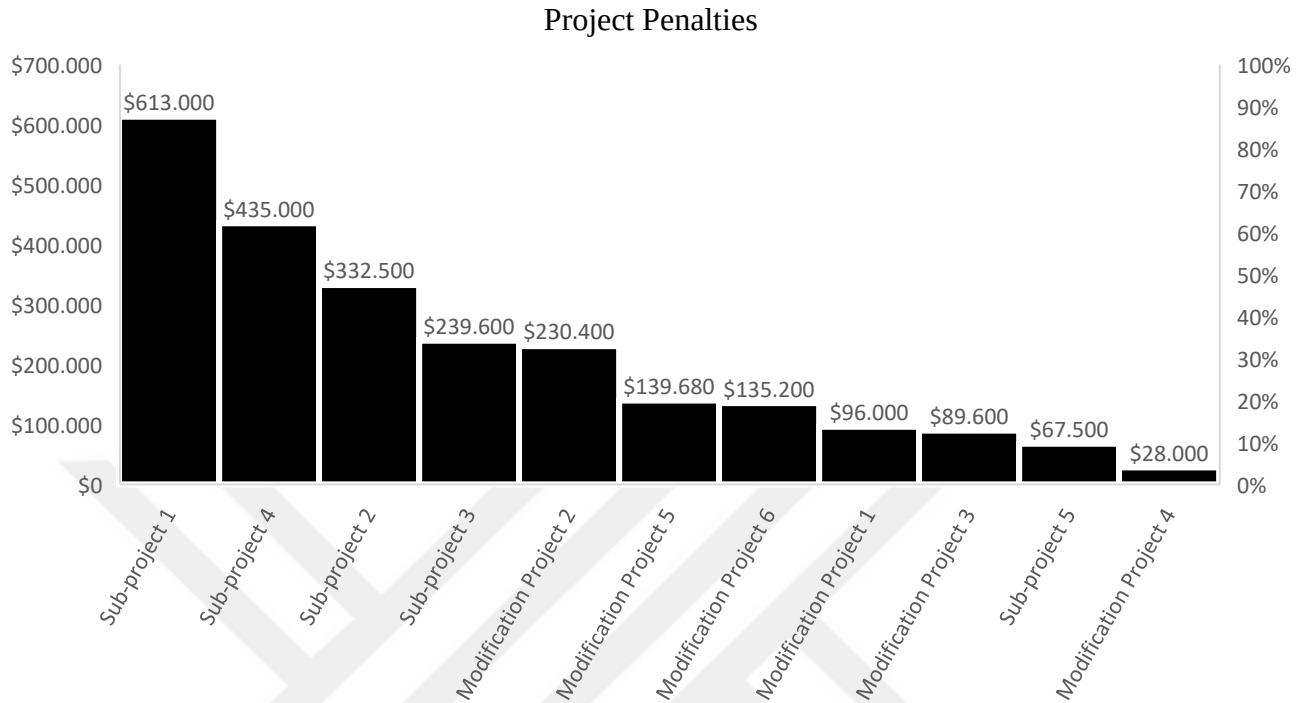


Figure 6.2 Project Penalties Costs

In the context of project delays, it is imperative to acknowledge the multifaceted nature of the factors contributing to such occurrences. Extensive consultations with senior staff members have been instrumental in discerning the underlying causes of project delays, drawing upon their wealth of experiential insights and domain expertise. This comprehensive analysis has been visually represented through a Fish-bone diagram, effectively elucidating the primary sources of the problem. The identification of these root causes has been predicated on in-depth discussions pertaining to the challenges encountered during system operations, thereby serving as a foundational basis for subsequent model verification and validation processes.

To ensure the robustness of the findings, a plan has been devised to conduct a simulation study, should the primary causes of the problem diverge from the initial assumptions. This approach underscores a commitment to thoroughness and a dedication to accurately delineating the factors contributing to project delays. It reflects a proactive stance aimed at addressing potential deviations and ensuring the reliability of the analysis.

Furthermore, it is noteworthy that senior management's risk aversion assumes pivotal consideration in this context. The unique nature of each project, coupled with the non-standardized frequency of project arrivals, engenders an environment where risk mitigation assumes paramount importance. This risk aversion is reflective of a prudent approach to project management, acknowledging the inherent variability and complexity that characterizes each project endeavor. It underscores a strategic emphasis on preemptive risk management and a proactive stance towards addressing potential challenges, thereby aligning with best practices in project management and organizational resilience.

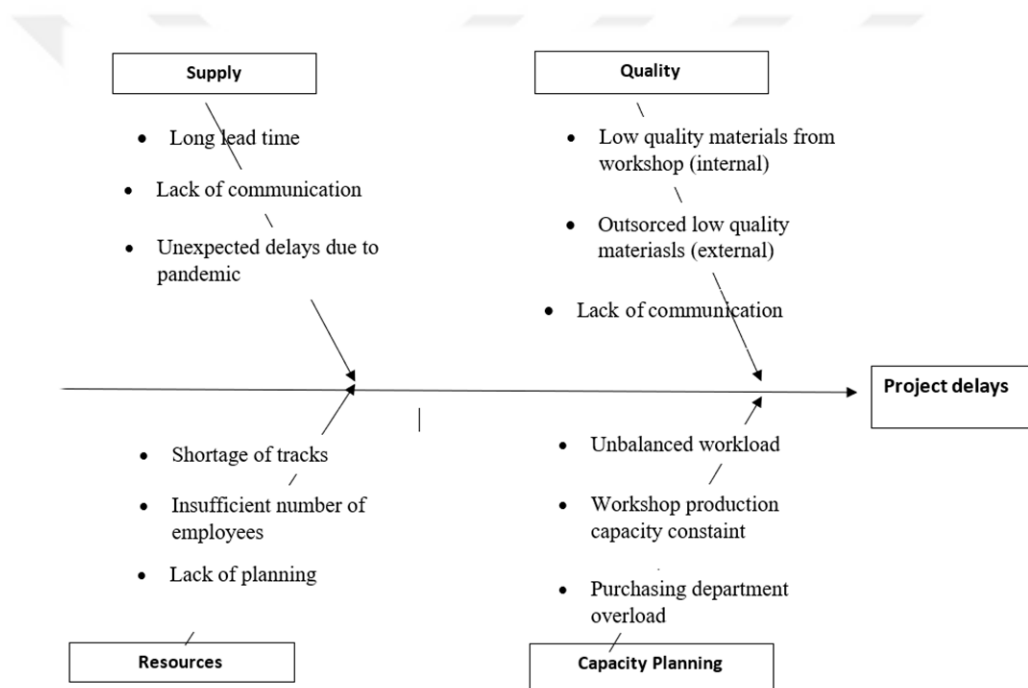


Figure 6.3 Fish-bone diagram

To minimize project delays, the causes are divided into 4 main categories (supply, quality, resource, capacity) as shown in Figure 6.3 Fish-bone diagram, and each category is examined and analyzed in detail to find root cause of the defined problem. An in-depth analysis of the supply problem revealed that the materials required for the project are mainly sourced from European and, in particular, American sources, which results in longer lead time.

With the impact of the pandemic, unpredictable and very long lead times is created a supply problem. Since there is no automated material tracking system between supply and production, it is very difficult to track parts and have control over them. Due to the existing manual Excel-based tracking system, significant delays are experienced, leading to communication challenges and interpersonal tension.

When analyzing the quality problem, as seen in diagram there is a quality problem in both insourced and outsourced parts. Since the company in a foreign trade zone, import transactions take a lot of time. Much time is lost, mostly because the parts are waiting at customs, and a workshop was established in the free zone to prevent this. As the insourced parts are produced in facility which located in free zone area, we can consider this area as being capable of improvement. However, the same cannot be said for the parts that come from suppliers, but the problem can be solved by changing the supplier or by an agreement with the supplier.

When analyzing the resource constraint, discussions with staff revealed that some people were overwhelmed by the workload and that some vehicles has very long waiting times that creates conflicts between people and decrease efficiency. Last problem that addressed is capacity of workshop. Top management decided that 30% of demand has to be met from workshop, this management decision to create a constraint by reducing flexibility.

6.1.1. Research Objectives and Hypothesis Formulation

This research endeavor was undertaken with three primary objectives, as delineated in Figure 6.4 Objectives 1 and 3 can be categorized as strategic imperatives for the organization, with their successful attainment potentially yielding long-term enhancements to the company's financial performance. Conversely, Objective 2 focuses on operational excellence and can thus be classified as a tactical goal. The impact of Objective 2 is quantifiable in terms of process efficiency improvements in the short to medium term. These objectives collectively address both strategic and operational aspects of the organization, with the potential to yield substantial improvements in overall performance and competitive positioning.

Objective 1: Reduction of project delays in order to minimize the economic impact of penalties on project profitability.

Objective 2: Identification of defects and bottlenecks in the supply and production process and improvement of process efficiency with a holistic view.

Objective 3: Execution of the feasibility study for the workshop relocation project at the plant, which is the new investment decision.

Figure 6.4 Objective of Thesis

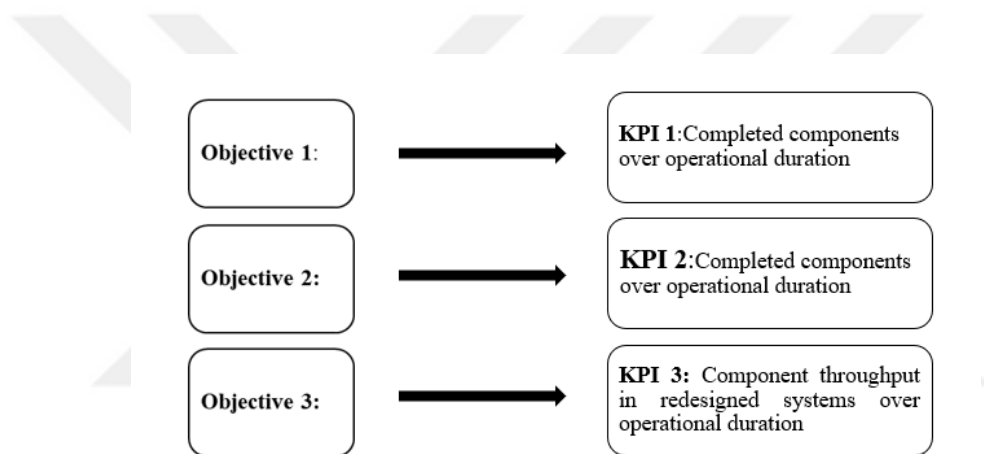


Figure 6.5 Objective-Aligned Key Performance Indicator Formulations

Figure 6.4 delineates the thesis objectives, while Figure 6.5 presents the key performance indicators (KPIs) that facilitate the analysis of objective attainment. The KPIs depicted herein are predominantly quantifiable through mathematical means; however, it is noteworthy that there exist additional performance metrics classified as non-tangible.

Sustainability emerges as one of the paramount objectives among these non-tangible metrics. The equilibration of workload intensity for personnel holds significant importance in mitigating the risk of over-exertion. Furthermore, the strategic design of positions to incorporate redundancy through backup measures represents a crucial long-term initiative for corporate entities.

The juxtaposition of tangible and intangible performance indicators provides a comprehensive framework for assessing organizational efficacy. This multifaceted approach to performance evaluation aligns with contemporary management theories that emphasize holistic organizational health beyond mere quantitative benchmarks. The inclusion of sustainability as a key non-tangible metric reflects the growing recognition of its importance in modern corporate strategy. This aligns with the triple bottom line concept, which posits that organizational success should be measured not only by financial performance but also by social and environmental impacts. The emphasis on workload balancing and position redundancy underscores the significance of human resource management in achieving long-term organizational resilience. These strategies are congruent with current research on organizational behavior and human capital management, which highlight the importance of employee well-being and institutional knowledge preservation for sustained corporate success.

The primary objective of this research is to provide a comprehensive and quantifiable definition of the problem by calculating the monetary equivalence of penalty costs. Subsequently, the study aims to analyze the causal factors contributing to these penalty costs. The final phase involves developing a strategic roadmap outlining the necessary steps for mitigating these identified causes.

The secondary objective focuses conducting a holistic analysis of the root causes underlying inefficiencies across various departmental processes. This analysis will inform the development of alternative solutions designed to either eliminate or significantly reduce the impact of the most critical causal factors.

The tertiary aim of this study is to evaluate the feasibility of relocating the workshop, currently situated in a separate facility, to within the main factory premises. The proposed simulation modeling methodology will be employed to simulate the potential impact of this investment decision on overall processes. Should the projected productivity increase prove sufficient, the study will provide actionable feedback to the organization regarding implementation strategies.

A comprehensive literature review has been conducted to support this research. Initially, seminal studies in simulation modeling were examined to elucidate the types of problems amenable to this methodology. Subsequently, research investigating and applying process analysis

techniques for developing valid and effective simulation models was reviewed. Finally, an in-depth analysis was performed on papers utilizing simulation-based optimization approaches for enhancing production efficiency across various domains. This analysis was crucial in determining the most appropriate methodological approach given the specific characteristics of the problem at hand.

6.1.2 Boundary Conditions and Constraints Identification

The production factors and constraints are delineated as follows:

- Two types of materials are categorized based on their yield and shear strength. In subsequent sections of the thesis, materials that do not require pre-machining or exhibit low yield and shear strength are referred to as "soft materials," while those necessitating pre-machining or demonstrating high yield and shear strength are denoted as "hard materials." The distribution of incoming parts reveals that 60% of the parts correspond to the category of soft materials, while the remaining 40% pertain to hard materials. This ratio has been meticulously computed through an exhaustive analysis encompassing all essential parts associated with the 16 projects. Comprehensive details pertaining to this calculation are meticulously documented in the annexes, providing a thorough and transparent account of the analytical process and its outcomes.
- There are 4 machines in the workshop, three of which are used for machining soft materials while other is used for pre-machining hard materials.
- The capacity of each machine is 1 and the set-up time varies according to the material type.
- There are 4 technicians and 1 supervisor working in the workshop, and 1 purchasing specialist working in the automation factory.
- Some of the parts manufactured in the workshop exhibit various issues such as defects, design errors, or quality problems. While certain issues can be rectified through reprocessing, others necessitate scrapping. Remanufacturing is essential for specific parts, addressing manufacturing defects, design errors, or material quality issues. According to historical analysis, 54% of the parts successfully complete the manufacturing process, 38% require rework, and 8% are ultimately scrapped. The quantities of parts initially entering the workshop and subsequently requiring reprocessing after leaving the factory differ. The

workshop meticulously records discarded items, enabling the calculation of the percentage of parts necessitating rework and those requiring scrapping. Notably, parts requiring rework consistently hold priority across all queues, with the exception of the truck and the procurement specialist.

- The transportation system within the company comprises four trucks dedicated to conveying materials between various facilities. The loading and unloading times for these trucks are meticulously collected. Upon completion of the manufacturing process for each part, the parts are transported in bundles, as transporting them individually would result in prohibitively high costs. Irrespective of the type of part, the transportation process commences once the number of parts waiting in the truck queue reaches 5. Each truck operates at a velocity of 30 km/h, which is equivalent to 500 minutes/meter as specified in the Arena. It's important to note that these speed limits are established in accordance with the company's stringent occupational safety and health policies, underscoring the company's unwavering commitment to ensuring a safe working environment for all employees.
- In the event that the queue of the purchasing specialist accumulates more than 20 pieces awaiting processing, a directive is in place to reroute these pieces to the workshop's manufacturing queue. This decision is made under the assumption that the workshop has the capacity to manufacture these parts, albeit based on incomplete or unavailable data. This strategic reallocation of parts ensures that the workflow remains optimized and that production targets can be met, even in the face of unexpected surges in demand or processing requirements.

6.2 Phase 2: Comprehensive Process Mapping and Systemic Analysis

In this phase of the study, an integrated approach was employed to map the processes occurring across all facilities. This comprehensive process map encompasses transportation systems, workshop production, automated factory production, procurement processes, and quality management systems. The development of this intricate process architecture was executed through a systematic methodology, leveraging Microsoft Visio as the primary visualization tool. The process mapping procedure was conducted in two primary stages:

Process mapping is a schematic representation of the extant system's process architecture. This delineation of operational flow serves as a critical antecedent to simulation modeling, a relationship that merits further exploration.

The significance of process mapping as a preliminary step in simulation modeling cannot be overstated. When simulation modeling is initiated without a comprehensive process map, the subsequent verification and validation of the model become exceedingly challenging, regardless of the tracking mechanisms employed. This difficulty arises from the lack of a clear, systematic understanding of the underlying processes that the simulation aims to replicate.

In the context of this research, the initial approach did not incorporate process mapping, leading to substantial impediments during the modeling phase. This oversight necessitated a return to foundational steps, wherein a *de novo* process mapping exercise was undertaken. This retrospective implementation of process mapping yielded dual benefits:

- **Enhanced Validation and Verification:** The detailed process map provided a robust framework against which the simulation model could be verified and validated, ensuring fidelity to the real-world system.
- **Facilitated Modeling Process:** With a clear visual representation of the system's workflow, the construction of the simulation model was significantly streamlined, reducing complexity and potential errors.

This experience underscores the critical role of process mapping in the simulation modeling lifecycle. It serves not only as a valuable tool for system understanding but also as an indispensable asset for ensuring the accuracy and reliability of the resultant simulation model. Future research endeavors in this domain would be well-advised to prioritize comprehensive process mapping as an integral component of the preliminary analysis phase.

This expanded version maintains an academic tone, provides more context, and emphasizes the importance of process mapping in simulation modeling. It also highlights the specific experiences and lessons learned from this research project.

6.2.1 Expert Consultation and Workflow Elicitation

In the Expert Consultation and workflow elicitation phase, which is a crucial step for comprehensive process mapping, all the steps outlined in Chapter 5.2.1 of the proposed methodology were meticulously implemented. The process unfolded as follows:

➤ **Structured interviews with domain specialists**

Initially, structured interviews were conducted with employees who had been with the company for many years. During these sessions, experienced staff shared their insights on process bottlenecks, inefficient or non-functional processes, and suggestions for improvement.

- **Documentation review of existing process guidelines** Following the interviews, the existing process maps within the company were thoroughly examined.
- **Identification of key process nodes and decision points** expert experience to create a process draft was crucial at this stage. The study analyzed and identified discrepancies between processes that exist on paper and those that occur in practice. Considerable time was allocated to this phase to ensure that these differences were properly identified and that the process map to be created accurately reflected the actual system. Subsequently, decision points and process nodes were identified. These can be found in Chapter 6.2.3 of the study, which presents the determined decision points and process nodes in detail.
- **Delineation of inter-departmental process flows** in the final stage; a collaborative effort was undertaken where the process flow was shared with other stakeholder departments using Visio. This interdepartmental collaboration proved highly valuable, as it allowed teams with expertise in specific areas to clarify aspects of the process that were not fully understood by others. This ensured that the processes were efficient, universally comprehensible, and acceptable to all parties involved.

By adhering to these steps, the study ensured a comprehensive and accurate mapping of the processes, incorporating both formal documentation and practical insights from experienced staff across various departments. This thorough approach provided a solid foundation for subsequent analysis and improvement initiatives.

6.2.2 Onsite Observational Analysis

This section of the study consists of systematic onsite observation, time motion study, and informal staff interview components.

➤ Systematic onsite observation

Following the expert consultation and workflow elicitation phase, a comprehensive onsite observation was conducted. Given the company's multiple locations, each factory was visited in conjunction with resident experts to gather necessary observations and notes. This systematic approach ensured a thorough examination of all operational sites. The processes described by the experts were meticulously compared with the existing process maps and the real-time observations made during these visits. This triangulation method allowed for a more accurate representation of the actual processes in place, highlighting any discrepancies between documented procedures, expert accounts, and observed practices.

➤ Time motion study

To gather essential data for the study, an intern Industrial Engineer was assigned to conduct a time and motion study over a three-month period. This extended duration allowed for a comprehensive analysis of work processes, capturing variations that might occur over time due to factors such as seasonality or production cycles. The specific areas for data collection were clearly delineated in the form of notations, as detailed in section 6.3.1 of the study. This structured approach to data collection ensured consistency and relevance to the overall research objectives, providing quantitative insights into process efficiencies and potential areas for improvement.

➤ Informal staff interviews

Upon analyzing inconsistencies between the reported processes and those observed in practice, a series of informal staff interviews were conducted. These interviews were strategically separated from those with upper management to encourage open and candid responses from the operational staff. This approach yielded illuminating data about certain processes that had not been fully captured in previous stages of the research. The informal nature of these interviews allowed for a more nuanced understanding of day-to-day operations and unofficial workarounds that may have developed over time.

Following these interviews, the importance of accurately defining processes for improvement purposes was communicated to the entire team. This step was crucial in fostering a collective understanding of the project's objectives and the potential benefits of process optimization. Subsequently, a coordination meeting was organized where the designed process map was shared with all teams. This collaborative session allowed for final adjustments and refinements, ensuring that the final process map was comprehensive, accurate, and endorsed by all relevant stakeholders, this multi-faceted approach, combining expert consultation, systematic observation, quantitative analysis, and informal staff input, provided a robust foundation for the process mapping exercise, ensuring that the final output accurately reflected the operational reality of the organization.

6.2.3. Process Mapping by Suitable Software

Process mapping was conducted using Microsoft Office Visio, utilizing data obtained from the studies in sections 6.2.1 and 6.2.2. This approach provided a significant advantage in capturing a holistic view of the study, as it effectively illustrated processes and material flows across different locations.

Furthermore, working with Visio offered an additional benefit by facilitating collaborative work through shared access for multiple individuals. This methodology eliminated the need for constant email correspondence and provided a more efficient means of conducting discussions between departments and locations. Additionally, the ease of use and standardization of Visio supported a more productive execution of the study.

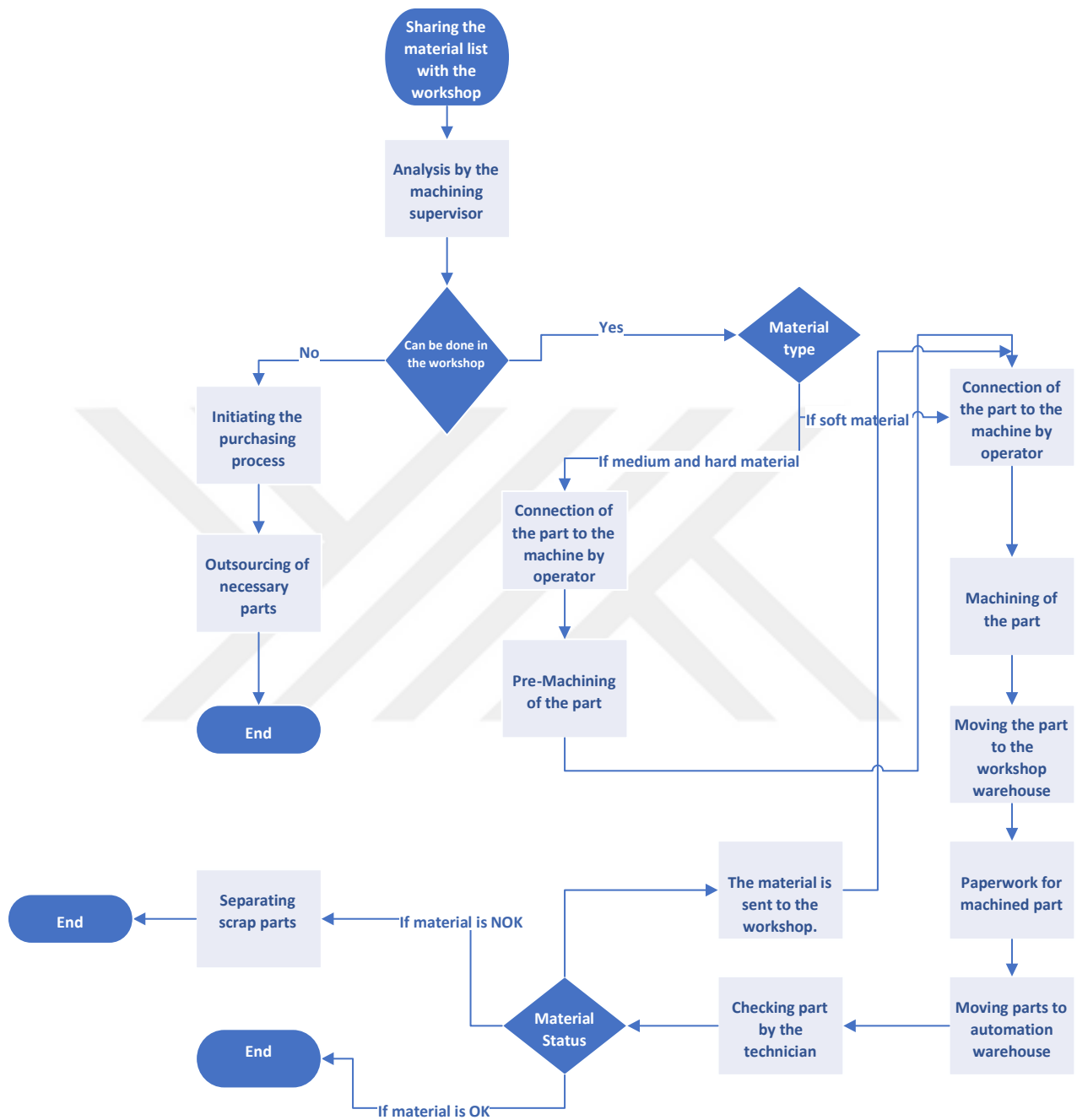


Figure 6.6 Process Mapping of Current System

6.3 Phase 3: Advanced Simulation Model Development and Validation

This section of the thesis presents details on the collection of data essential for simulation modeling. Two distinct data collection methods were employed. The first method aimed to maximize the number of observations through time studies, while the second method involved obtaining data through computer automation of CNC machines.

During the time study, the industrial engineering trainee meticulously collected data related to various industrial processes and operations over the course of three months, spanning from September 2022 to November 2022. The intern, who demonstrated a high level of proficiency in the methodology, ensured that outlier data, which encompassed extreme situations or anomalies, was deliberately omitted from the observations. This careful curation of the data aimed to provide a more accurate and representative dataset for analysis and interpretation.

Upon reviewing the Fish-Bone diagram created in the preceding section, it becomes apparent that the primary factor contributing to project delays is associated with issues of missing, inaccurate, and substandard quality. Essentially, by reducing product cycle times, the system's performance criteria can be significantly enhanced. Consequently, the system was modeled using collected data to assess the dwell times of components within the system and their respective placements.

Given the company's project-oriented approach, specific variables such as project arrival times and material requisition dates are uncertain. Therefore, the subsequent chapter focuses on the imperative analysis of inputs. This analysis delves into the unpredictability of project timelines and material needs, aiming to develop strategies that can accommodate and mitigate the impact of these uncertainties on project schedules and resource allocation. Additionally, the chapter explores methods to optimize the utilization of available data to enhance decision-making processes and improve overall project efficiency.

Table 6.2 presents a comprehensive delineation of inter-station distances, quantified in metric units (meters). This tabular representation provides a precise spatial analysis of the infrastructure layout, offering critical insights into the physical distribution and proximity of operational nodes within the system.

Table 6.2 Distance between stations

Stations (meter)	Entrance	Workstation	Workshop Warehouse	Automation Warehouse	Exit
Entrance	–	1000	750	5000	500
Workstation	1000	–	600	3000	2000
Workshop Warehouse	750	600	–	3500	1000
Automation Warehouse	5000	3000	3500	–	4500
Exit	500	2000	1000	4500	–

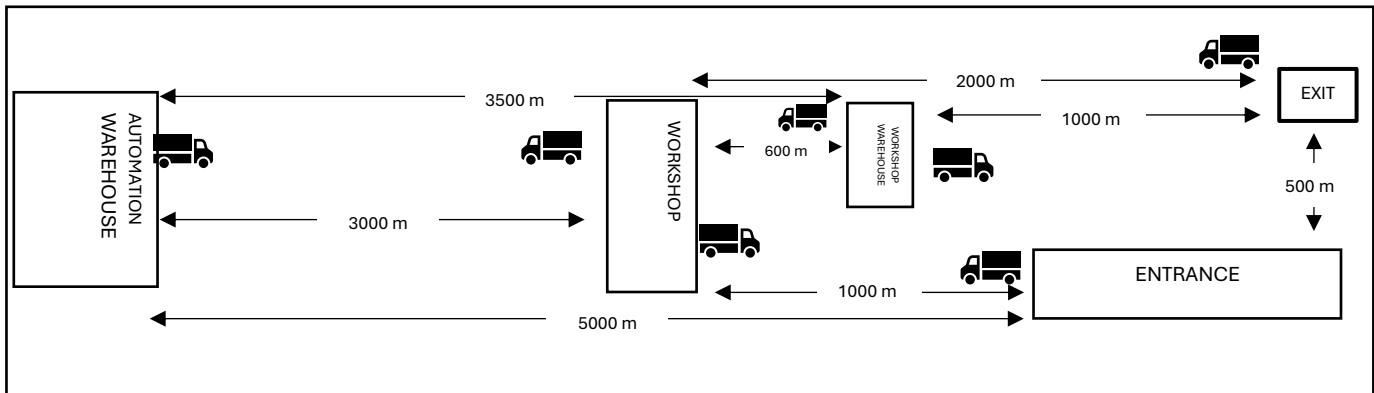


Figure 6.7 Visualization of distance between stations

As depicted in Figure 6.7, the transportation of goods between stations is facilitated through the use of trucks. Despite the relatively short distances between facilities, it has been observed that the waiting times associated with this transportation process are considerably prolonged. Recognizing the significance of this issue, a comprehensive investigation into the underlying causes of these extended waiting times is imminent.

The forthcoming initiative to optimize waiting times will encompass a meticulous evaluation of resource sufficiency and a targeted focus on bottleneck areas within the transportation system. This in-depth study is designed to meticulously identify and address the root causes of the prolonged waiting times, with the overarching objective of enhancing operational efficiency and minimizing delays within the system.

By delving into the intricacies of resource allocation, operational processes, and potential constraints, this initiative seeks to unearth the specific factors contributing to the extended waiting times. Subsequently, the findings will inform the development and implementation of strategic interventions aimed at streamlining operations, mitigating bottlenecks, and ultimately fostering a more agile and responsive transportation system. The ultimate goal is to optimize the utilization of resources, enhance overall operational fluidity, and bolster the system's capacity to meet transportation demands efficiently and expeditiously.

6.3.1. Data Collection and Input Analysis

Data collection and analysis processes are critical preliminary stages in simulation modeling, directly impacting the accuracy and reliability of the model. Recent research has emphasized the importance of these processes and introduced innovative approaches to enhance their effectiveness.

Data collection forms the foundation of simulation modeling. Barlas and Heavey (2016) emphasized the need for a systematic and structured data collection process. The authors adhered to the principle that "without correct data, there can be no correct model" (p. 908), highlighting the critical nature of this initial phase. The data collection process aims to obtain sufficient and quality data relevant to the model's objectives.

Technological advancements have revolutionized data collection methods. Xu et al. (2018) examined the use of IoT (Internet of Things) based data collection systems in simulation modeling. These systems enable real-time and more comprehensive data collection, enhancing the accuracy and timeliness of simulation inputs.

Following data collection, the focus shifts to data analysis. Law (2019) investigated the role of input analysis in simulation modeling, highlighting the importance of determining statistical distributions of data. Law stated, "correct input distributions directly impact the reliability of simulation results" (p. 66), clearly demonstrating the effect of data analysis on simulation model performance.

The quality and reliability of collected data are paramount in the data analysis process. Montevechi et al. (2021) examined the impact of data quality on simulation results, emphasizing the importance of data validation and cleaning processes. The authors concluded that "simulations conducted with unreliable data can lead to misleading results" (p. 1203), underscoring the critical role of data quality in the analysis phase.

In recent years, the use of artificial intelligence and machine learning techniques in data analysis has increased. Zhu et al. (2020) focused on using deep learning algorithms for automatic analysis of input data and determination of appropriate distributions. This approach yields faster and more accurate results compared to traditional methods, optimizing the data analysis process.

In conclusion, data collection and analysis processes form the foundation of simulation modeling. Effective execution of these processes enhances the accuracy and reliability of the simulation model. Technological advancements and new approaches enable more efficient and effective implementation of these processes. Researchers and practitioners in simulation modeling can create more successful and reliable models by giving due importance to the data collection and analysis stages.

List of notations

Dependent variables

$L_{i,t}$: Loading time of the material that comes at time t in observation i

$U_{i,t}$: Unloading time of the material that comes at time t in observation i

$S_{i,t}$: Technical analysis time by the supervisor of the material that comes at time t in observation i

$T_{n,i,t}$: Processing time by technician of the material that comes at time t in observation i

$M_{n,i,t}$: Machining time of the material that comes at time t in observation i

$P_{i,t}$: Purchasing time by the purchasing specialist of the material that comes at time t in observation i

Independent variables

n : Number of sources

i : observation

t : Arrival time

The notation system utilized in this research facilitated the systematic analysis of stochastic processes within operational frameworks. It enabled precise data collection, capturing temporal and observational variations in process components. This structured approach allowed for the quantification of variability and uncertainty in each process step. The collected data were subsequently fitted to appropriate statistical distributions, transforming empirical observations into robust stochastic representations. This methodology established a foundation for developing high-fidelity simulation models. Ultimately, the notation system served as a crucial bridge between raw process data and sophisticated stochastic modeling, enhancing the overall rigor and applicability of the research outcomes.

Table 6.3 Processing time of resources part 1

Observation (i)	Arrival time (t)	Loading Time ($L_{i,t}$)	Unloading Time ($U_{i,t}$)	Supervisor Time ($S_{i,t}$)	$T_{1,i,t}$	$T_{2,i,t}$	$T_{3,i,t}$	$T_{4,i,t}$	$M_{1,i,t}$	$M_{2,i,t}$	Purchasing Specialist ($P_{i,t}$)
1	3,25	4,71	4,51	9,71	4,30	7,79	10,81	3,80	13,42	27,41	19,54
2	3,58	5,11	4,42	10,94	4,77	7,24	6,93	4,71	14,59	26,07	21,42
3	4,98	3,88	4,14	10,90	3,87	9,26	7,36	3,23	14,55	22,79	16,88
4	3,37	5,27	4,26	9,75	2,26	8,40	8,53	4,67	10,32	26,97	20,81
5	4,22	4,84	4,10	9,91	1,01	9,30	9,41	5,56	13,84	24,42	16,78
6	3,33	5,89	4,91	10,46	4,43	9,40	8,05	3,16	10,63	23,62	20,02
7	4,72	4,99	5,80	10,19	4,08	10,21	10,16	5,31	10,82	26,67	16,18
8	4,07	3,87	5,19	11,40	4,83	7,41	9,48	4,07	10,43	26,60	22,44
9	3,50	5,27	5,59	10,97	5,35	5,95	7,32	5,51	10,49	27,14	22,88
10	3,80	3,72	5,36	11,48	4,33	8,25	7,78	5,57	11,67	26,55	21,23
11	4,97	5,77	4,09	8,00	4,41	6,29	7,72	4,21	13,52	26,49	21,67
12	4,62	4,92	4,09	11,15	5,62	7,89	8,18	4,30	13,20	26,23	18,87
13	3,22	3,52	5,76	8,91	4,94	8,64	5,91	4,12	11,73	25,77	18,10
14	4,84	3,10	5,93	11,92	4,31	5,44	3,24	5,56	12,39	22,92	21,07
15	4,48	3,04	4,13	10,45	3,56	5,87	9,35	5,40	11,48	22,95	23,22
16	4,80	3,34	5,59	8,86	5,19	5,83	9,76	4,40	11,40	27,60	21,17
17	4,76	3,09	5,53	11,45	4,14	6,36	8,17	4,31	10,64	24,83	22,94
18	5,00	3,47	4,32	8,66	4,33	7,47	10,23	4,93	13,18	24,70	17,64
19	4,32	3,28	4,47	8,76	4,57	6,95	6,07	3,32	11,98	25,60	23,39
20	4,18	5,96	4,30	11,38	4,42	10,67	7,63	5,02	12,98	25,08	17,50
21	4,30	5,19	5,48	10,57	4,27	9,89	8,09	5,80	12,78	25,24	17,78
22	4,31	3,32	4,51	10,42	4,35	7,03	5,45	3,92	13,52	26,01	23,62
23	3,88	5,98	4,98	8,99	3,67	7,04	10,34	3,54	11,32	26,39	19,11
24	3,18	3,70	4,13	9,81	4,28	7,54	6,27	5,19	12,04	25,09	24,84
25	3,67	4,33	4,14	11,02	3,76	8,73	5,53	4,76	11,32	22,78	22,85

Table 6.4 Processing time of resources part 2

Observation (<i>i</i>)	Arrival time (<i>t</i>)	Loading Time (<i>L_{i,t}</i>)	Unloading Time (<i>U_{i,t}</i>)	Supervisor Time(<i>S_{i,t}</i>)	<i>T_{1,i,t}</i>	<i>T_{2,i,t}</i>	<i>T_{3,i,t}</i>	<i>T_{4,i,t}</i>	<i>M_{1,i,t}</i>	<i>M_{2,i,t}</i>	Purchasing Specialist (<i>P_{i,t}</i>)
26	4,76	4,93	5,13	10,49	2,47	9,09	10,31	5,68	10,80	27,31	21,16
27	4,16	5,34	4,41	10,97	3,29	9,58	9,61	4,82	11,82	27,52	18,70
28	3,56	5,79	5,87	8,69	3,67	8,05	6,75	3,22	13,93	26,35	22,42
29	4,13	4,21	5,14	10,37	3,27	9,21	9,78	3,40	11,31	25,31	23,81
30	3,84	4,43	5,58	11,05	3,93	8,47	7,99	5,07	13,01	23,97	21,69
31	4,43	4,44	4,86	10,95	4,13	7,72	6,13	5,84	13,62	23,55	24,30
32	4,63	3,64	4,15	10,21	4,57	8,59	7,00	4,46	11,50	20,42	16,07
33	3,71	3,10	5,16	11,41	3,03	7,59	10,13	3,52	9,71	25,35	18,40
34	3,68	3,87	5,87	9,38	3,91	8,13	8,09	5,92	13,10	26,05	18,56
35	4,28	4,47	4,54	9,16	2,84	8,67	8,74	3,56	10,14	28,62	18,90
36	3,57	3,32	5,06	11,45	3,68	7,24	7,34	4,87	11,56	26,84	16,09
37	3,53	5,15	4,17	9,63	3,89	6,86	4,87	5,50	11,41	23,44	23,45
38	3,85	5,14	4,96	8,14	2,51	5,39	7,13	5,82	12,80	25,09	19,37
39	4,27	3,51	4,69	10,74	3,36	10,47	6,37	3,10	12,23	27,71	18,71
40	3,75	3,48	4,89	10,72	4,04	6,72	10,47	3,43	9,66	25,60	21,71
41	3,54	4,40	4,17	10,89	4,17	7,58	6,36	3,75	11,37	25,37	19,13
42	3,27	3,59	5,47	9,56	3,59	5,18	9,33	3,88	13,25	24,85	19,56
43	4,49	3,46	4,76	11,67	3,32	7,66	7,64	4,48	13,14	26,11	17,92
44	3,42	3,05	4,48	10,06	3,99	8,99	9,11	3,41	11,12	27,59	23,26
45	4,37	3,51	4,19	9,35	4,72	7,82	8,93	3,97	13,22	26,49	21,33
46	4,91	3,32	4,58	8,30	3,46	9,40	7,64	4,07	12,29	27,25	24,24
47	4,22	5,37	5,40	10,49	3,05	8,42	7,49	3,25	13,58	25,15	18,42
48	3,09	5,30	4,31	8,37	3,92	9,98	9,52	3,35	12,81	26,96	22,02
49	4,33	5,09	4,39	10,60	4,55	6,30	7,75	5,55	14,67	24,03	18,85
50	4,49	3,46	4,76	11,67	3,32	7,66	7,64	4,48	13,14	26,11	17,92

The arrival time of the parts was calculated by considering the arrival of the first project as the reference point, denoted as $t=0$. A total of 50 distinct observations were recorded, and these observations were utilized to establish probability distributions for the arrival times of the parts.

It is crucial to emphasize that the data presented in Table 6.3 and 6.4 are meticulously expressed in minutes, offering a granular breakdown of the arrival times and their corresponding frequencies. These detailed observations play a pivotal role as fundamental inputs for the forthcoming statistical analysis. They enable the comprehensive characterization of the arrival time patterns, laying the groundwork for the development of predictive models aimed at gaining deeper insights into and effectively managing the arrival process of parts within the system.

By meticulously documenting the arrival times and their frequencies, the data in Table 6.3 and 6.4 provide a rich source of information that is instrumental in discerning underlying patterns and trends. This, in turn, facilitates the identification of key temporal dynamics and variations within the arrival process. Leveraging this data, statistical analyses can be employed to uncover correlations, distributions, and probabilities associated with arrival times, thereby paving the way for the formulation of robust predictive models.

The development of predictive models based on this comprehensive analysis holds significant promise in enhancing the system's capacity to anticipate and adapt to arrival time variations. This advancement is crucial in fostering a more agile and responsive operational framework. By leveraging data-driven insights, the organization can proactively optimize resource allocation, streamline operational processes, and bolster overall system efficiency.

Predictive models enable the organization to forecast potential disruptions and adjust strategies, accordingly, ensuring minimal impact on operations. This foresight allows for dynamic scheduling and resource management, reducing downtime and improving service delivery. The ability to anticipate variations in arrival times also facilitates better coordination across departments, enhancing communication and collaboration.

Furthermore, the integration of predictive analytics into the operational framework strengthens the organization's competitive edge. By continuously refining these models with real-time data, the organization can maintain a high level of adaptability in a rapidly changing environment. This

adaptability not only improves customer satisfaction by ensuring timely service but also enhances operational resilience, allowing the organization to withstand unforeseen challenges. In summary, the strategic implementation of predictive models transforms data into actionable intelligence, driving efficiency and innovation. This approach not only optimizes current operations but also positions the organization for sustained success in the future.

6.3.2. Statistical Analysis and Distribution Fitting

Given the stochastic nature of the data, a comprehensive input analysis was conducted to determine the probability distributions for all parameters utilized in the simulation model. This analysis involved processing a maximum number of observations to ensure a robust and representative dataset.

The primary objective of this input analysis was to discern the most suitable probability distribution that accurately characterizes the arrival time data. To achieve this, a range of candidate distributions including beta, empirical, Erlang, exponential, gamma, Johnson, lognormal, normal, Poisson, triangular, uniform, and Weibull distributions were considered. By systematically evaluating the goodness-of-fit for each distribution against the observed data, the analysis aimed to identify the distribution that best aligns with the empirical observations.

This rigorous assessment not only facilitates the selection of the most appropriate probability distribution but also provides valuable insights into the underlying statistical properties of the arrival time data. By discerning the optimal distribution, the simulation model can effectively capture the inherent variability and randomness in part arrivals, thereby enhancing its predictive accuracy and reliability. Ultimately, this input analysis serves as a critical step in ensuring that the simulation model faithfully represents the complex dynamics of part arrivals within the operational system.

Chi-Square and Kolmogorov-Smirnov tests were applied to check the suitability of the distribution with Arena Input Analyzer tool. The hypotheses used in determining the distributions are as follows. Both tests were applied for all parameters and graphics and related documents are available in the appendices.

Chi-Square Hypotheses

H₀: The data originate in the distribution whose parameters are given.

H₁: The data does not originate in the distribution whose parameters are given.

When conducting the Chi-Square test and evaluating the results, it was observed that all chi-square p-values, as depicted in Table 6.5, exceeded the significance level of 0.05. Consequently, based on this analysis, the null hypothesis (H₀) cannot be rejected. This implies that there is insufficient evidence to conclude that the data does not stem from the distribution with the specified parameters.

In light of the Chi-Square test outcomes, the data is interpreted as being derived from the distribution characterized by the given parameters. This finding underscores the consistency between the observed data and the anticipated distribution, affirming the suitability of the chosen distributional assumptions for representing the underlying stochastic process. As a result, this validation provides confidence in the use of the specified distribution for modeling the arrival time data, thereby bolstering the reliability and accuracy of subsequent simulation and predictive analyses.

Kolmogorov-Smirnov Hypotheses

H₀: The sample is consistent with the distribution $N(\mu, \sigma^2)$

H₁: The sample is not consistent with the distribution $N(\mu, \sigma^2)$

When the Kolmogorov-Smirnov test results are considered, it is observed that all p-values exceed the significance threshold of 0.05, as indicated in Table 6.5. Consequently, in accordance with the test outcomes, the null hypothesis (H₀) cannot be rejected. This indicates that there is insufficient evidence to refute the notion that the data is consistent with the distribution characterized by the provided parameters.

The findings from the Kolmogorov-Smirnov test affirm the compatibility of the observed data with the specified distribution and its associated parameters. This consistency underscores the appropriateness of the chosen distributional assumptions for representing the stochastic behavior

of the arrival time data. By validating the adherence of the data to the given distribution, this analysis reinforces the confidence in utilizing the specified distribution for modeling purposes within the simulation framework. Ultimately, this verification enhances the robustness and reliability of the simulation model, ensuring that it accurately captures the stochastic dynamics of part arrivals within the operational system.

Table 6.5 Distribution Fit Analysis for Process Activities

	Distribution	Square Error	Chi-Square p-value	Kolmogorov-Smirnov p-value
Interval	Unif (3,5)	0,00038	0,06755	0,08901
Truck Loading	Unif (3,6)	0,00171	0,05080	0,07810
Truck Unloading	Unif (4,6)	0,00077	0,06841	0,09935
Supervisor	Unif (8,12)	0,00150	0,06455	0,05902
Technician 1	Norm (4,0.8)	0,00051	0,06153	0,06762
Technician 2	Norm (8,1.4)	0,00118	0,05081	0,08032
Technician 3	Norm (8,2)	0,00097	0,05750	0,09768
Technician 4	Unif (3,6)	0,00034	0,06379	0,09132
Machining (M1)	Norm (12,1.2)	0,00211	0,07262	0,06203
Pre-treatment (M2)	Norm (26,1.2)	0,00152	0,06325	0,05375
Purchasing Specialist	Unif (16,25)	0,00111	0,07279	0,06577

A comprehensive analysis of each station within the system has been conducted, beginning with an in-depth examination of the material flow at each stage. The subsequent content provides a condensed yet comprehensive overview of the findings from these detailed examinations.

The parts used in the lines produced in the automation factory are produced in the workshop. If the materials to be used as inputs in the automation factory are technically producible, they are manufactured in the workshop. Products that cannot be manufactured due to technical difficulties, such as parts that must be made on a 5-axis machine, are shared with the purchasing department and outsourced. Due to the length of customs clearance, most parts are manufactured in the workshop.

The process proceeds as follows. Once the BOM (Bill of Material) is shared by the global team with the workshop, the parts are analyzed by the supervisor and a decision is made as to whether

the parts will be manufactured in-house (insourced or outsourced). If the parts are outsourced, the purchasing process is initiated by the purchasing specialist. As there is only 1 purchasing specialist, if the number of parts in the queue is more than 20, the parts are sent to the workshop for insourcing in order not to block the process. Some parts cannot technically be insourced, although there is no data on this statistic, it is assumed that all parts over 20 in the queue can be insourced.

The parts to be produced in the workshop are divided into two types of material, soft and hard. Hard materials require pre-machining and then go through the same process as soft parts. First, the materials are attached to the machines and processed by the technicians. Attaching the materials to the machine is referred to as "set-up time" in the following sections. After this, the necessary machining is carried out on CNC machines and then the materials are sent to the warehouse for documentation, which is completely manual, and stored in groups of 5 to be transported to the automation workshop. There is a quality control process before pre-assembly and some parts are successfully completed, some parts are discarded as scrap and some parts have to be reworked and returned to the workshop. Related statistics are given in the following sections, and it is known that quality is the most important and critical issue as a bottleneck. Due to the lack of an automated material tracking system, the current location of parts cannot be known, and the assembly process cannot be interrupted.

6.3.3. Conceptual Model Design and Abstraction

In Chapter 7, the system, referred to as the current system, is extensively delineated. This section of the thesis initially provides a comprehensive overview of the elements and blocks utilized in the simulation model. Subsequently, it delves into the performance indicators of the present situation, offering a detailed analysis of its operational efficacy and functionality.

- **Stations:** 5 stations in the system were identified as entrance, workstation, workstation warehouse, automation warehouse, exit.
- **Attributes:** The attributes element is used to define the properties of the parts. The features of the parts such as arrival time, part type, priority and status are defined.
- **Counters:** It is used to measure how many of the parts in the system were scrap, how many required reworks, and how many were successful, and for the validation of the model.

- The subsequent images display the arena simulation model, comprising various interconnected blocks, providing a visual representation of the model's components and their interactions from the initial stages to the final stages. The system was run for 720 minutes with 50 repeats.

Trace	Sequences	Distances	Transporters	Stations	Attributes	Resources	Queues	Tallies	Replicate	Counters	DStats	Outputs
	routes0n0	ms01	truck	EnterpriseStation Workstation Warehouse0nhouse AutomationWarehouse EnterpriseStation	TimeIn PartType Priority Status	Purchaser Machine1 Supplier Technician1 Technician2 Technician3 Machine2	Truck Purchase2 Machine12 Machine22 Technician2 Technician3	FlowTime	1440	CountMissedOrdersP CountShippedParts CountResourcesLeft	N2(1) N2(2) N2(3) N2(4) N2(5) N2(6) N2(7)	TaskFlowTime
							Supplier Technician2 Technician3				truck01 truck02 N2(8) N2(9) N2(10) N2(11) N2(12) N2(13) N2(14)	

Figure 6.8 depicts the sequential process within the system, starting from the creation of components, followed by the assignment of attributes, entry into the truck queue, the time required for loading, and the transfer process along the designated route.

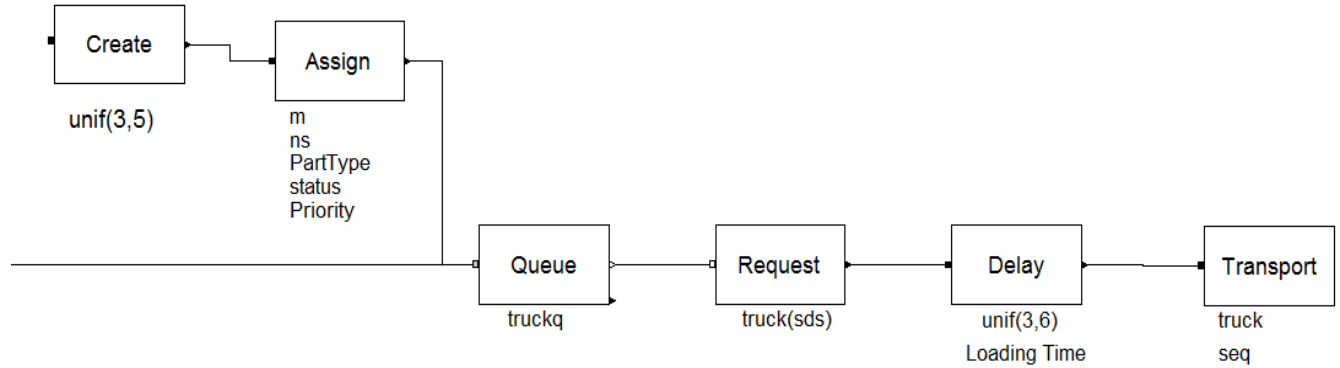


Figure 6.9 Entity generation and assignment of attributes process

Figure 6.9 provides a detailed depiction of the sequential processes involved in the system, utilizing block diagrams to enhance clarity and understanding. The process begins with the unloading of components into the workshop, a critical step that ensures all necessary materials are available for subsequent operations. Following this, the trucks are released, allowing them to proceed to their next tasks or destinations, thereby optimizing logistics and workflow efficiency.

Next, the process involves queuing for the supervisor, which is essential for maintaining order and ensuring that each task receives the appropriate oversight and approval. This step is crucial for quality control and adherence to operational standards. Finally, the supervisor is released upon the completion of the technical analysis, signifying that all necessary evaluations and assessments have been conducted. This release marks the conclusion of the process, ensuring that all components and operations meet the required specifications and standards.

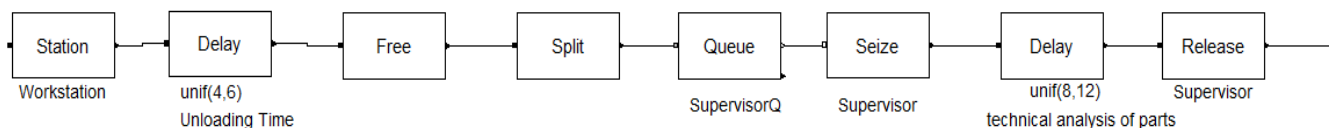


Figure 6.10 Conducting technical analysis of parts

Figure 6.10 consists of various routes through which components progress based on specific probabilities. The initial divergence is determined by whether the components can be processed within the workshop. Components that cannot be processed internally enter the purchasing queue, reserving their place. If the number of components waiting in the queue exceeds 20, they are automatically redirected to the workshop for processing. (It is assumed, technically, that all redirected components can be processed in the workshop.) Components that are to be processed internally follow different routes depending on their type. The first section illustrates the processing and subsequent grouping of soft components, while components taking the second branch are initially processed in the pre-processing machine and then follow the path of type 1 components from the first branch. The final step of the model shown below is formed by the group element, where components are grouped in sets of five.

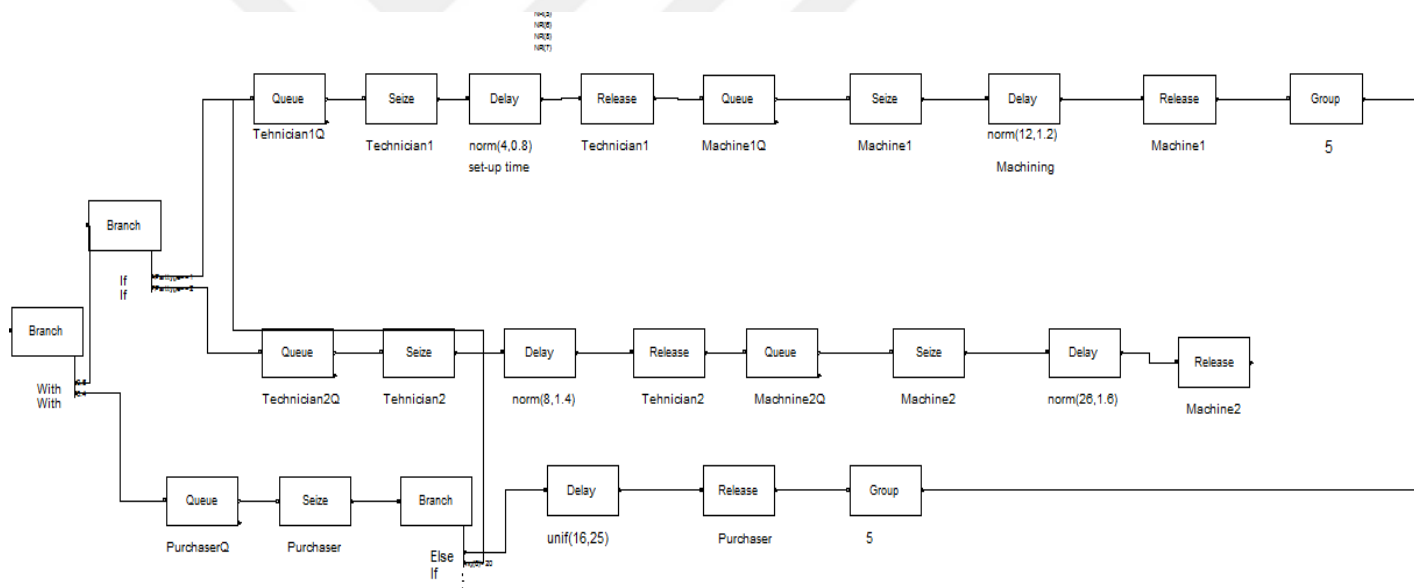


Figure 6.11 Movement of parts according to the rules

Figure 6.11 illustrates the process beginning with the entry and unloading of components into the workshop inventory. This is followed sequentially by the queuing for Technician 3, the

completion of necessary paperwork procedures, and finally, the release of Technician 3.

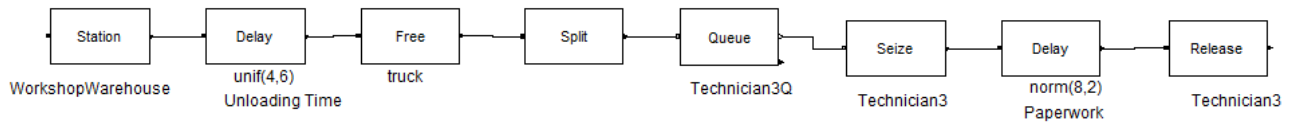


Figure 6.12 Documentation process of materials

Figure 6.12 illustrates the process that begins with the transportation of components to the automated warehouse and the unloading of trucks. Following this initial stage, the components undergo a quality control process conducted by Technician 4. Although the process involves queuing for each resource and subsequent release after processing, these repetitive steps are not detailed in this section for brevity.

The transportation to the automated warehouse ensures that components are efficiently organized and stored, facilitating streamlined operations. The unloading of trucks is a critical step that allows for the timely availability of components for further processing. Quality control by Technician 4 is essential for maintaining high standards and ensuring that all components meet the required specifications. This step is crucial for preventing defects and ensuring the reliability of the final products

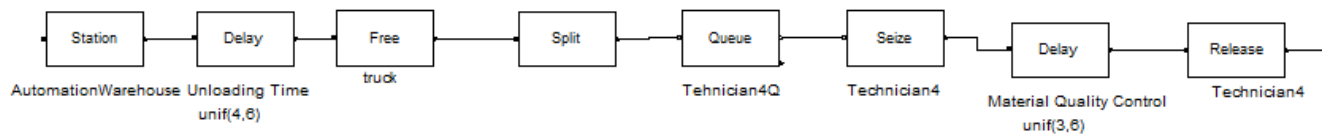


Figure 6.13 Quality control process of materials

After quality control is conducted by Technician 4, components are categorized as successful, requiring rework, or designated as scrap. Components needing rework are assigned a priority of 1, as they are expected on the assembly line. This entire process is depicted in Figure 6.13 through the flow of elements.

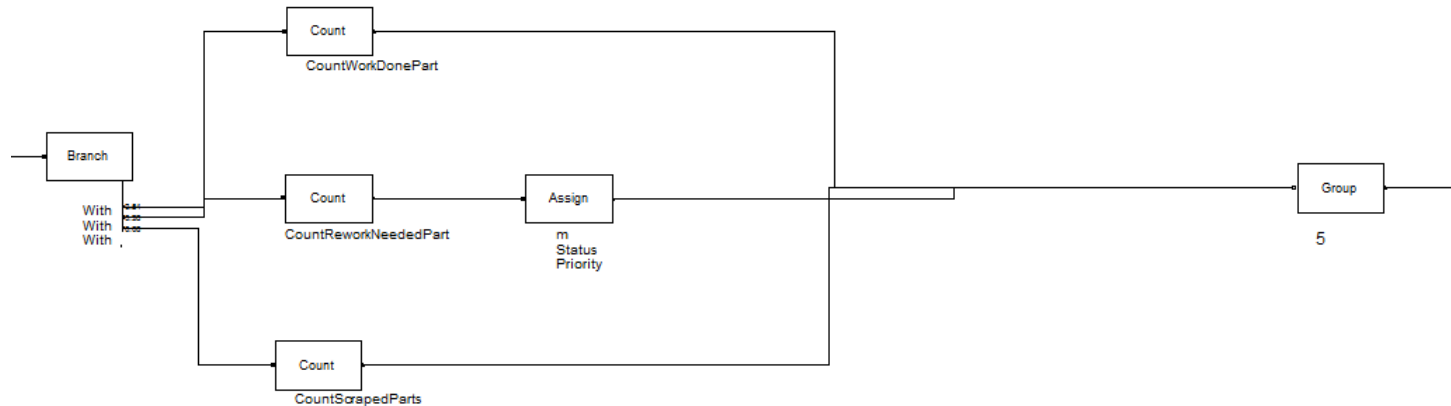


Figure 6.14 Counting parts according to quality control results

Figure 6.14 illustrates the final stage of the simulation modeling, where components proceed to the exit and trucks are released. To measure the duration that components remain within the system, a Tally block is utilized. This duration is commonly referred to as cycle time in the industry and is a critical metric used in performance measurement systems.

The cycle time provides valuable insights into the efficiency and effectiveness of the operational process. By analyzing this metric, organizations can identify bottlenecks, optimize workflows, and enhance overall productivity. The use of the Tally block allows for precise tracking and analysis, ensuring that the system operates at optimal performance levels.

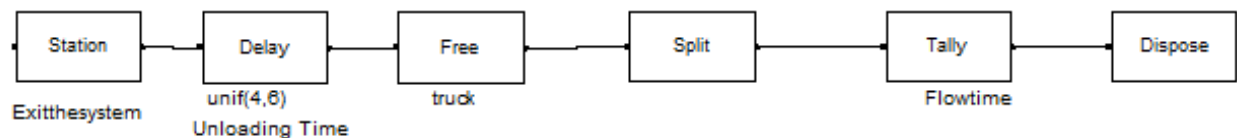


Figure 6.15 Disposals of parts from the system

Since the images of the simulation modeling were provided in segments, Figure 6.16 has been created to establish coherence and more clearly convey the relationships between them. Figure 6.16 serves as a comprehensive overview, integrating the segmented images into a unified representation. This holistic approach facilitates a clearer understanding of the interconnected processes and enhances the ability to analyze the system as a whole. By presenting the simulation in its entirety, Figure 6.16 aids in identifying patterns, dependencies, and potential areas for optimization within the model. In the context of process visualization, decision-containing processes are represented through the utilization of rhomboid shapes. This symbolic convention is consistently applied in Figure 6.16, where processes encompassing statistical distributions are depicted using rhomboids.

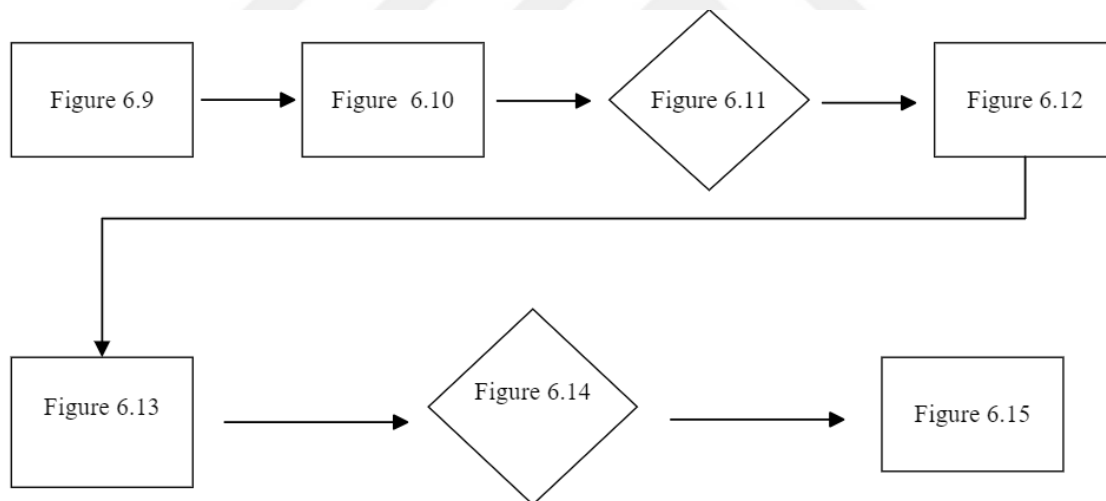


Figure 6.16 Resource-Oriented Process Flow

In Figure 6.16, the aim is to visualize the flow of components between resources, adopting a holistic approach. Figure 6.16 provides a comprehensive depiction of how components transition across various resources within the system. This visualization is designed to offer a clearer understanding of the dynamic interactions and dependencies present in the model. By illustrating the flow pathways, Figure 6.16 enhances the ability to identify potential inefficiencies and areas for improvement, thereby supporting more informed decision-making and optimization strategies.

6.3.4. Verification and Validation Protocols

This study implemented comprehensive validation and verification protocols to ensure the accuracy and reliability of the developed simulation model. These protocols were employed to assess how well the model represents the real system and to verify its conformity to design specifications. The verification process was conducted to confirm that the simulation model was correctly implemented and adhered to the design specifications. This process encompassed the following steps:

- **Code Review:** The source code of the simulation model underwent scrutiny by experienced programmers to check for errors or inconsistencies.
- **Module Testing:** Each model component was individually tested to ensure it produced correct outputs for expected inputs.
- **Integration Testing:** After assembling the model components, tests were conducted to verify that inter-component interactions functioned correctly.
- **Boundary Value Analysis:** Boundary values and extreme cases were tested to evaluate the model's behavior under extreme conditions.

The validation process was implemented to assess how accurately the simulation model represents the real system. This process included the following steps:

- **Face Validity:** Domain experts examined model outputs and compared them with real system behaviors.
- **Historical Data Validation:** Simulation results were compared with historical data collected from the existing system. This comparison included key performance indicators such as production volumes, cycle times, and resource utilization.
- **Expert Evaluation:** Domain experts and experienced operators examined model behavior and outputs, assessing their consistency with real system behavior.

The findings from the validation and verification processes supported the model's reliability and validity. Expert evaluations confirmed that the model's general behavior and outputs adequately represented the real system.

In conclusion, the applied validation and verification protocols demonstrated that the developed simulation model possessed sufficient accuracy and reliability for the study's objectives. These protocols clearly delineated the model's strengths and limitations, providing valuable insights for interpreting the study's results and identifying areas for future enhancement.

6.4 Phase 4: Robust Output Analysis and Strategic Recommendation Synthesis

In this phase of the proposed methodology, the statistical outputs of the current system were initially examined. These statistical analyses form the foundation for all subsequent studies in this research. After identifying bottlenecks, it was recognized that proper capacity planning had not been implemented. Consequently, the Process Analyzer, a module of ARENA software, was utilized to analyze the impact of changes in machine configurations on system efficiency.

Furthermore, based on the statistical outputs of the existing system, alternative scenarios were developed. Output analysis was conducted for these alternative scenarios, enabling a comparative assessment of efficiency across different systems.

Finally, a feasibility study was performed on the company's investment consideration of relocating the workshop within the factory premises. The system performance of this proposed relocation was compared both with the alternative scenarios and the current system.

This comprehensive approach ensures a thorough evaluation of the existing system, explores potential improvements through scenario analysis, and assesses the viability of proposed structural changes, providing a robust basis for decision-making and system optimization.

6.4.1. Statistical Analysis of Current System Performance

In this study, the one of the primary objectives is to enhance operational efficiency by identifying operational defects and bottlenecks, thereby reducing penalty costs resulting from project delays. Consequently, the number of parts produced during the simulation period has been established as a measurement criterion. It is assumed that the greater the number of parts produced within the simulation time, the corresponding decrease in project delays will be significant.

The time spent by the parts within the system is tracked by the “Tnow” parameter within the tally element. Table 6.6 presents the statistical data maintained within the tally element for each resource. The observation counts in this Table 6.6 serves as a reference point for comparing the proposed scenarios in subsequent sections.

Table 6.6 Resource Waiting Rates in the Current System

TALLY VARIABLES				
Waiting Times	Average	Minimum	Maximum	Observations
Machine1Q	0	0	0	46
Machine2Q	23.484	0	76,151	19
SupervisorQ	16.45	0	374,5	87
Technician1Q	0.31815	0	4,011	46
Technician2Q	0,11957	0	1,578	19
Technician3Q	0.0224	0	7.558	71
Technician4Q	28.089	0	49.265	48
PurchaserQ	11.429	0	36,176	22
truckq	29.471	0	62.441	165

Tablo 6.6 presents the waiting times for various resources, including machines, supervisors, technicians, purchasers, and trucks. The average, minimum, maximum, and number of observations are provided for each resource's waiting time. This data highlights the imbalance in resource utilization, with certain resources experiencing prolonged wait times, indicating potential bottlenecks or inefficiencies in the system.

As depicted in Table 6.6, it is evident that Machine 2, Supervisor, Technician 4, Purchaser, and Trucks exhibit prolonged wait times. Upon examining the waiting times for Machine 1 and Machine 2, as well as the workload of the technicians, this imbalance becomes apparent. In order to establish efficient and balanced resource utilization, areas for improvement will be explored in the subsequent sections.

To visually compare the waiting times provided in Table 6.6, the graph depicted in Figure 6.17 has been created. Based on Figure 6.17, considering the simulation outputs of the current system,

it can be inferred that the truck, Technician 4, Machine 2, Supervisor, and Procurement Specialist constitute bottlenecks within this system.

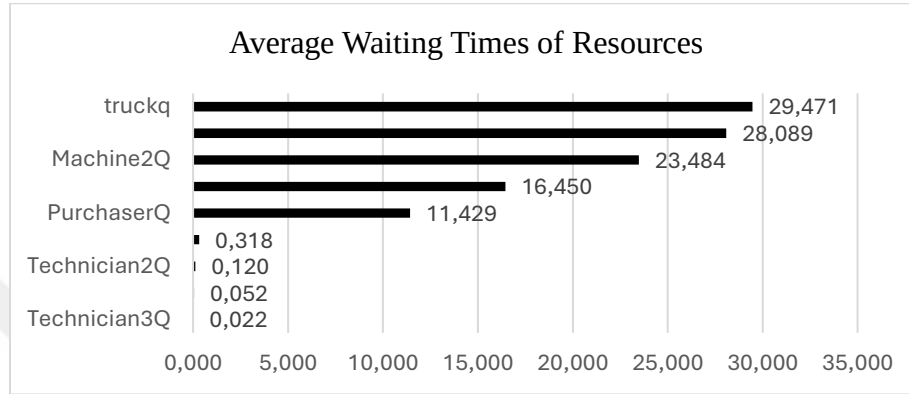


Figure 6.17 Average Waiting Times for Resources in Scenario 1

In production systems, just as assembly lines are balanced, it is beneficial to consider each resource as an assembly line. Balancing the loads of machines and the workloads of employees is expected to bring advantages to the company and enhance operational efficiency both in the short term and long term.

Table 6.7 Utilization rates for resources in current system

Utilization Rate	Average NR	Average NQ
Machine1	0,248	0
Machine2	0,692	0,619
Supervisor	0,724	39,4
Technician1	0,257	0,02
Technician2	0,218	0,00316
Technician3	0,87	6,8912
Technician4	0,851	6,2214
Purchaser	0,822	0,389
Truck	0,924	1,4482

Upon examining Table 6.7, it is evident that, consistent with Figure 6.18, those with high waiting times in the queue also exhibit high utilization rates. For instance, technician 4, machine 2, the supervisor, and the procurement specialist not only have the highest waiting times in the queue but also demonstrate elevated utilization rates.

This correlation suggests that these resources are operating at or near their capacity limits, indicating potential inefficiencies within the system. Addressing these bottlenecks by optimizing resource allocation and balancing workloads could lead to improved system performance and reduced waiting times, ultimately enhancing overall productivity and efficiency.

Table 6.8 Quantity of Components by Type in Current System

Count Output	# of Observation
Work Done Part	33
Rework Needed Part	23
Scrapped Part	4

Disregarding the minor differences arising from the specific distributions that generate the parts in the system, system efficiency has been calculated as the ratio of the number of parts entering and exiting the system during the simulation time. This measure allows for a comparison between scenarios. Both statistical ratios and system efficiency will be utilized in the subsequent sections to conduct a comparative analysis of the scenarios. The minor discrepancies between the scenarios have been overlooked due to the parts being generated from certain distributions.

In line with the extended waiting times, it is notable that the Supervisor, Purchaser, Machine 2, and Trucks are experiencing elevated utilization rates. This situation gives rise to several issues, including high occupancy rates, extended cycle times, prolonged waiting periods, diminished quality, and a system that is overly reliant on specific individuals rather than system itself.

The analysis of the current system model yields the following interpretation: the upcoming sections will present scenarios that have been formulated based on the results of this analysis. The identification of areas for improvement serves as the cornerstone for these scenarios.

1. The Supervisor stands out with the lengthiest waiting time and the highest utilization rate, as highlighted in Figure 6.24. This circumstance can be attributed to the presence of a lone supervisor possessing advanced technical expertise and capabilities within the automation plant. Additionally, the company's decision to internally source 60% of the parts further exacerbates this situation. The consideration of hiring an additional supervisor may be contemplated as an alternative scenario, as it is likely to reduce the waiting time and enhance the utilization rate. Furthermore, in light of the fact that pending parts for the procurement specialist are being redirected to the workshop supervisor, planning should consider the interrelation between these two resources.
2. There exists a considerable backlog for the purchasing specialist. When the quantity of parts awaiting attention by the purchasing specialist surpasses 20, these parts are redirected to the workshop for internal machining. This aspect of the process necessitates improvement, as it leads to additional transportation and an augmented workload for the workshop. To address this bottleneck, one potential solution can be the recruitment of an additional purchasing specialist, or alternatively, a reduction in the proportion of outsourced parts in favor of workshop-based manufacturing. It is important to note that parts are not outsourced exclusively based on their technical feasibility; therefore, prioritizing in-house production over outsourcing or augmenting the number of procurement specialists can effectively enhance the process (Scenario 4).
3. When reviewing the simulation results, it is observed that the waiting time for the truck is lengthy. However, discussions with technicians who have been with the company for an extended period indicate that due to the grouping and transportation of parts, the waiting time is actually brief. Upon analysis of the simulation data, improvement in the number of trucks is considered an area for enhancement and will be addressed as an alternative scenario in the subsequent section.
4. Another significant factor contributing to the prolonged waiting time for the truck is the absence of communication following the completion of parts. The lack of an automated

equipment tracking system means that finished parts cannot promptly enter the transportation queue, consequently leading to extensive queues.

5. As delineated in section 6.3.1, Input Analysis, it is revealed that 38% of the components are directed back to the workshop for reprocessing as a result of quality issues, while 8% are ultimately discarded. The reprocessing of materials engenders supplementary expenses in terms of transportation, labor, and machining, whereas scrapped parts incur costs related to labor and raw materials. Given the diminished efficiency of workshop production attributable to substandard quality, the recruitment of a quality engineer may be contemplated as an alternative scenario.
6. As evidenced in Table 6.4, the utilization of Technician 3 and the wait times in the queue are notably elevated. This is primarily attributed to the entirely manual nature of the paperwork system, wherein the compilation of incoming documents and the input of quality values into the system are carried out by a single individual, thereby amplifying the waiting time for parts. It is believed that implementing enhancements in this area could yield a substantial impact on the overall system.
7. When evaluating the utilization rates and queue lengths of Machine 1 and Machine 2, it is evidently clear that there exists an imbalance between the lines. While three of the machines have been configured to process soft parts, one has been configured to perform pre-processing on hard parts. Subsequently, based on the simulation outputs in the subsequent section, efforts have been directed towards revising this configuration of machines to generate an alternative scenario. The prioritized scenario involves evaluating the change in machine configuration, as it is anticipated to incur no additional cost.

When evaluating all these analyses and comments, the following questions arise regarding resources:

- ❖ How many supervisors are required under ideal conditions?
- ❖ How many procurement specialists are required under ideal conditions?

- ❖ What should be the optimum number of resources?
- ❖ Is it ideal to establish an automated Material Tracking System considering the investment and outputs?
- ❖ Is it meaningful to employ a quality engineer considering the cost?
- ❖ Are the operating systems of Machine 1 and Machine 2 ideal, or would making changes to their configurations be beneficial?
- ❖ What percentage of the total material requirement should be constituted by the parts to be produced in the workshop?

This chapter presents a comprehensive approach to simulation-based scenario analysis and multi-objective optimization of a complex system. The study begins with an exploration of Process Analyzer methodologies and optimization techniques, setting the foundation for a detailed examination of various system configurations.

The core of the chapter revolves around the development and analysis of alternative scenarios, each targeting specific aspects of system enhancement:

- Scenario 1: Optimization of Machine Configuration Parameters
- Scenario 2: Optimization through Fleet Size Adjustment
- Scenario 3: Quality Enhancement through Human Resource Allocation
- Scenario 4: Supply Chain Optimization via Procurement Expertise
- Scenario 5: Operational Oversight Enhancement

These scenarios are meticulously crafted to explore potential improvements in different facets of the system, from operational efficiency to supply chain management.

The Output Analysis section provides a critical evaluation of the outcomes from these scenarios, offering insights into the comparative efficacy of different optimization strategies.

Subsequently, the chapter delves into the simulation model development for the re-design System. This process incorporates a rigorous statistical analysis of current system performance, establishing a benchmark against which proposed improvements can be measured.

The chapter concludes with an economic comparison of the current, optimized, and designed systems. This comparative analysis offers a comprehensive cost-benefit assessment, facilitating informed decision-making regarding system modifications.

By integrating advanced simulation techniques, scenario analysis, and multi-objective optimization methodologies, this chapter presents a sophisticated approach to enhancing complex system performance. It provides valuable insights into the interplay between various system components and the potential impacts of strategic modifications.

6.4.2. *Process Analyzer and Optimization*

Running the simulation by altering each parameter and evaluating the statistics can be a time-consuming process. Given the necessity to perform this procedure multiple times to determine the optimal number of resources, Arena's Process Analyzer, which enables the automatic execution of different processes and comparison of results, has been utilized. The subsequent section focuses on the comparison of scenarios and the calculation of the optimal number of resources.

When evaluating the statistical analysis results of the current system, it became evident that the disparity in utilization rates between Machine 1 and Machine 2 necessitated a reassessment of capacity planning. To address this, the Process Analyzer tool within the Arena Simulation software was employed to propose necessary actions and optimize the system's performance.

In the initial configuration, a total of five CNC machines were allocated based on the anticipated workload, with a division into preprocessing and processing stages. Specifically, three machines were designated for the processing phase, while two machines were allocated for preprocessing. This allocation aimed to balance the workload and maximize efficiency.

The Process Analyzer tool was instrumental in reevaluating this capacity planning. By simulating various scenarios and analyzing the outcomes, the tool provided insights into the optimal distribution of resources. This reevaluation was crucial in ensuring that the system could manage the projected workload effectively, minimizing bottlenecks and enhancing overall productivity.

Through this process, the capacity planning was refined, aligning machine utilization rates more closely with operational demands and improving the system's efficiency. The use of the Process Analyzer facilitated a data-driven approach to decision-making, ensuring that the capacity planning was both robust and adaptable to changing conditions.

Table 6.9 Process Analyzer Outputs

Scenario Properties		Controls		Response	
No.	Program File	Machine 1	Machine 2	Utilization_ M1	Utilization_ M2
1	Production Current System	3	2	21%	73%
2	Production Current System	1	4	42%	49%
3	Production Current System	4	1	30%	80%
4	Production Current System	2	3	45%	69%

By employing the "Identify the Best Scenario" feature of the Process Analyzer, the scenario was systematically re-executed to ascertain the most optimal configuration. Notably, the scenario 2 emerged as the preferred choice, predicated upon the careful evaluation of utilization rates.

This method facilitated the discernment of the most effective scenario by meticulously considering the productive utilization rates of the machines, thereby enhancing the precision and reliability of the analysis.

6.4.3. Scenario Planning and What-if Analysis

In this section of the thesis, the development of alternative scenarios has been focused on, with the following objectives:

- To address the multifaceted challenges identified in the comprehensive problem definition phase (Objectives 1 & 2 referred to in Chapter 1.3)
- To optimize system performance by targeting the meticulously identified bottlenecks and inefficiencies (Objectives 1 & 2 referred to in Chapter 1.3)

- To formulate and evaluate a range of potential solutions that can effectively minimize these bottlenecks and enhance overall system efficiency (Objectives 1 & 2 referred to in Chapter 1.3)

Our work in this chapter is driven by the recognition of the inherent complexity and interdependence of various operational components within the system under study. By developing and exploring multiple potential solutions, we aimed to:

1. Mitigate the risks associated with single-solution approaches
2. Uncover potential synergies between different operational aspects
3. Anticipate and analyze possible secondary effects of proposed changes
4. Optimize resource allocation across various improvement initiatives

Through this methodical approach to scenario development, we have sought to provide a comprehensive analysis that not only addresses immediate operational challenges but also lays the groundwork for long-term, sustainable improvements in system performance. This section details our process of scenario creation, analysis, and evaluation, offering insights into the potential impacts and feasibility of each proposed solution.

Our methodology for developing these scenarios involves a systematic approach that combines data-driven analysis with expert insights. Initially, we conduct a thorough examination of the identified bottlenecks, utilizing advanced analytical tools to quantify their impact on system performance. Subsequently, we engage in collaborative brainstorming sessions with subject matter experts to generate a diverse array of potential solutions.

These solutions are then refined and categorized into distinct scenarios, each targeting specific aspects of the system's performance. The scenarios are designed to be both comprehensive in their approach to problem-solving and feasible in their implementation within the existing operational framework.

By developing and analyzing these alternative scenarios, we aim to provide decision-makers with a robust set of options, each accompanied by a detailed assessment of its potential impacts, resource requirements, and expected outcomes. This approach not only addresses the immediate

bottlenecks but also paves the way for long-term, sustainable improvements in system performance.

Scenario 1: Optimization of Machine Configuration Parameters

When examining the utilization rates and average queue lengths of Machine 1 (Capacity 3) and Machine 2 (Capacity 2), it is evident that there is an imbalance in the production line. Although the parts return to Machine 1 after pre-processing, there is no waiting time at Machine 1 due to the processing times. In this scenario, it is recommended to set the capacity of Machine 1 to 2 and Machine 2 to 3, meaning that the number of machines performing pre-processing and processing should be changed. The objective of this alternative scenario is to increase the number of parts completing the process, reduce the cycle time, and optimize the utilization rates of the machines. This scenario does not incur any additional cost, as the technicians and the supervisor can make the configuration changes.

Table 6.10 Resource Waiting Rates in Scenario 1

TALLY VARIABLES				
Waiting Time	Average	Minimum	Maximum	Observations
Machine1Q	0.27952	0	22.356	67
Machine2Q	17.584	0	48.197	34
SupervisorQ	15.48	0	59,42	95
Technician1Q	0.30753	0	6.482	67
Technician2Q	0,16551	0	1,951	34
Technician3Q	0.0352	0	8,49	82
Technician4Q	17.542	0	50,089	62
PurchaserQ	12.759	0	39,142	26
truckq	27.453	0	58.782	55

Table 6.10 presents a comprehensive statistical summary of the data recorded in the tally block for each resource following the implementation of modifications specified in Scenario 1. This summary encompasses the mean, minimum, and maximum values of waiting, as well as the total number of observations for each resource. The tabulated data provides a quantitative basis for

assessing the impact of the scenario-based changes on resource utilization and system performance, facilitating evidence-based decision-making in the context of process optimization.

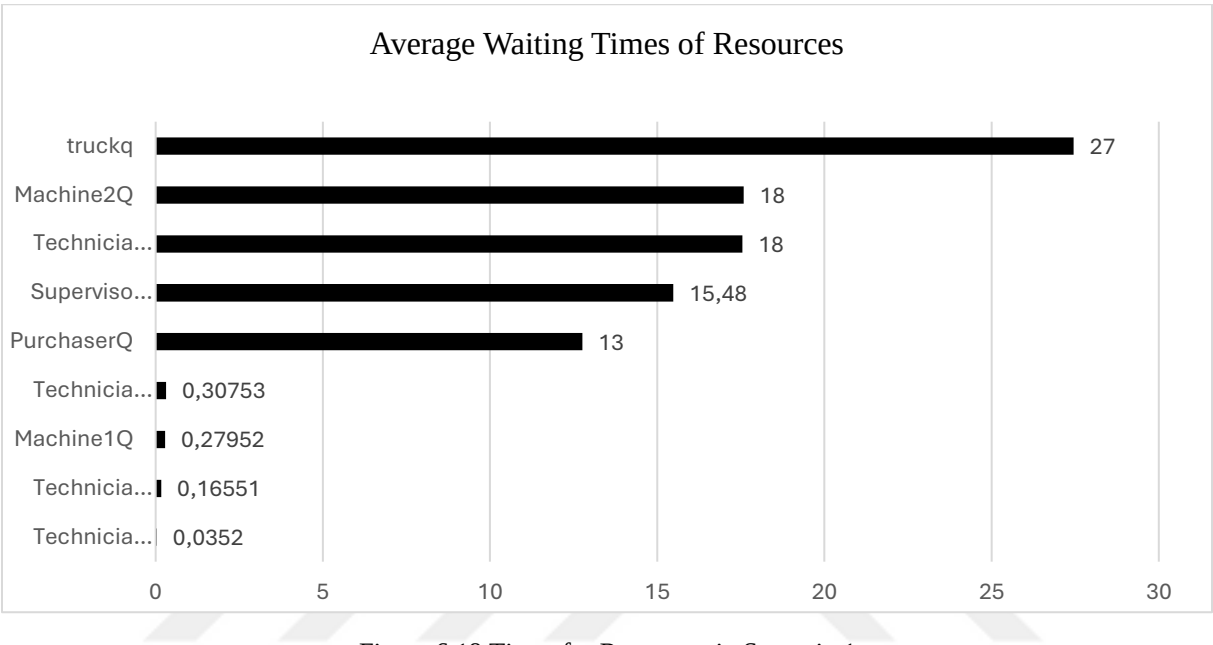


Figure 6.18 Times for Resources in Scenario 1

Figure 6.18 presents a visual representation of the data provided in Table 6.7, utilizing a bar chart to illustrate the mean waiting times. This graphical depiction serves dual purposes: firstly, to facilitate the ranking of waiting times, and secondly, to enhance the ease of analysis. The bar chart format was specifically chosen for its efficacy in displaying comparative data, allowing for immediate visual assessment of the relative magnitudes of waiting times across different categories or resources.

The transformation of tabular data into this graphical format offers several analytical advantages. As observed in Table 6.11, the utilization rate of Machine 1 has increased, while that of Machine 2 has decreased, indicating a shift towards a more balanced approach. This strategy is expected to reduce the time components spend within the system and increase the output quantity. By redistributing workloads more evenly between the machines, the system aims to minimize bottlenecks and enhance overall efficiency. This balanced approach not only optimizes resource utilization but also contributes to a smoother workflow, potentially leading to higher productivity and reduced operational delays.

Table 6.11 Utilization rates for resources in scenario 1

Utilization Rate	Average NR	Average NQ
Machine1	0,413	0,282
Machine2	0,721	0,475
Supervisor	0,702	40,8
Technician1	0,392	0,02
Technician2	0,218	0,00316
Technician3	0,1745	6,8912
Technician4	0,851	6,2214
Purchaser	0,8965	0,389
Truck	0,924	1,4482

Table 6.11 presents a comprehensive analysis of resource utilization and queue dynamics following the implementation of Scenario 1. Specifically, it delineates two critical performance metrics for each resource within the simulated system: the mean Number in Resource (NR) and the mean Number in Queue (NQ).

Table 6.12 Quantity of Components by Type in Scenario 1

Count Output	# of Observation
Work Done Part	33
Rework Needed Part	24
Scrapped Part	5

Table 6.12 presents an analysis of the outcomes following the implementation of Scenario 1, utilizing the count element to quantify three critical performance indicators: the number of parts that successfully completed the system, those requiring rework, and those designated for scrap. This tripartite categorization provides a nuanced understanding of the system's efficiency and effectiveness under the new scenario conditions.

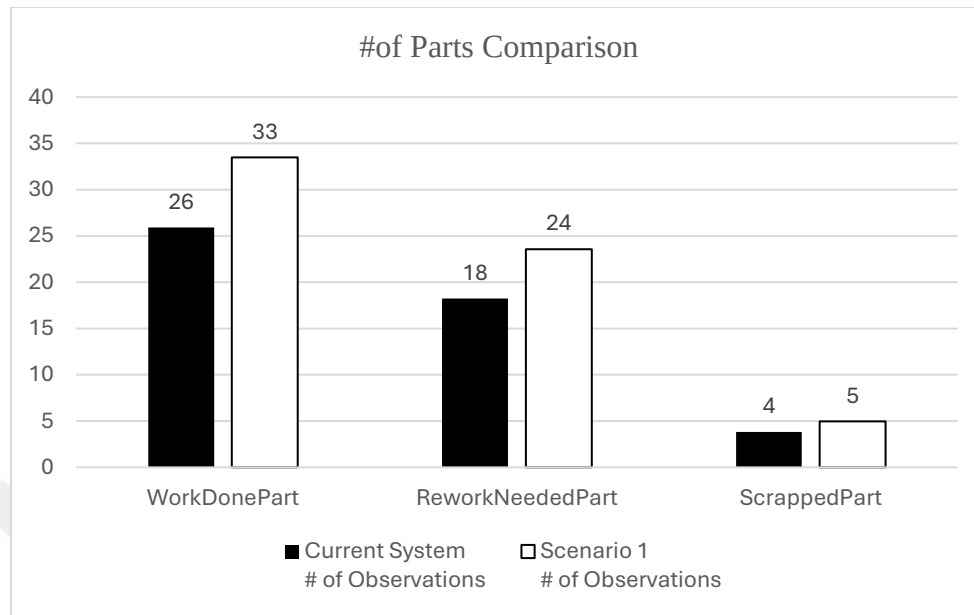


Figure 6.19 A comparison of the completed part counts between the current system and Scenario 1.

Figure 6.19 presents a comparative analysis of KPIs between the current system and the system after the implementation of Scenario 1. This visual representation serves as a critical tool for evaluating the efficacy of the proposed changes and their impact on overall system performance. When evaluating the output analysis of scenario 1, it is observed that when the number of resources for Machine 1 (Capacity decreased to 1) and Machine 2 (Capacity increased to 3) are changed, the utilization rates of both resources increased, and the queue length of M2 decreases from 0,619 to 0,475.

The implementation of the proposed scenario has yielded remarkable results, with system efficiency experiencing a substantial increase from 0.55 to 0.65, without incurring any additional costs. This significant improvement in operational efficiency was achieved through strategic optimization efforts within the existing operational framework, demonstrating the company's commitment to continuous improvement and cost-effective solutions.

Given the substantial enhancement in system performance and the absence of any associated costs, this scenario has been strongly recommended for implementation by the company's leadership team. The positive impact of this efficiency gain extends far beyond mere numerical

metrics, as it translates directly into increased productivity, reduced waste, and improved resource utilization.

Consequently, the company can expect to realize substantial cost savings, particularly in the form of reduced penalty costs associated with delays, missed deadlines, or production shortfalls. These penalties, which can often be a significant financial burden, are now expected to be mitigated, thereby improving the company's bottom line and enhancing its overall profitability.

Scenario 2: Logistic Optimization through Fleet Size Adjustment

When examining the outputs of the current system, it is observed that there are significantly long queues at the truck loading points. This bottleneck is a critical impediment to the overall efficiency of the production process. The primary objective of this analysis is to enhance the throughput of completed parts per unit time by augmenting the fleet of trucks. This strategy aims to alleviate the congestion at loading points and improve the overall flow of materials through the system.

In this context, the associated costs have been meticulously assessed and categorized into two distinct forms:

- **Truck Rental Fees:** These are recurring costs associated with leasing additional trucks on a temporary basis.
- **Purchase Costs:** These represent the capital expenditure required for acquiring new trucks outright.

The decision between renting and purchasing additional trucks involves a complex interplay of factors. It can summarize such as short- and long-term financial implications, cash flow priorities, depreciation consideration, maintenance and taxes.

In order to facilitate a comprehensive comparison with other scenarios, the costs have been calculated on an annual basis. This annualization of costs allows for a standardized comparison across different time horizons and investment strategies. An in-depth examination of the vehicle market reveals that the rental option presents a significantly more advantageous proposition.

Specifically, the annual truck rental cost has been calculated as 600,000 TL/year. This figure encompasses:

- The base rental fee for the trucks
- Any associated maintenance costs covered by the rental agreement
- Potential insurance costs included in the rental package
- Any other recurring expenses directly tied to the rental arrangement

Table 6.13 Resource Waiting Rates in Scenario 2

TALLY VARIABLES				
Waiting Time	Average	Minimum	Maximum	Observations
Machine1Q	0,000	0	0,00	74
Machine2Q.	0,000	0	71,14	19
SupervisorQ	14,188	0	31,59	89
Technician1Q	0,227	0	3,45	74
Technician2Q	0,171	0	1,22	19
Technician3Q	0,014	0	6,94	71
Technician4Q	21,041	0	33,53	70
PurchaserQ	40,127	0	32,71	28
truckq	13,485	0	27,00	148

Table 6.13 presents a comprehensive statistical summary of the data recorded in the tally block for each resource following the implementation of modifications specified in Scenario 2. This summary encompasses the mean, minimum, and maximum values of waiting, as well as the total number of observations for each resource. The tabulated data provides a quantitative basis for assessing the impact of the scenario-based changes on resource utilization and system performance, facilitating evidence-based decision-making in the context of process optimization.

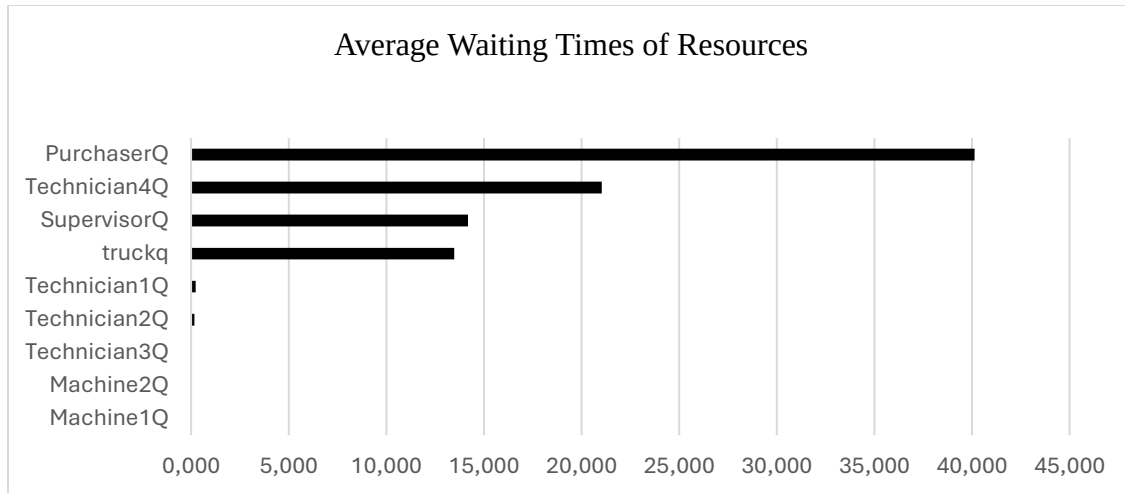


Figure 6.20 Average Waiting Times for Resources in Scenario 2

Figure 6.20 presents a visual representation of the data provided in Table 6.13, utilizing a bar chart to illustrate the mean waiting times. As illustrated in Figure 6.21, a critical examination of resource utilization and associated queue times reveals significant bottlenecks in the system. The data indicate that four key resources exhibit substantially higher waiting times compared to other elements: Purchaser, technician 4, supervisor and truck. Figure 6. 20 presents a visual representation of the data provided in Table 6.13 utilizing a bar chart to illustrate the mean waiting times.

Table 6.14 Utilization rates for resources in scenario 2

Utilization Rate	Average NR	Average NQ
Machine1	0,399	0,319
Machine2	0,692	0,522
Supervisor	0,741	30,854
Technician1	0,413	0,019465
Technician2	0,218	0,00218
Technician3	0,870	9,22
Technician4	1,241	5,92
Purchaser	1,046	0,326
Truck	1,189	0,728

Table 6.14 presents a comprehensive analysis of resource utilization and queue dynamics following the implementation of Scenario 2. As delineated in Table 6.13, a comprehensive analysis of resource utilization reveals significant disparities in waiting time ratios across various operational entities. The data elucidate a hierarchical structure of resource constraints, with three key categories demonstrating markedly elevated waiting time ratios: Supervisor, Technician 3, Technician 4.

Table 6.15 presents an analysis of the part completion following the implementation of Scenario 2. When the number of trucks is doubled, as expected, the utilization rate decreases while the waiting time in the queue is reduced. The critical aspect here is the impact of this improvement on productivity. To assess this, an examination of the completion rate of components in Table 6.15 reveals that the number of successfully completed components increased from 26 in the current system to 38 in the improved system.

Table 6.15 Quantity of Components by Type in Scenario 2

Count Output	# of Observation
Work Done Part	38
Rework Needed Part	27
Scrapped Part	6

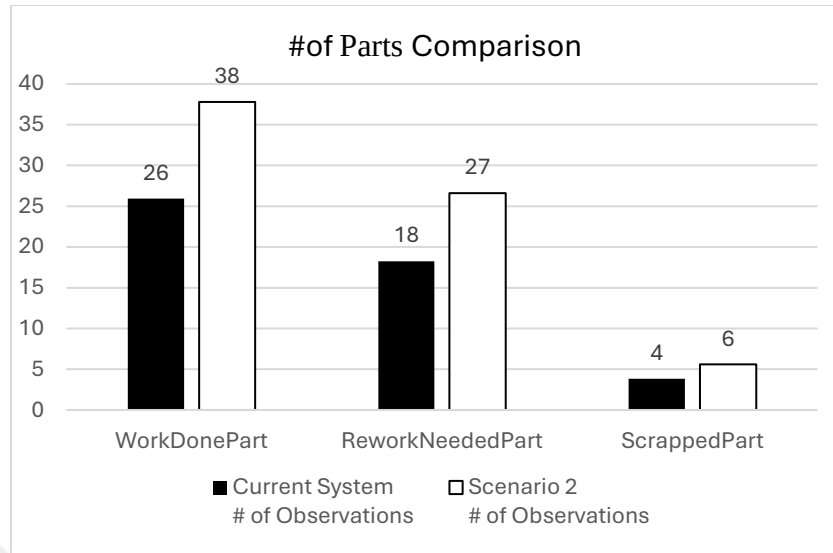


Figure 6.21 A comparison of the completed part counts between the current system and Scenario 2.

Figure 6.21 presents a comparative analysis of KPIs between the current system and the system after the implementation of scenario 2. The determination of the ratio of parts necessitating rework and those being discarded is based on a statistical analysis of historical data. As the quantity of parts subjected to quality control procedures rises, a proportional increase in the aforementioned defective parts is anticipated. This enhancement indicates a significant boost in productivity, as the system can now handle a greater volume of work within the same timeframe. By alleviating bottlenecks and optimizing resource allocation, the improved system demonstrates increased efficiency and effectiveness in processing tasks, ultimately leading to higher output and better performance. Consequently, upon scrutinizing the parts that have been successfully completed, a notable surge of 46.1% is observed. This suggests that augmenting the fleet of trucks has a substantial effect on overall productivity.

Scenario 3: Quality Enhancement through Human Source Allocation

In Scenario 3, the number of successfully completed parts in the workshop, when compared to the rates of scrap and rework, is not particularly high due to existing quality issues. It is anticipated that improvements in this area could enhance various processes, including procurement, supervision, and costs associated with re-production. Consequently, this scenario involves the employment of a quality engineer to facilitate a reevaluation of the current model.

As illustrated in Figure 6.22, positioning the quality engineer immediately after the design team is expected to preemptively address potential issues before production commences. This strategic placement aims to refine the design process, thereby mitigating problems that could arise during manufacturing. The integration of a quality engineer is projected to lead to significant improvements across multiple operational facets, contributing to enhanced efficiency and reduced costs.

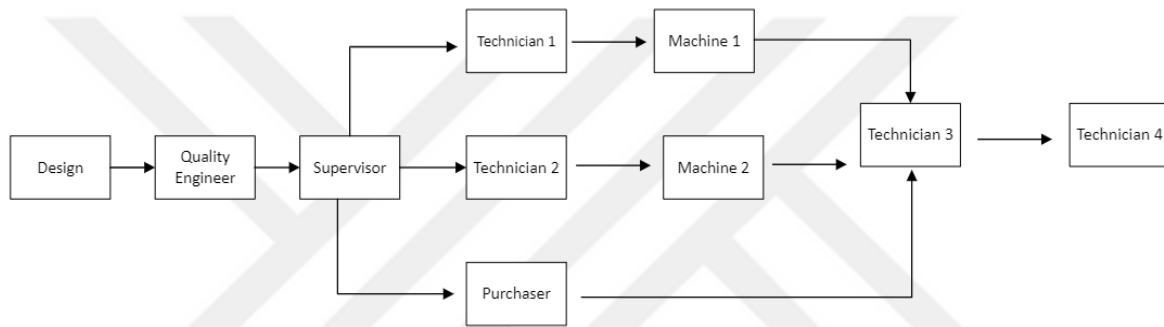


Figure 6.22 Process Flow with Newly Hired Quality Engineer

Figure 6.22 illustrates the entire process subsequent to the declaration of the quality engineer position. In this context, the employment of a quality engineer is hypothesized to significantly enhance production quality by meticulously analyzing existing quality issues within the workshop's production line and developing effective solution strategies. It is projected that such an intervention will increase the percentage of parts successfully completed without necessitating rework from 54% to 68%. Concurrently, the proportion of parts requiring rework is expected to decrease from 38% to 26%, and the scrap rate is anticipated to decline from 8% to 6%. The financial implications of hiring a quality engineer have been carefully considered, with the annual salary and benefits calculated at 650,000 TL, based on a monthly remuneration of 50,000 TL. This investment is evaluated against the potential cost savings and efficiency gains, providing a comprehensive analysis of the cost-benefit scenario associated with this strategic employment decision.

Table 6.16 Resource Waiting Rates in Scenario 3

TALLY VARIABLES				
Waiting Time	Average	Minimum	Maximum	Observations
Machine1Q	0,006	0	0,35	55
Machine2Q	20,470	0	82,15	28
Supervisor Q	14,259	0	35,15	92
Technician1 Q	0,295	0	3,96	52
Technician2 Q	0,185	0	1,42	22
Technician3 Q	0,002	0	6,88	78
Technician4 Q	15,985	0	31,51	52
Purchaser Q	42,124	0	34,25	30
Truck Q	27,140	0	61,25	134
Quality Q	12,256	0	22,14	62

Table 6.16 presents a comprehensive statistical summary of the data recorded in the tally block for each resource following the implementation of modifications specified in Scenario 3. This summary encompasses the mean, minimum, and maximum values of waiting, as well as the total number of observations for each resource. The tabulated data provides a quantitative basis for assessing the impact of the scenario-based changes on resource utilization and system performance, facilitating evidence-based decision-making in the context of process optimization.

Upon examining the outcomes of Scenario 3, as detailed in Table 6.17, it is evident that the waiting times at each resource have decreased compared to the current system. The introduction of a quality engineer immediately following the design team—effectively at the inception of the process—clearly exerts a positive influence on system efficiency.

This strategic integration of a quality engineer is expected to streamline operations, thereby reducing delays, and enhancing overall productivity. The subsequent sections of this study delve into the number of parts successfully completed, providing a comprehensive analysis of the quality engineer's impact on system performance. This analysis underscores the potential improvements in operational efficiency and product quality attributable to this intervention.

Figure 6.23 presents a visual representation of the data provided in Table 6.17, utilizing a bar chart to illustrate the mean waiting times. As illustrated in Figure 6.24, a critical examination of

resource utilization and associated queue times reveals significant bottlenecks in the system. The data indicate that four key resources exhibit substantially higher waiting times compared to other elements: Purchaser, technician 4, machine 2 and supervisor. Figure 6. 23 presents a visual representation of the data provided in Table 6.17, utilizing a bar chart to illustrate the mean waiting times.

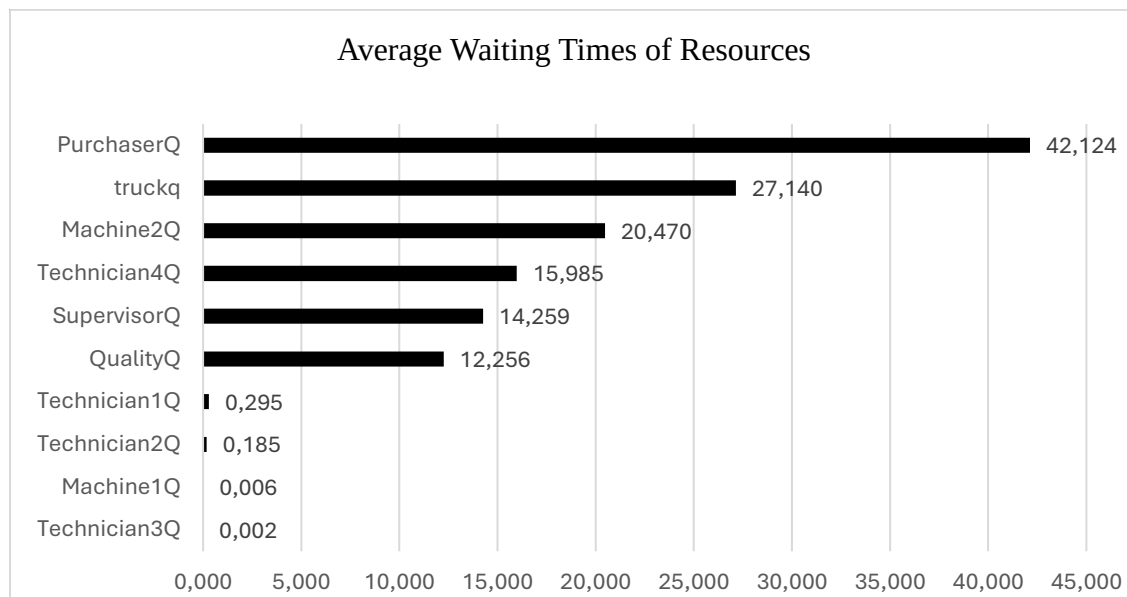


Figure 6.23 Average Waiting Times for Resources in Scenario 3

As illustrated in Figure 6.23, the employment of a quality control engineer has led to an increase in the waiting time for the procurement specialist. This outcome is anticipated, given that parts not meeting the desired standards are directly transferred to the procurement department. When examining the utilization rates and queue waiting times for other resources, as presented in Table 6.17, it becomes evident that the introduction of a quality control engineer does not negatively impact these areas. The analysis suggests that while the procurement process experiences increased waiting times, the overall system benefits from improved resource utilization and efficiency.

This strategic deployment of a quality control engineer thus enhances the quality assurance process without adversely affecting other operational facets. The observed increase in waiting time for the procurement specialist can be attributed to the more stringent quality control measures now

in place. As substandard parts are identified and redirected to procurement, it naturally results in a higher workload for this department. However, this increased scrutiny at the quality control stage is likely to yield long-term benefits in terms of reduced defects, improved product quality, and enhanced customer satisfaction.

Furthermore, the data indicates that other departments and resources maintain their efficiency levels, suggesting that the new quality control measures have been successfully integrated into the existing workflow without causing disruptions. This balanced approach to quality improvement demonstrates the company's commitment to enhancing product standards while maintaining operational efficiency across all departments.

Table 6.17 Utilization rates for resources in scenario 3

Utilization Rate	Average NR	Average NQ
Machine1	0,226	0,185
Machine2	0,510	0,598
Supervisor	0,707	32,480
Technician1	0,246	0,025
Technician2	0,218	0,003
Technician3	0,784	5,962
Technician4	0,922	4,258
Purchaser	0,747	0,395
Truck	0,868	1,345
Quality Engineer	0,753	2,125

Table 6.18 delineates the outcomes of part completion following the implementation of Scenario 3. The data reveal significant improvements in production efficiency and quality metrics. The number of successfully completed parts has increased to 42, while the number of parts requiring rework has decreased to 16.

This marked improvement in production outcomes demonstrates the efficacy of the changes implemented in Scenario 3. The increase in successfully completed parts, coupled with the

reduction in parts requiring rework, indicates a substantial enhancement in overall process quality and efficiency.

Table 6.18 Quantity of Components by Type in Scenario 3

Count Output	# of Observation
Work Done Part	42
Rework Needed Part	16
Scrapped Part	4

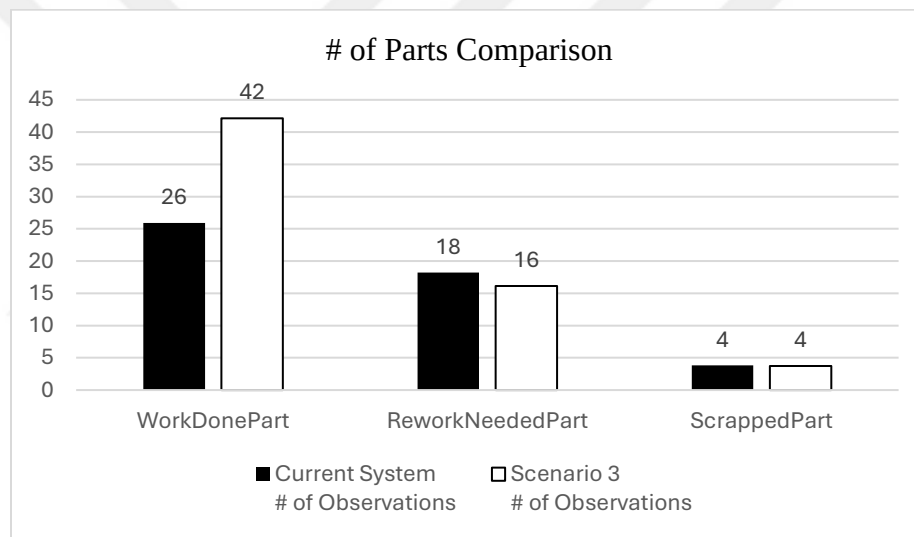


Figure 6.24 comparison of the completed part counts between the current system and Scenario 3.

Figure 6.24 presents a comparative analysis of KPIs between the current system and the system after the implementation of scenario 3. Statistically, despite the system producing a relatively dwindling number of parts, it is observed that the completed part count has increased from 26 to 42, representing a 60% increase. This notable improvement can be attributed to the meticulous efforts of the quality engineer in mapping the production process and establishing robust quality checks with the design team before the commencement of production.

By implementing these measures, the quality engineer has effectively minimized the proportion of parts requiring rework and those being scrapped, thereby significantly enhancing the overall

efficiency and productivity of the production process. This underscores the pivotal role of initiative-taking quality management practices in driving substantial improvements within the manufacturing workflow.

Scenario 4: Supply Chain Optimization via Procurement Expertise

Upon a detailed examination of the current system outputs, it has been observed that the queue length for the procurement specialist is notably higher than those for other resources. This bottleneck presents a significant challenge, as it impedes the overall efficiency of the production process. Similar to other scenarios, the primary objective in addressing this issue is to enhance the throughput, thereby increasing the number of products completed per unit of time and reducing the overall cycle time.

In this context, it is crucial to consider the financial implications associated with the procurement process. The annual salary and benefits for the senior purchasing specialist have been calculated to amount to 960,000 TL, based on a monthly remuneration of 80,000 TL. This financial commitment underscores the importance of optimizing the procurement process to ensure that the investment in human resources translates into tangible improvements in system performance. By effectively addressing the bottleneck, the organization can achieve greater efficiency and cost-effectiveness, ultimately enhancing its competitive advantage.

Table 6.19 Resource Waiting Rates in Scenario 4

TALLY VARIABLES				
Waiting Time	Average	Minimum	Maximum	Observations
Machine1Q	0,000	0	0,00	49
Machine2Q	21,528	0	85,42	19
SupervisorQ	14,250	0	32,15	97
Technician1Q	0,309	0	4,22	49
Technician2Q	0,240	0	1,05	25
Technician3Q	0,021	0	6,52	78
Technician4Q	26,054	0	52,17	76
PurchaserQ	16,428	0	25,65	45
truckq	26,951	0	58,12	135

Table 6.19 presents a comprehensive statistical summary of the data recorded in the tally block for each resource following the implementation of modifications specified in Scenario 4. This summary encompasses the mean, minimum, and maximum values of waiting, as well as the total number of observations for each resource. The tabulated data provides a quantitative basis for assessing the impact of the scenario-based changes on resource utilization and system performance, facilitating evidence-based decision-making in the context of process optimization.

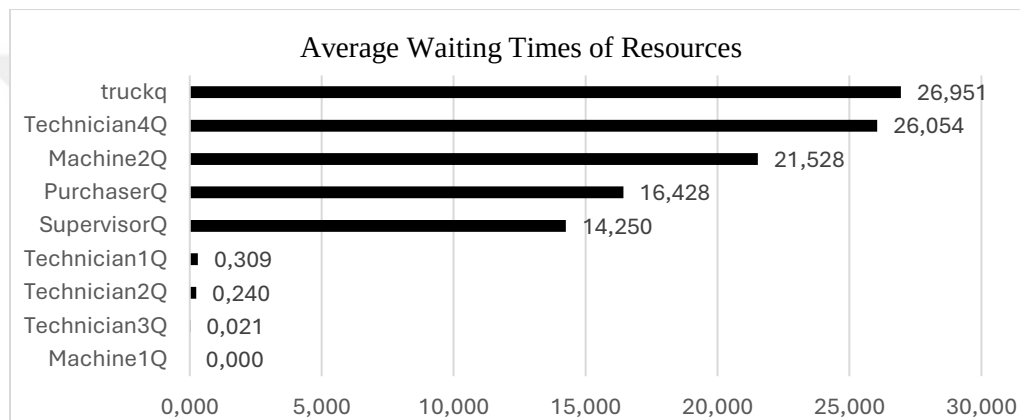


Figure 6.25 Average Waiting Times for Resources in Scenario 4

Table 6.20 Utilization rates for resources in scenario 4

Utilization Rate	Average NR	Average NQ
Machine1	26%	0
Machine2	19%	0,584
Supervisor	370%	35,65
Technician1	27%	0,0214
Technician2	29%	0,00274
Technician3	96%	5,415
Technician4	135%	5,985
Purchaser	32%	0,174
Truck	567%	0,982

Table 6.20 presents a comprehensive analysis of resource utilization and queue dynamics following the implementation of Scenario 4. As delineated in Table 6.17, a comprehensive analysis of resource utilization reveals significant disparities in waiting time ratios across various operational entities. The data elucidate a hierarchical structure of resource constraints, with three key categories demonstrating markedly elevated waiting time ratios: Truck, technician 4, machine 2.

Table 6.21 Quantity of Components by Type in Scenario 4

Count Output	# of Observation
Work Done Part	41
Rework Needed Part	29
Scrapped Part	6

Table 6.21 delineates the outcomes of part completion following the implementation of Scenario 4. The data reveal significant improvements in production efficiency and quality metrics. The number of successfully completed parts has increased to 44, while the number of parts requiring rework has increased to 16.

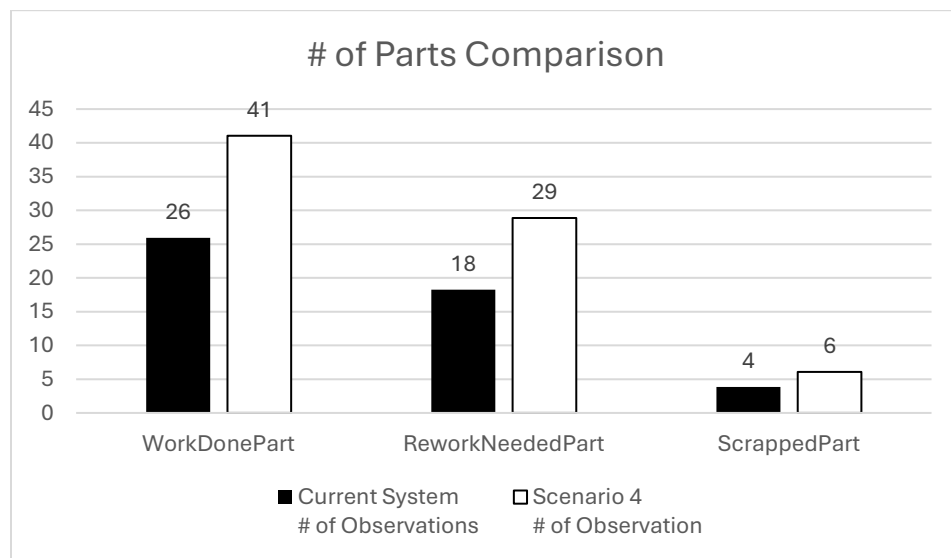


Figure 6.26 A comparison of the completed part counts between the current system and Scenario 4.

Figure 6.26 presents a comparative analysis of KPIs between the current system and the system after the implementation of scenario 4. When reviewing Figure 34, it is observed that the number of successfully completed parts has increased by 57%. This represents a significant improvement in production efficiency. Such a substantial increase highlights the effectiveness of strategic interventions in the manufacturing process. The bottleneck previously identified in the procurement phase, as noted by expert observers, can be effectively addressed by increasing the number of resources allocated to this area, as demonstrated in this scenario. This adjustment alleviates the constraints and enhances throughput.

However, as with other scenarios, it is imperative to conduct a thorough analysis comparing the investment costs with the performance outcomes. This evaluation aims to identify the most optimal scenario, balancing financial expenditure with improvements in efficiency and productivity. By doing so, the organization can make informed decisions that maximize return on investment while ensuring sustainable operational enhancements.

Scenario 5: Technical Expertise Increase through Human Source

As outlined in the preceding sections of this thesis, the initiation of both the workshop production process and the procurement process is contingent upon a technical analysis determining whether parts should be produced internally or externally. The current system simulation outputs clearly reveal a bottleneck within this framework. To address this issue, the scenario proposes an increase in the number of supervisor resources by one. This improvement aims to achieve the same objectives as in other scenarios: increasing the number of completed parts and reducing the cycle time. By alleviating the bottleneck, the production process can operate more efficiently, thereby enhancing overall productivity. In considering this adjustment, it is important to acknowledge the financial implications. The annual salary and benefits for the workshop supervisor have been calculated at 1,200,000 TL, based on a monthly salary of 100,000 TL. This investment in human resources is a strategic decision aimed at optimizing the production process, ensuring that the benefits of increased efficiency outweigh the associated costs. Through careful evaluation, the organization seeks to implement the most effective solution, balancing cost and performance to achieve sustainable improvements.

Table 6.22 Resource Waiting Rates in Scenario 5

TALLY VARIABLES				
Waiting Time	Average	Minimum	Maximum	Observations
Machine1 Q	0,000	0	0,00	48
Technician3 Q	0,003	0	6,52	79
Technician2 Q	0,184	0	1,59	22
Technician1 Q	0,412	0	3,95	45
Supervisor Q	8,745	0	16,52	102
Machine2 Q	26,214	0	72,15	23
Technician4 Q	26,254	0	47,53	69
Truck q	26,854	0	59,12	114
Purchaser Q	30,528	0	34,53	26

Table 6.22 presents a comprehensive statistical summary of the data recorded in the tally block for each resource following the implementation of modifications specified in Scenario 5. This summary encompasses the mean, minimum, and maximum values of waiting, as well as the total number of observations for each resource. The tabulated data provides a quantitative basis for assessing the impact of the scenario-based changes on resource utilization and system performance, facilitating evidence-based decision-making in the context of process optimization.

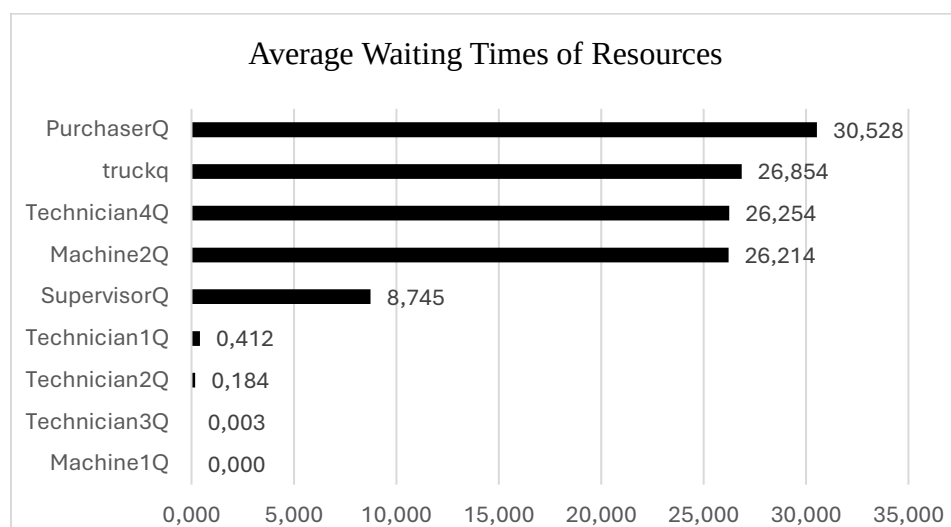


Figure 6.27 Average Waiting Times for Resources in Scenario 5

Figure 6.27 visually presents the waiting times of resources following the implementation of scenario 5. The analysis results reveal significant variations in waiting times among the resources. According to the observed data, the purchasing department has been identified as the resource with the longest waiting time. Subsequently, truck technician 4 and machine 2 emerge as the resources with the second and third highest waiting times, respectively. These findings offer important implications regarding resource utilization efficiency and workflow optimization. These findings offer important implications regarding resource utilization efficiency and workflow optimization. The data reveals significant improvements in production metrics, suggesting that the implemented changes have led to a more streamlined and effective use of resources throughout the manufacturing process.

Table 6.23 Utilization rates for resources in scenario 5

Utilization Rate	Average NR	Average NQ
Machine1	26%	0
Machine2	22%	0,51
Supervisor	389%	36,4
Technician1	25%	0,02
Technician2	25%	0,00295
Technician3	97%	6,35
Technician4	122%	5,419
Purchaser	19%	2,274
Truck	479%	1,426

Table 6.23 presents the utilization rates of resources following the implementation of scenario 5. This data provides crucial insights into the efficiency of resource allocation and usage within the system. Table 6.24 delineates the outcomes of part completion following the implementation of Scenario 5, offering a comprehensive view of the production process results. The data reveal significant improvements in production efficiency and quality metrics. Notably, the number of successfully completed parts has increased to 37, indicating an enhancement in throughput. Concurrently, the number of parts requiring rework has risen to 26. This increase in rework may suggest a need for further process refinement or quality control measures.

These findings underscore the complex interplay between production volume and quality assurance in manufacturing processes. The simultaneous increase in both completed parts and those requiring rework warrants further investigation into the underlying factors contributing to these outcomes. Such analysis could potentially inform future iterations of the production strategy, aiming to optimize the balance between output quantity and quality.

Table 6.24 Quantity of Components by Type in Scenario 5

Count Output	# of Observation
Work Done Part	37
Rework Needed Part	26
Scrapped Part	6

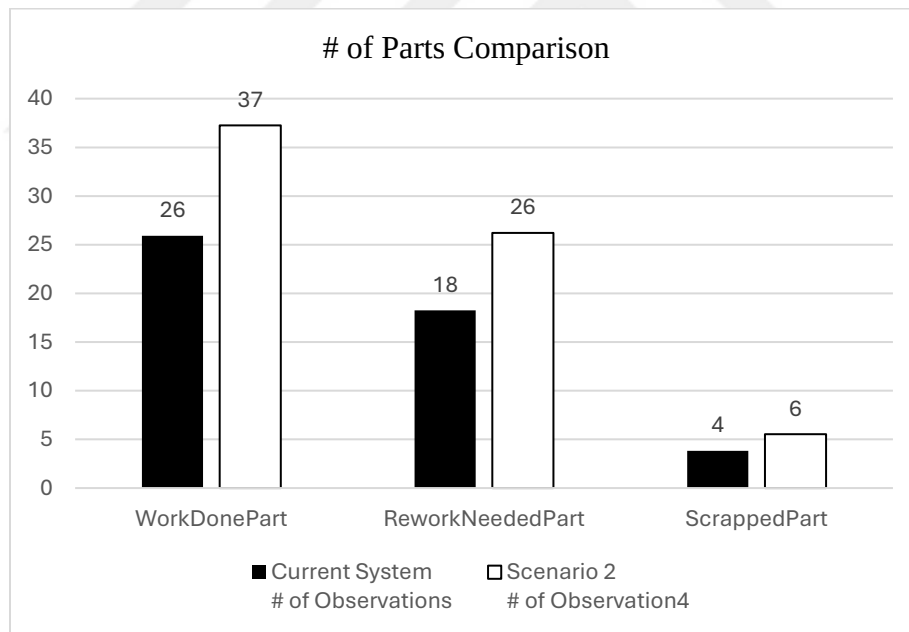


Figure 6.28 A comparison of the completed part counts between the current system and Scenario 3.

Figure 6.28 presents a comparative analysis of KPIs between the current system and the system after the implementation of scenario 5. When comparing the current system with the simulation results of Scenario 5, it is observed that the number of parts successfully completed without

requiring rework has increased by 42%. Although this improvement is not as substantial as that observed in Scenario 4, a forty two percent enhancement in production performance is nonetheless significant and should not be underestimated.

This improvement underscores the potential for meaningful gains in efficiency and productivity, even if they are not the most dramatic among the scenarios considered. As with all scenarios, it is essential to adopt a holistic perspective when evaluating the entire system. This comprehensive approach ensures that all aspects of the production process are considered, leading to more informed decision-making.

Moreover, it is prudent to calculate the payback period relative to the investment costs. By doing so, the organization can develop a strategic plan that not only enhances performance but also ensures financial sustainability. This approach is expected to yield more rational and sustainable solutions, aligning improvements in production efficiency with the organization's long-term goals.

When comparing the current system with the simulation results of Scenario 5, it is evident that the number of parts successfully completed without requiring rework has increased by 42%. Although this improvement is not as pronounced as that observed in Scenario 4, a forty two percent enhancement in production performance is nonetheless significant and should not be underestimated.

Table 6.25 Comparison of Statistical Parameters in Scenarios

Scenarios	Scenario 1 Machine Configuration		Scenario 2 Logistic Optimization		Scenario 3 Quality Enhancement		Scenario 4 Supply Chain Optimization		Scenario 5 Technical Expertise Increase	
Utilization Rate	NR Current Vs.	NQ Current	NR Current	NQ Current Vs.	NR Current	NQ Current	NR Current Vs.	NQ Current	NR Current	NQ Current
Machine1	↑ 42%	↑ 22%	↑ 12%	↓ -5%	↑ 5%	↑ 15%	↑ 2%	↑ 12%	↑ 25%	↑ 33%
Machine2	↑ 4%	↓ -23%	↑ 17%	↓ -4%	↑ 8%	↑ 12%	↑ 11%	↑ 21%	↑ 39%	↑ 45%
Supervisor	↓ -3%	↑ 4%	↑ 3%	↓ -15%	↑ 58%	↓ -47%	⇒ 0%	↓ -5%	↑ 89%	↓ -94%
Technician1	↑ 53%	⇒ 0%	↑ 7%	↓ -3%	↓ -4%	↑ 19%	↑ 17%	↑ 24%	↑ 35%	↑ 42%
Technician2	↓ -5%	⇒ 0%	↑ 14%	↓ -8%	⇒ 0%	↓ -2%	↑ 32%	↑ 19%	↑ 16%	↑ 9%
Technician3	↑ 9%	↑ 5%	↑ 5%	↓ -18%	↓ -10%	↑ 19%	↑ 10%	↓ -21%	↑ 11%	↑ 5%
Technician4	↓ -2%	↑ 7%	↑ 9%	↓ -4%	↑ 42%	↓ -32%	↑ 4%	↑ 7%	↑ 15%	↓ -8%
Purchaser	↑ 3%	↓ -9%	↑ 1%	↓ -14%	↑ 4%	↓ -17%	↓ -44%	↓ -14%	↑ 14%	↑ 28%
Truck	↓ -2%	↓ -8%	↑ 129%	↓ -30%	↑ 7%	↓ -7%	↑ 4%	↑ 35%	↓ -10%	↑ 8%
Quality Engineer					↑ 100%					

Table 6.25 illustrates the average number of entities being processed by each resource at any given moment during the simulation, as well as the average number of entities waiting in queue, for five alternative scenarios generated based on the current scenario.

In Scenario 1, where machine configuration is adjusted, Machine 1's previously low NR rate increases by 42%, while Machine 2's waiting time decreases by 23%. Such a positive impact on both resources is uniquely possible in Scenario 1. Due to the increased capacity of Machine 1, Technician 1's NR rate also increases by 53%. Given that Technician 1's NR and NQ rates were quite low in the current scenario, this increase does not pose any problems. Examination of other resources reveals no significant or major increases or decreases. As this improvement incurs no cost, implementation of this scenario has been recommended to the company.

Statistical analysis of Scenario 2 demonstrates that increasing the number of trucks raises the NR rate for each resource while decreasing the NQ rate. This analysis indicates that the truck resource was creating a bottleneck due to capacity limitations, and its improvement results in an overall system efficiency increase.

Analysis of this graph reveals that, as expected, in Scenario 3 the employment of a Quality Engineer results in a 100% increase in utilization for that position, which was previously vacant. Concurrently, as parts undergo quality engineer approval before reaching the supervisor, inter-layout part movements are minimized. The 58% increase in the supervisor's NR rate is a clear indicator of this change. Additionally, there is a substantial increase in the number of parts

completed by the technician performing visual quality control, as evidenced by the 42% increase in the technician's NR rate.

Upon evaluating the outputs of Scenario 4, which involves the employment of a purchasing engineer, it is observed that while the number of parts purchased per capita decreases by 44%, the queue length for parts reduces by 14%. Although this 14% reduction in waiting time may appear modest, it has a significant impact on the overall system efficiency. This underscores the importance of assessing the effect of each resource in conjunction with its impact on the entire system.

Scenario 5 shows an increase in both the number of entities being processed and queue lengths. This situation indicates that system performance needs optimization and suggests that the system is approaching its capacity limit. Efficiency could be improved through capacity expansion, process improvements, or workflow adjustments. However, capacity expansion was not investigated as it falls outside the scope of this research. In Scenario 5, Machine 1 shows an NR of 25% and an NQ of 33%, indicating intensive use of the machine and a significant queue formation. Similarly, Machine 2 in Scenario 5 displays an NR of 39% and an NQ of 45%, pointing to high utilization and long queues. Naturally, increasing the number of supervisors has led to an increase in the number of parts analyzed by supervisors while reducing the waiting time of parts at this resource.

Overall, this analysis underscores the complex interplay between resources and the necessity of considering both individual resource performance and system-wide effects when optimizing operational efficiency. To facilitate a deeper understanding, graphical representations of these metrics are provided below. These visualizations enable a clearer comparison of how each resource's performance metrics have been influenced by the changes.

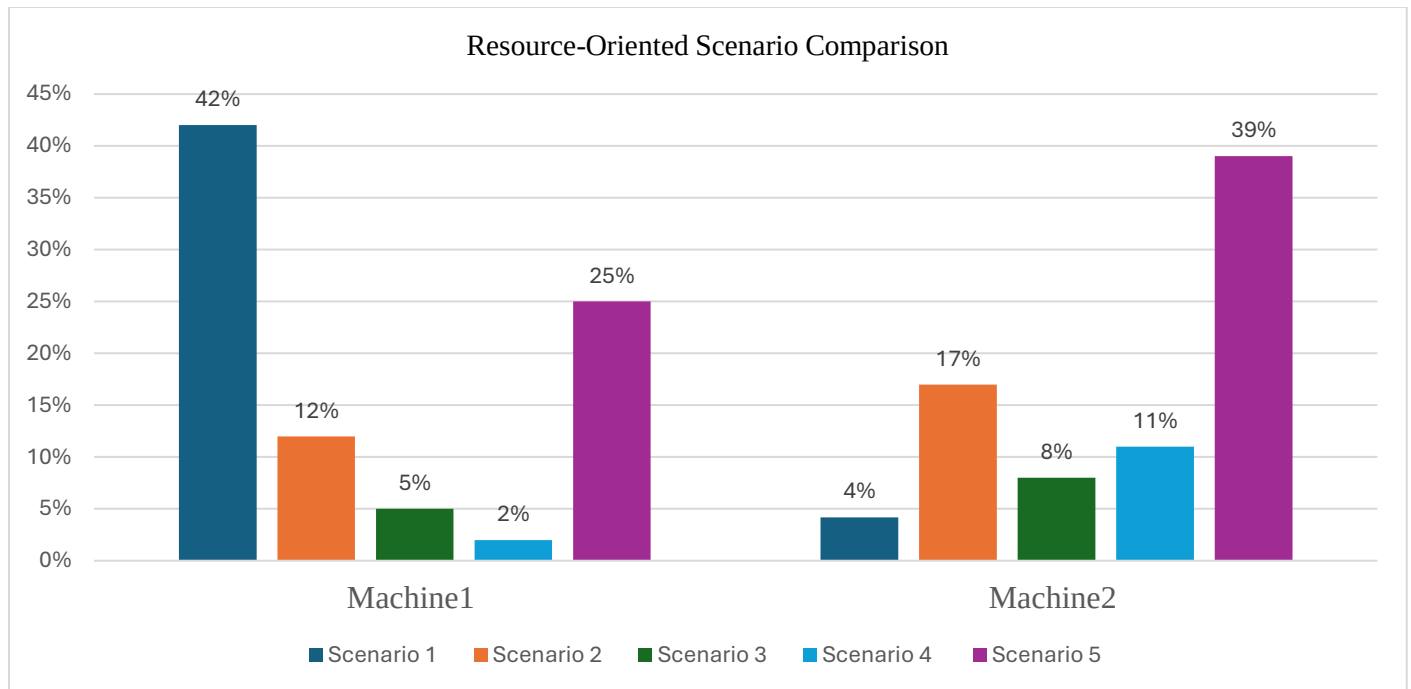


Figure 6.29 Resource oriented scenario comparison (machines)

Figure 6.29 provides information on which scenarios yield the highest to lowest beneficial utilization rates for Machine 1 and Machine 2. According to this graph:

For Machine 1, the scenarios are ranked from highest to lowest utilization rate as follows:

Scenario 1 > Scenario 5 > Scenario 2 > Scenario 3 > Scenario 4

For Machine 2, the ranking is as follows:

Scenario 5 > Scenario 2 > Scenario 4 > Scenario 3 > Scenario 1

This analysis highlights the varying effectiveness of different scenarios in optimizing machine utilization.

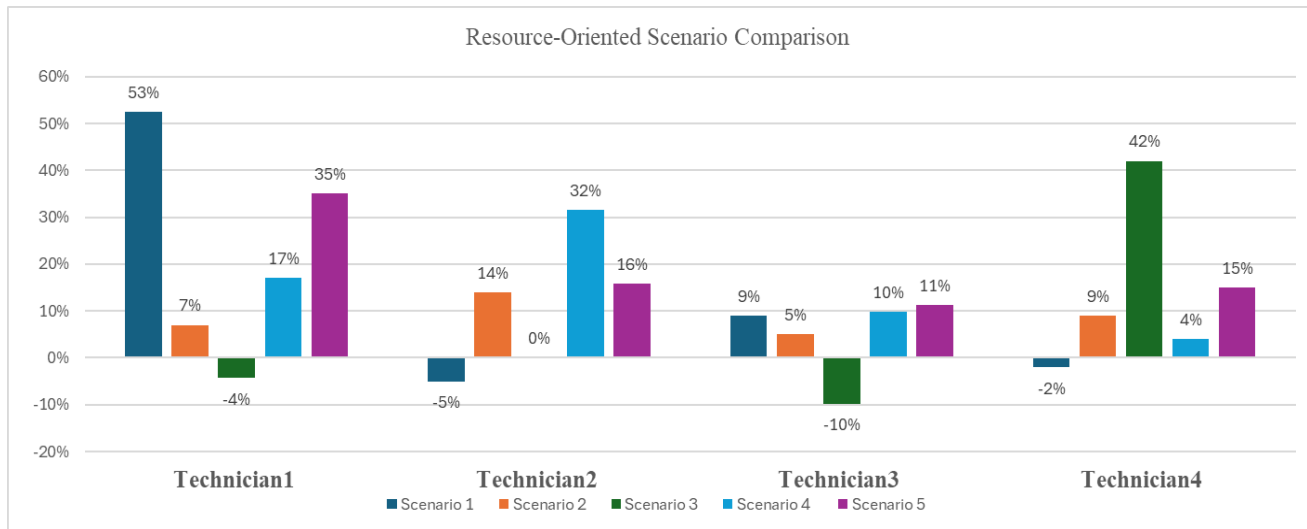


Figure 6.30 Resource-oriented scenario comparison (technicians)

Figure 6.30 offers a detailed comparative analysis of the beneficial utilization rates for each technician across five distinct scenarios, benchmarked against the current system. This analysis is pivotal in understanding how different scenarios impact the efficiency and productivity of individual technicians.

The data reveals the following rankings of scenarios from best to worst utilization for each technician:

Technician 1: Scenario 1 > Scenario 5 > Scenario 4 > Scenario 2 > Scenario 3

Technician 2: Scenario 4 > Scenario 5 > Scenario 2 > Scenario 3 > Scenario 1

Technician 3: Scenario 5 > Scenario 4 > Scenario 1 > Scenario 2 > Scenario 3

Technician 4: Scenario 3 > Scenario 5 > Scenario 2 > Scenario 4 > Scenario 1

This analysis provides critical insights into the varying effectiveness of each scenario in optimizing technician utilization rates. The differences in scenario performance highlight the need for a tailored approach to resource management. For instance, Scenario 1 appears to be most effective for Technician 1, while Scenario 4 is optimal for Technician 2. These variations suggest that a one-size-fits-all strategy may not be appropriate, and that customization based on specific technician needs and scenario characteristics is essential.

Understanding these differences is crucial for strategic planning and resource allocation. By identifying which scenarios maximize utilization for each technician, organizations can make informed decisions that enhance operational efficiency. This targeted approach allows for the allocation of resources in a manner that aligns with the strengths and preferences of each technician, thereby optimizing overall productivity.

In conclusion, the comparative analysis of technician utilization rates across scenarios provides valuable insights that can drive strategic improvements. By leveraging this data, organizations can implement targeted strategies that enhance efficiency and productivity, ultimately leading to improved operational outcomes. This analysis underscores the importance of scenario-based planning in achieving optimal resource utilization.

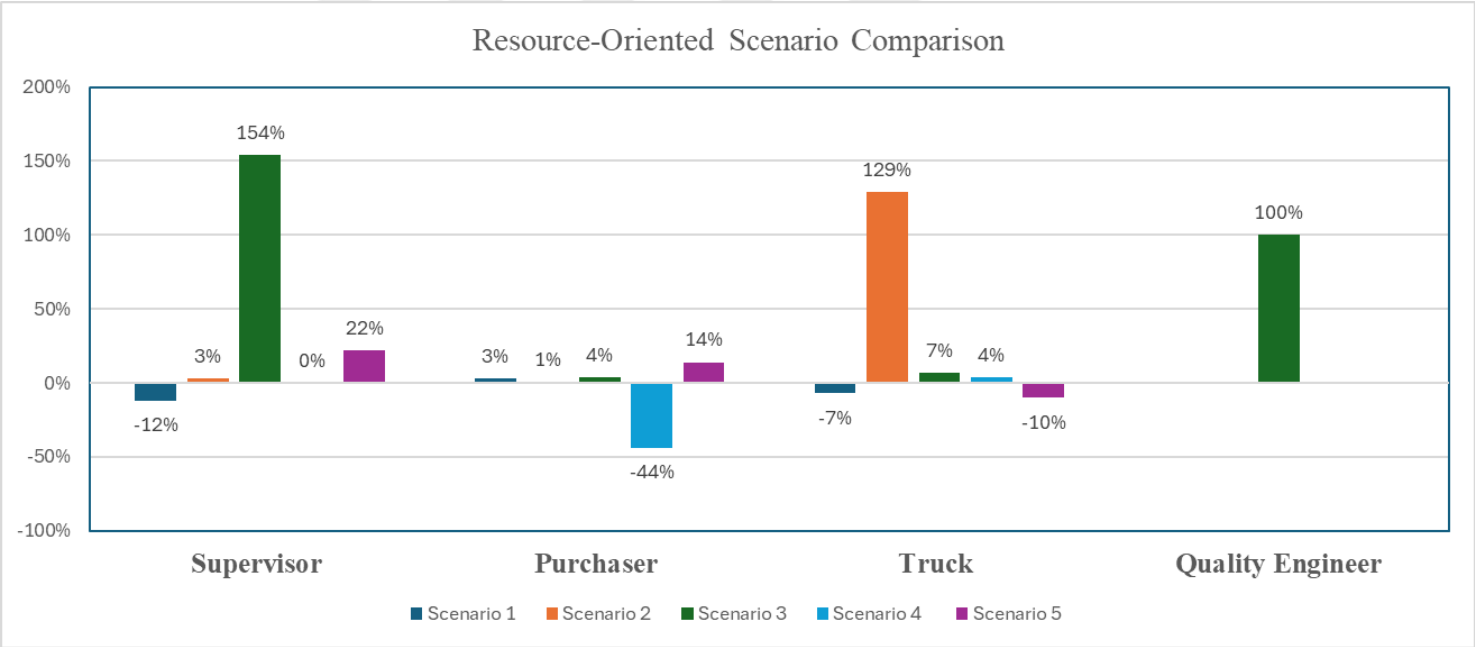


Figure 6.31 Resource-oriented scenario comparison

Figure 6.31 provides a comprehensive comparison of the beneficial utilization rates for various roles, including Supervisor, Purchaser, Truck, and Quality Engineer, across multiple scenarios. This analysis is essential for understanding how different scenarios influence the efficiency and productivity of these roles.

The data reveals the following rankings of scenarios from best to worst utilization for each role:

Supervisor: Scenario 3 > Scenario 5 > Scenario 2 > Scenario 4 > Scenario 1

Purchaser: Scenario 5 > Scenario 3 > Scenario 1 > Scenario 2 > Scenario 4

Truck: Scenario 2 > Scenario 3 > Scenario 4 > Scenario 1 > Scenario 5

Quality Engineer: Appears only in Scenario 3

This analysis highlights the varying effectiveness of scenarios in optimizing utilization rates for each role. For the Supervisor, Scenario 3 offers the highest utilization, suggesting it aligns well with their operational requirements. Conversely, the Purchaser benefits most from Scenario 5, indicating a different set of priorities or conditions that enhance their productivity.

The Truck's utilization is maximized in Scenario 2, which may reflect logistical efficiencies or scheduling advantages inherent in this scenario. The Quality Engineer's presence solely in Scenario 3 underscores a unique or specialized requirement that this scenario fulfills.

Understanding these differences is crucial for strategic planning and resource allocation. By identifying which scenarios maximize utilization for each role, organizations can tailor their strategies to enhance operational efficiency. This targeted approach allows for the allocation of resources in a manner that aligns with the specific needs and strengths of each role, thereby optimizing overall productivity.

In conclusion, the comparative analysis of utilization rates across roles and scenarios provides valuable insights that can inform strategic decision-making. By leveraging this data, organizations can implement targeted strategies that enhance efficiency and productivity, ultimately leading to improved operational outcomes. This analysis underscores the importance of scenario-based planning in achieving optimal resource utilization and highlights the need for a nuanced approach to managing diverse roles within an organization.

Table 6.26 Comparison of Scenarios by Completed Parts Count

	Current System	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Work Done Part	26	33	38	42	41	37
Rework Needed Part	18	24	27	16	29	26
Scrapped Part	4	5	6	4	6	6
Comparison		27%	46%	63%	58%	44%

When Table 6.26 is evaluated in isolation, it is observed that the configuration change between Machine 1 and Machine 2 had no discernible effect on the rates of parts designated for scrap or requiring rework. However, this reconfiguration positively impacted the number of parts produced per unit time by 14%, thereby increasing productivity.

The employment of a quality engineer resulted in both an increase in the number of parts produced and a decrease in the quantity of parts requiring rework. In addition to these two effects, it also had a 12% positive impact on reducing the number of parts designated as scrap.

As with all scenarios, it is crucial to adopt a holistic perspective when evaluating the entire system. This comprehensive approach ensures that all aspects of the production process are considered, leading to more informed decision-making. Additionally, calculating the payback period relative to the investment costs is essential. By doing so, the organization can develop a strategic plan that not only enhances performance but also ensures financial sustainability, providing more rational and enduring solutions.

In the context of the factory, the number of parts completed within a day is directly linked to reducing project delays. Therefore, the parts that successfully pass quality control, as counted in the counter block, have been established as a key comparison parameter. Table 6.26 illustrates the proportions of parts that were successfully completed, required rework, or were scrapped for each scenario during the same simulation period.

Based solely on this table, the best scenarios compared to the current system are, in order, Scenario 3, Scenario 4, Scenario 2, and Scenario 5. This ranking provides valuable insights into the relative effectiveness of each scenario in enhancing production efficiency and minimizing waste.

6.4.4. Performance Metrics Evaluation and Benchmarking

The Pair T test is a parametric statistical test used to determine whether there is a statistically significant difference between the means of two related groups. This test is employed to compare related data sets, such as measurements of the same elements at different times or under different conditions.

In output analysis, the Pair T test is utilized to compare the means of each scenario with those of the current system, in order to ascertain whether each scenario differs significantly from the current system. This can be useful in determining which scenario's performance is significantly better or worse than the current system. Such information can aid in deciding which scenario may be more suitable for improving performance.

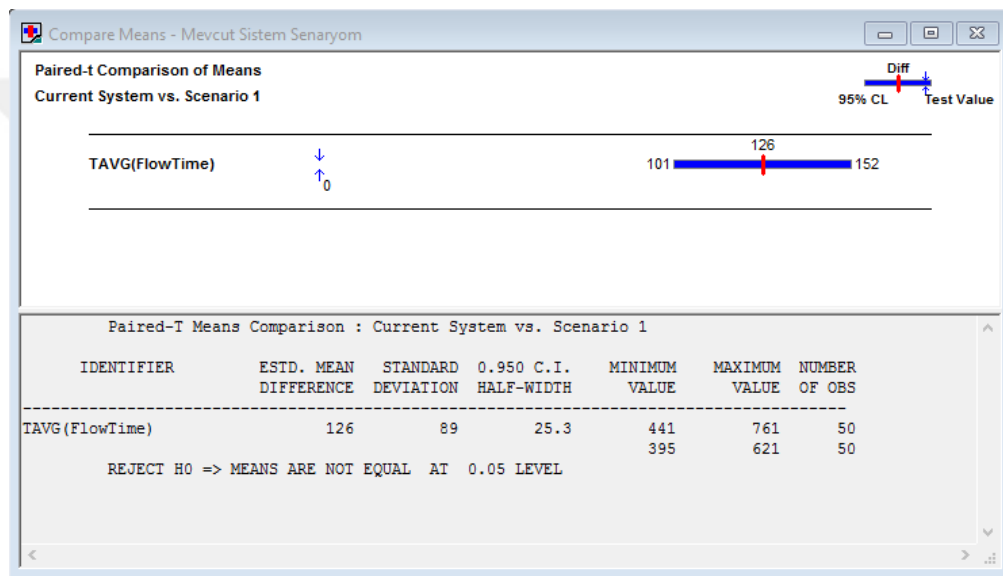


Figure 6.32 Paired- T comparison of current system and scenario 1

The screenshot of the Arena Output Analysis, which is called as Figure 6.32, displaying the analysis of the P test results below, includes the difference in average time spent in the system for two scenarios, the standard deviation, the minimum and maximum values, and finally, the number of observations.

Given that the confidence interval does not encompass zero, it can be inferred that the current system and Scenario 1 exhibit variance. This suggests that there is a statistically significant difference between the two systems. Furthermore, as indicated in the figure below, the null hypothesis (H_0) can be confidently rejected at a 95% confidence level, providing strong evidence in support of the observed variance between the systems.

Based on the results of the Pair T test conducted with 50 iterations for both scenarios, it can be inferred that Scenario 1 outperforms the current scenario. Considering that the confidence interval does not include zero, it can be deduced that the current system and Scenario 2 demonstrate variability. This implies a statistically noteworthy distinction between the two systems. Moreover, as illustrated in the figure below, the null hypothesis (H_0) can be decisively dismissed at a 95% confidence level, furnishing compelling evidence in favor of the noted variability between the systems.

The data obtained from running the system 50 times for each scenario and analyzing it with a Pair T test suggests that Scenario 1 performs better than the current scenario.

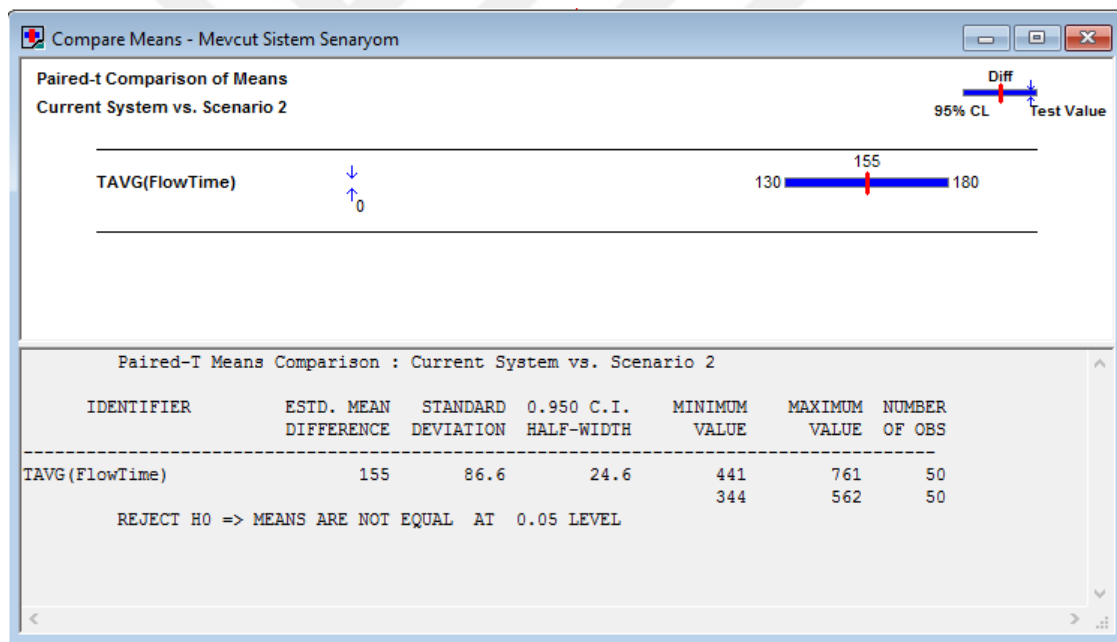


Figure 6.33 Paired -T comparison of current system and scenario 2

The exclusion of zero from the confidence interval suggests that there is a difference in variability between the current system and Scenario 2, indicating a statistically significant contrast between the two. Furthermore, Figure 6.33 provides strong evidence supporting the observed variability between the systems by confidently rejecting the null hypothesis (H_0) at a 95% confidence level.

The fact that zero is excluded from the confidence interval implies that Scenario 2 and the current system differ in variability, pointing to a statistically significant difference between the two. Furthermore, by firmly rejecting the null hypothesis (H_0) with a 95% confidence level, the diagram below offers compelling evidence in favor of the observed variability between the systems.

The statistical significance of the difference between the current system and Scenario 4 is indicated by the exclusion of zero from the confidence interval, which implies that there is a variation in variability between the two. Additionally, the Figure 6.34 confidently rejects the null hypothesis (H_0) with a 95% confidence level, offering strong evidence in favor of the observed variability between the system.

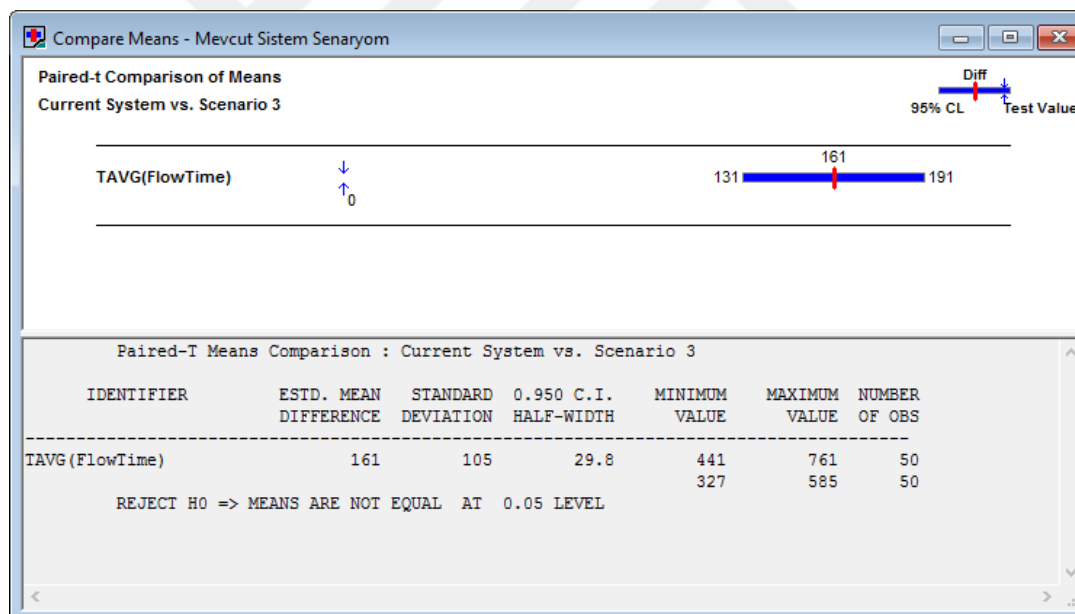


Figure 6.34 Paired -T comparison of current system and scenario 3

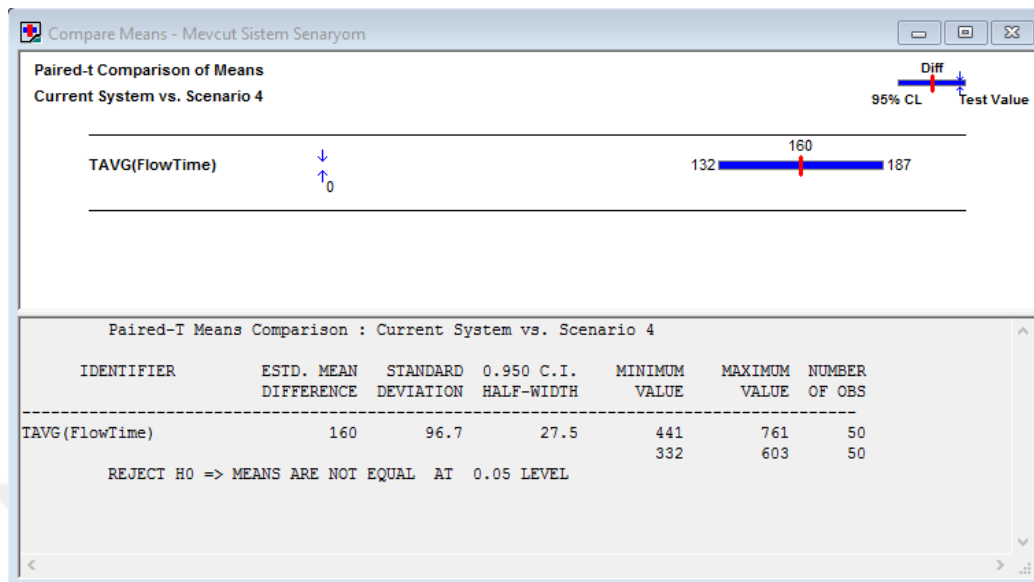


Figure 6.35 Paired -T comparison of current system and scenario 4

The absence of zero in the confidence interval indicates a statistically significant difference between the current system and Scenario 4, highlighting variability between the two.

Moreover, Figure 6.36 robustly rejects the null hypothesis (H_0) at a 95% confidence level, providing compelling evidence of the observed differences between the systems.

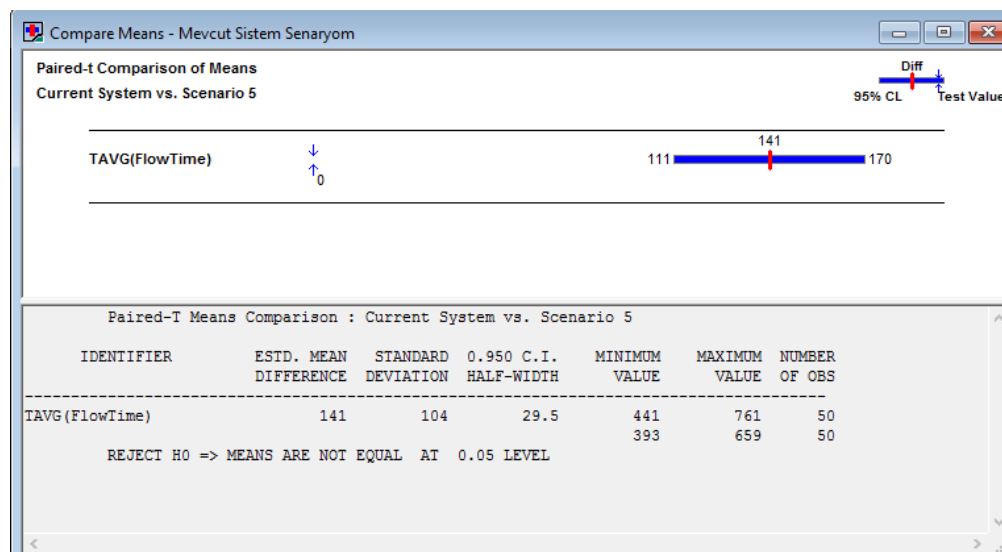


Figure 6.36 Paired -T Comparison of Current System and Scenario 5

The absence of zero in the confidence interval indicates a statistically significant difference between the current system and Scenario 5, highlighting variability between the two. Moreover, Figure 6.37 robustly rejects the null hypothesis (H_0) at a 95% confidence level, providing compelling evidence of the observed differences between the systems.

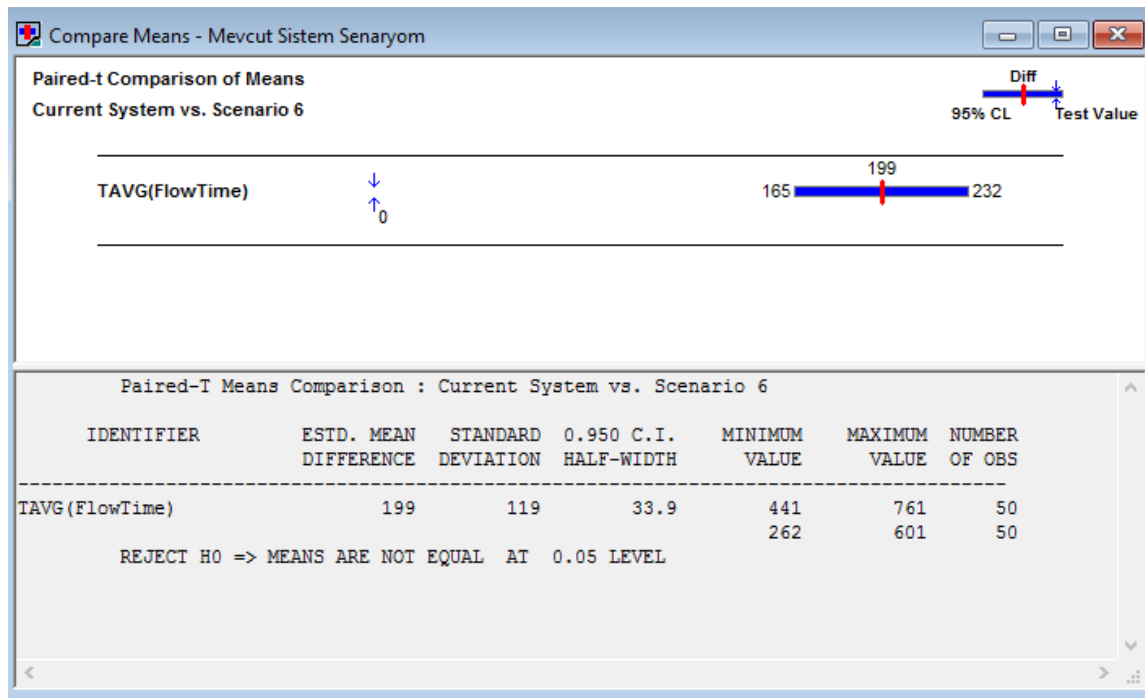


Figure 6.37 Paired -T comparison of current system and scenario 6

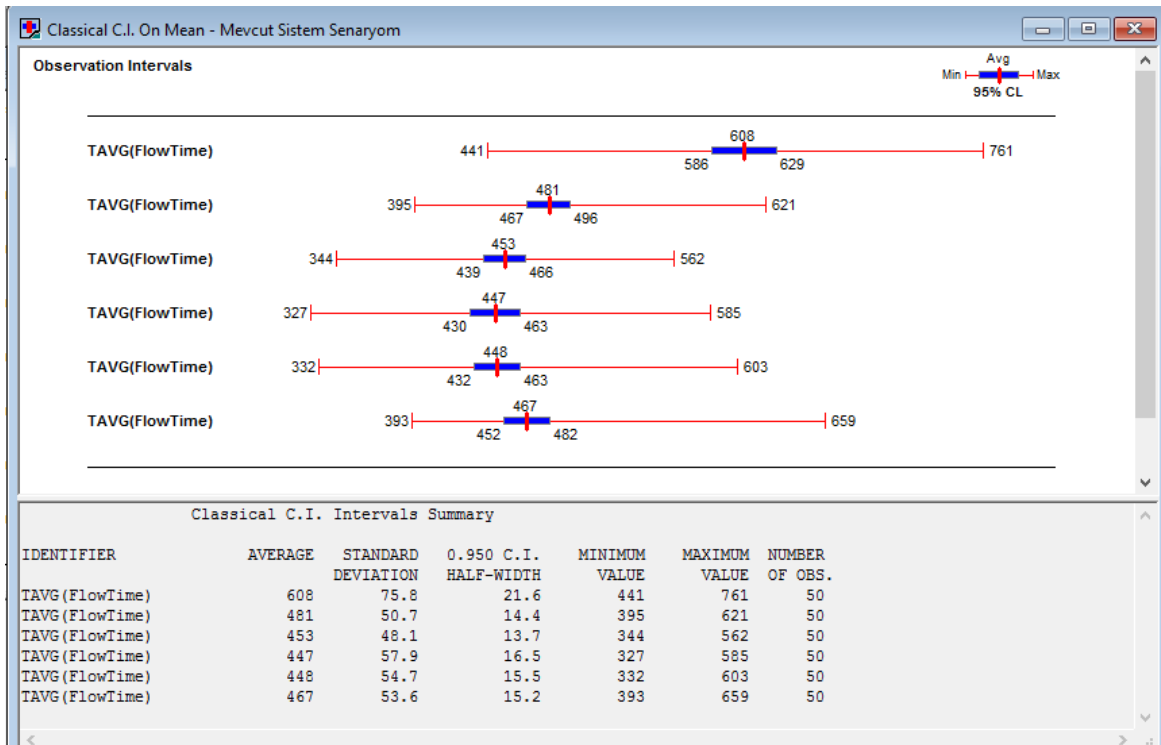


Figure 6.38 Paired- T comparison of current system and alternative scenarios

The results of the Pair T test comparing the average durations of the current system, and the proposed five systems are presented in Figure 6.38. The analysis indicates a clear superiority of each scenario over the current system. Considering the time spent by the scenarios in the system, specifically the cycle time, the ranking from best to worst can be established as follows: Scenario 3 > Scenario 4 > Scenario 2 > Scenario 5 > Current State.

This analysis aligns with the statistical values maintained within the simulation. Notably, the number of successfully completed parts in Scenario 3 is the highest, whereas this rate is lowest in Scenario 5.

Given that cycle time cannot be the sole parameter influencing the company's decision-making process, the impact of the improvement on performance, as well as the investment cost, is of significant importance. Therefore, the next step of the study focuses on examining the relationship between performance enhancement and investment cost.

6.4.5. Conceptual Model Design for Redesigned System

As observed in previous sections, the transportation and tracking of materials between the automation factory and the workshop have been shown to have a negative impact on system efficiency. To completely mitigate this issue, the relocation of the workshop into the automation factory is being considered. Given the high investment cost associated with such a move, conducting a simulation to calculate the system's efficiency before undertaking such an endeavor would provide a significant advantage.

The objective is to compare the expected performance improvement with the previous scenarios to determine the most suitable scenario. By doing so, the study aims to make an informed decision regarding the anticipated performance enhancement in comparison to the investment cost, thereby ensuring that the chosen scenario aligns with the overarching goals of the company.



Figure 6.39 Modeling elements of designed system

As illustrated in Figure 6.39, unlike the current system, the elements sequence, distance, transporters, and stations are absent. Apart from these modifications, the remaining elements are identical to those in the existing system.

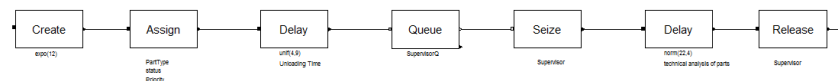


Figure 6.40 The first view of the newly designed system simulation

Figure 6.40 illustrates the processes within the newly designed system, encompassing the creation of parts, the assignment of part types, statuses, and priorities, the queuing for supervisor review, the execution of technical analysis, and the subsequent release by the supervisor. This visual representation delineates the sequential workflow and interdependencies of these critical operational stages, providing a comprehensive overview of the system's architecture and functionality.

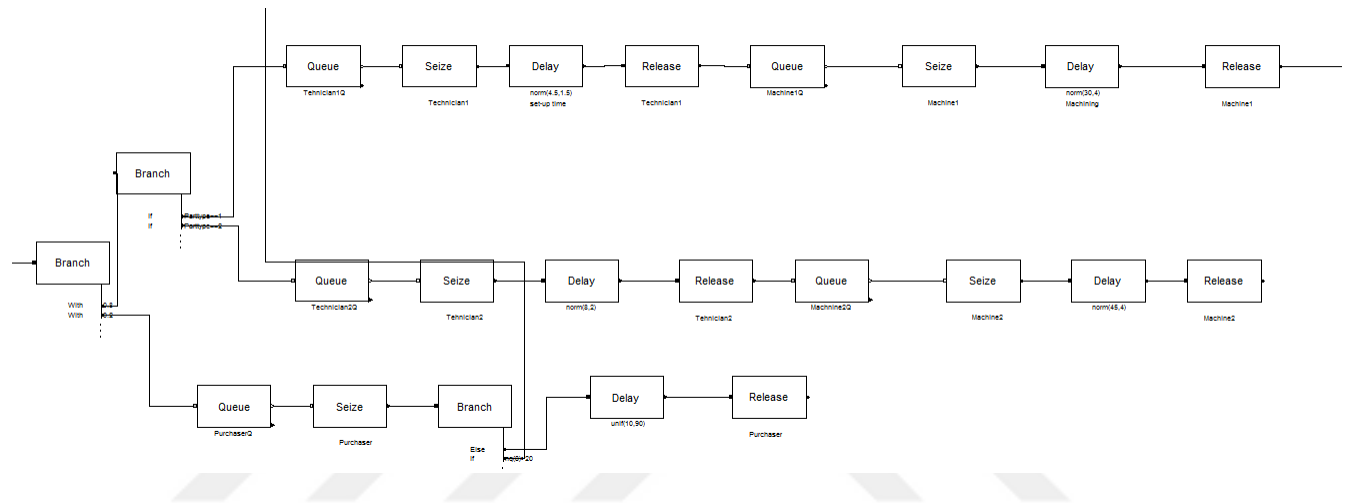


Figure 6.41 The second view of the newly designed system simulation

Figure 6.41 illustrates a complex sequence of processes within the system. Initially, parts undergo bifurcation based on their technical feasibility. Feasible parts are routed to the workshop, where they diverge into different pathways contingent upon their type. Type 1 parts proceed directly to processing on Machine 1, while harder parts destined for Machine 2 first undergo a pre-processing stage before being processed on Machine 1. Conversely, technically unfeasible parts enter a distinct workflow: they are queued for supervisor review, initiating a procurement process. Upon completion of the procurement, the supervisor releases these parts. This diagrammatic representation elucidates the intricate decision-making pathways and operational sequences within the system, highlighting the differentiated treatment of parts based on their characteristics and technical requirements, and demonstrating the system's adaptability to varying part specifications and production demands.

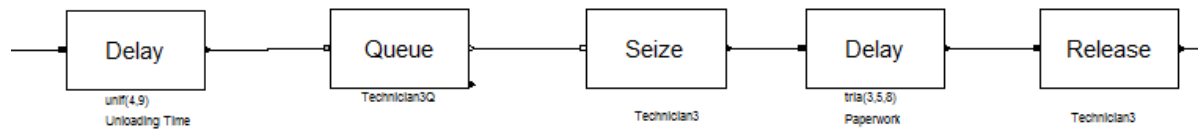


Figure 6.42 The third view of the newly designed system simulation

Figure 6.42 illustrates the execution of administrative documentation processes, colloquially referred to as "paperwork," by Technician 3.

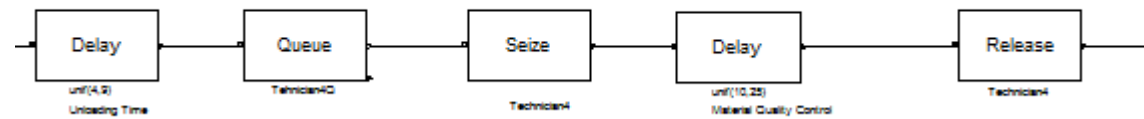


Figure 6.43 The fourth view of the newly designed system simulation

Figure 6.43 delineates the quality control process as executed by Technician 4. This diagrammatic representation elucidates the specific role and responsibilities assigned to Technician 4 within the broader quality assurance framework.

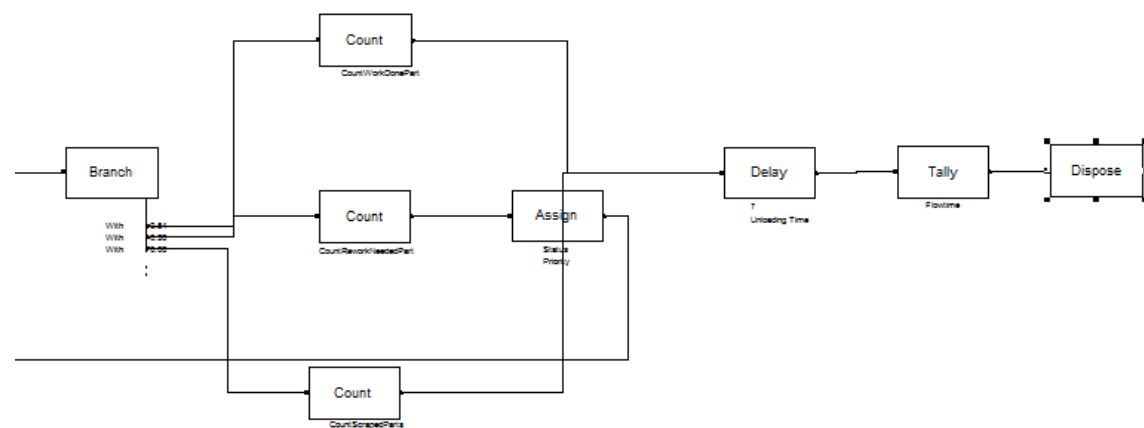


Figure 6.44 The fifth view of the newly designed system simulation

Figure 6.44 illustrates the processes of enumeration and documentation for three distinct categories of parts: those successfully completed, those requiring rework, and those designated for scrap.

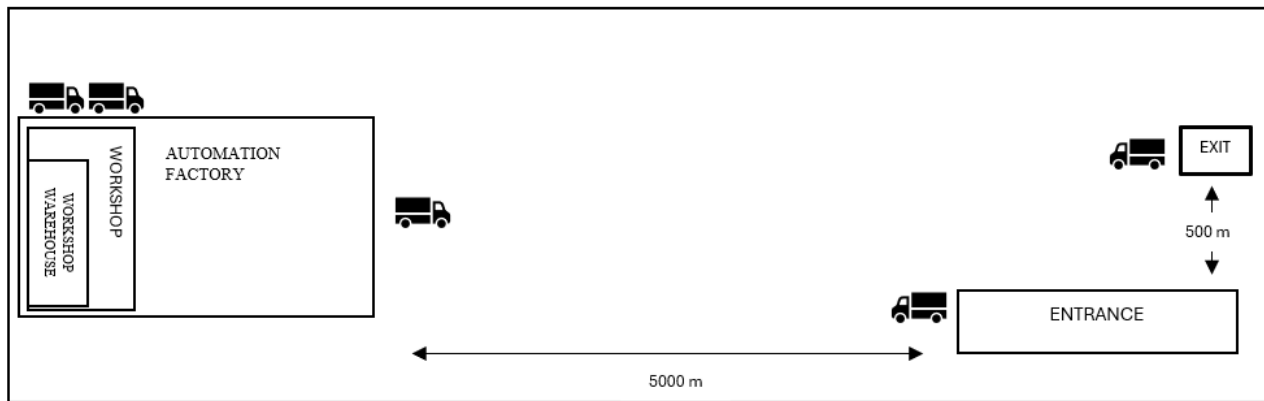


Figure 6.45 Distance Between Stations in the Newly Designed System

The figure 6.45 above illustrates the new layout that has been established as a result of relocating the workshop to the automation factory. This strategic reconfiguration has yielded dual benefits: a significant reduction in inter-station distances and the elimination of transportation requirements between the automation facility and the workshop. Such optimization of spatial arrangements and process flow contributes to enhanced operational efficiency. The diminished physical separation between workstations likely facilitates more streamlined material handling and improved communication among production units. Concurrently, the integration of previously disparate facilities mitigates the need for inter-site material transfer, potentially reducing logistical complexities, transportation costs, and the risk of damage or delay associated with the movement of components or products. This holistic approach to layout design and process integration exemplifies principles of lean manufacturing and operational excellence.

6.4.6. Performance Metric Evaluation for Redesigned System

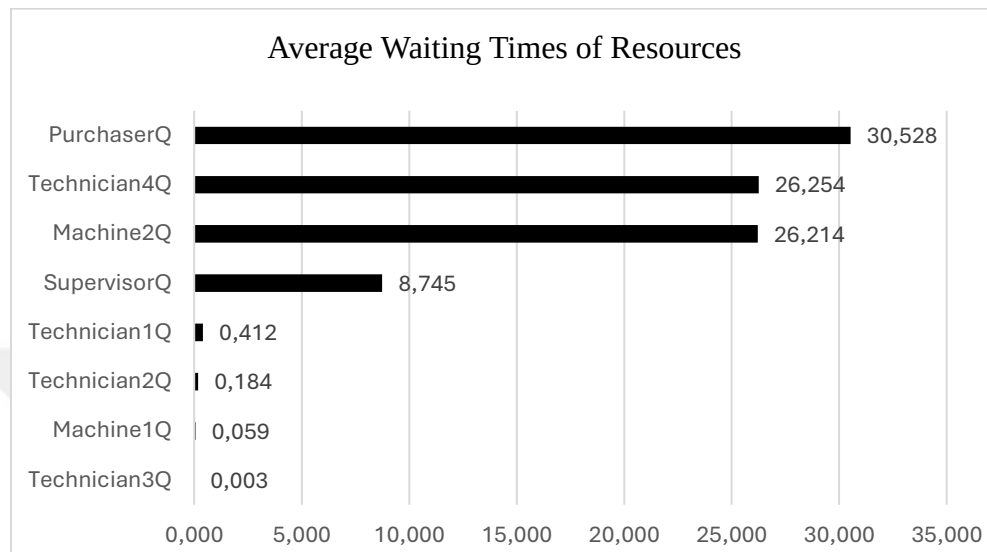


Figure 6.46 Average Waiting Times of Resources in Scenario 6

Figure 6.46 illustrates the resource idle rates within the newly designed system. The analysis reveals that four specific resources exhibit the highest mean waiting times in this scenario. These resources, in order of their idle durations, are the procurement specialist, technician 4, machine 2, and the supervisor. This distribution of idle times provides valuable insights into potential bottlenecks or inefficiencies within the system. The extended waiting periods associated with these particular resources may indicate areas where process flow optimization or resource reallocation could yield significant improvements in overall system efficiency. Further investigation into the factors contributing to these elevated idle rates could inform targeted interventions to enhance resource utilization and streamline operations within the newly designed system.

Table 6.27 Quantity of components by type in the newly designed scenario

Count Output	# of Observation
Work Done Part	110
Rework Needed Part	15
Scrapped Part	4

Table 6.27 presents a comprehensive breakdown of key production metrics for the newly designed system. The table delineates three critical parameters: the quantity of completed parts, the number of parts necessitating rework, and the count of parts designated as scrap.

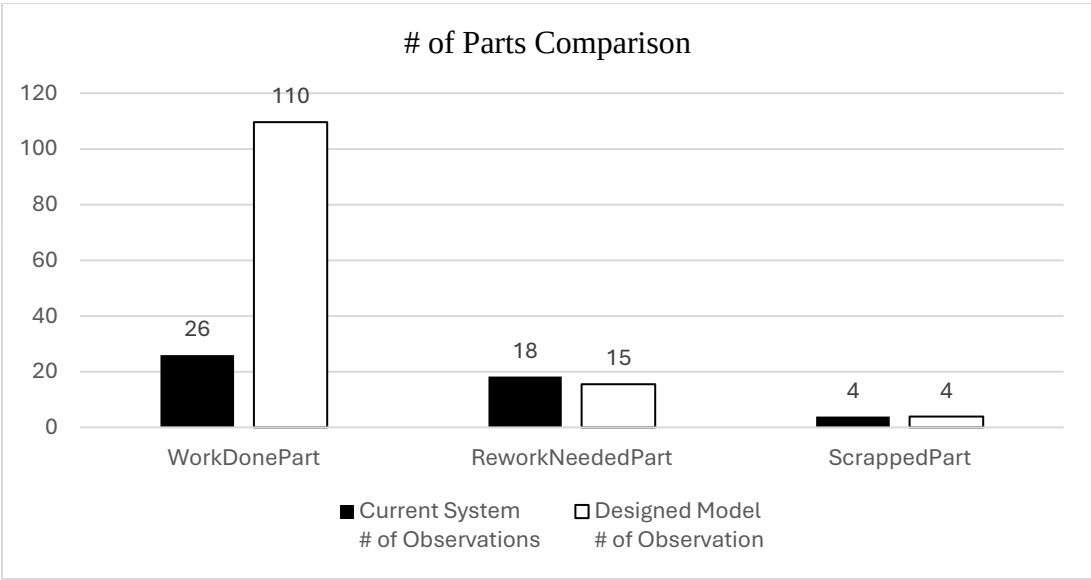


Figure 6.47 comparison of the completed part counts between the current system and Scenario 3

Figure 6.47 presents a comparative analysis of key performance indicators between the newly designed system and the existing system, focusing on completed parts, rework requirements, and scrap rates. The data reveal significant improvements in system efficiency and quality metrics. System efficiency increased substantially from 54% to 85%, indicating enhanced overall productivity. Concurrently, the proportion of parts requiring rework decreased markedly from 37.5% to 11%, suggesting improved first-pass yield and process stability. Additionally, the scrap rate diminished from 8% to 3%, signifying reduced material waste and enhanced quality control. These quantitative improvements collectively underscore the efficacy of the new system design in optimizing production processes, enhancing quality outcomes, and minimizing resource wastage.

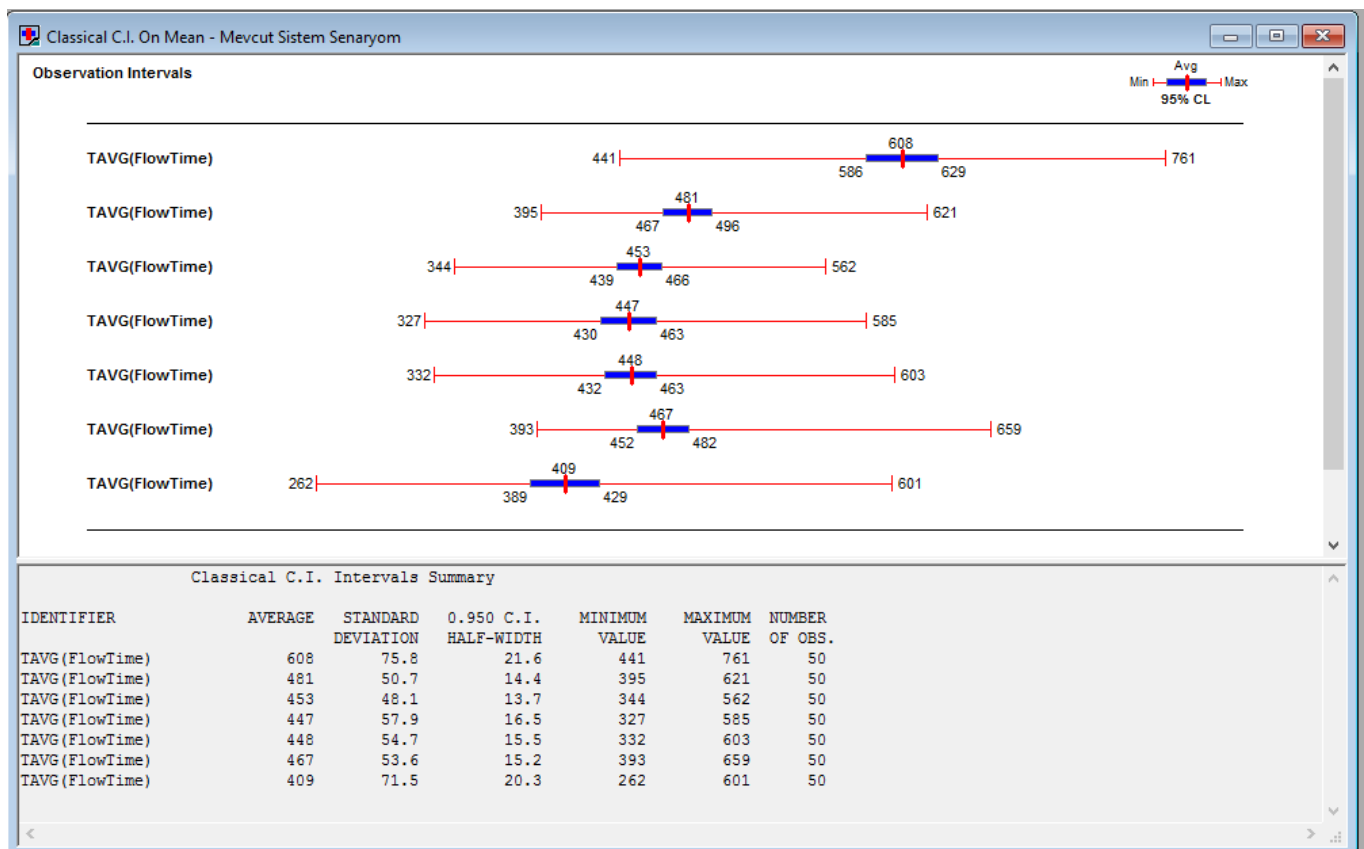


Figure 6.48 Paired -T comparison of current system, alternative and redesigned system

Figure 6.48 displays the tally values for the current scenario, alternative scenarios, and the newly designed system. Upon examination of this analysis, one might consider the newly designed system with the shortest flow time to be the optimal system. However, it is crucial to also examine the standard deviations at this juncture. In project-based firms, where each project is unique, high standard deviations are anticipated due to the inherent variability of projects. Therefore, in this context, the high standard deviation does not significantly impact the selection criteria.

Table 6.28 Comparison of Scenarios Using Statistical Parameters (Inc. Newly Designed Scenario)

Scenarios	Current System		Scenario 1 (Configuration of Machine 1 & Machine 2)		Scenario 2 (Increasing number of trucks)		Scenario 3 (Quality Engineer Hiring)		Scenario 4 (Purchasing Specialist Hiring)		Scenario 5 (Supervisor Hiring)		Scenario 6 (Newly Design System)	
Utilization Rate	Average NR	Average NQ	NR Current Vs. SC1	NQ Current Vs. SC1	NR Current Vs. SC2	NQ Current Vs. SC2	NR Current Vs. SC3	NQ Current Vs. SC3	NR Current Vs. SC4	NQ Current Vs. SC4	NR Current Vs. SC5	NQ Current Vs. SC5	NR Current Vs. SC5	NQ Current Vs. SC5
Machine1	25%	0%	67%	100%	61%	100%	-9%	100%	7%	100%	4%	100%	171%	100%
Machine2	69%	62%	4%	-23%	-73%	-16%	-80%	-3%	-73%	-6%	-68%	-18%	65%	-18%
Supervisor	72%	3940%	-3%	4%	368%	-22%	347%	-18%	411%	-10%	437%	-8%	16%	-8%
Technician1	26%	2%	53%	0%	61%	-3%	-4%	23%	7%	7%	-2%	0%	235%	0%
Technician2	22%	0%	47%	0%	0%	-31%	0%	-7%	32%	-13%	16%	-7%	97%	-7%
Technician3	87%	689%	-80%	0%	0%	34%	-10%	-13%	10%	-21%	11%	-8%	175%	-8%
Technician4	85%	622%	0%	0%	46%	-5%	8%	-32%	58%	-4%	44%	-13%	8%	-13%
Purchaser	82%	39%	9%	0%	-76%	-16%	-83%	2%	-61%	-55%	-77%	485%	104%	485%
Truck	92%	145%	0%	0%	573%	-50%	391%	-7%	514%	-32%	418%	-2%	-100%	-100%
Quality Engineer				100%		100%	100%	100%	100%	100%	100%	100%		

Table 6.28 presents a comprehensive comparative analysis of six alternative scenarios relative to the current scenario. This consolidated analytical approach offers significant value by providing a holistic view of the system's performance across multiple scenarios. The juxtaposition of these key performance indicators facilitates a nuanced understanding of resource utilization and queue dynamics. Such a comprehensive presentation of statistical analyses in a single, comparative format enhances the ability to discern patterns, identify bottlenecks, and evaluate the efficacy of proposed interventions across different operational configurations.

The utility of this analysis lies in its capacity to enable direct comparisons between scenarios, thereby illuminating the relative impacts of various operational adjustments on both individual resource performance and overall system efficiency. This method of data presentation is particularly conducive to informed decision-making, as it allows stakeholders to readily assess the trade-offs and potential benefits associated with each proposed scenario.

6.5 Economic Comparison of Optimized Scenarios and Redesigned system

The primary aim of this study is to identify bottlenecks within the company to enhance operational processes and thereby minimize project delays. Bottlenecks, often characterized by constraints in resources or processes, can significantly hinder productivity and efficiency. By systematically identifying and addressing these constraints, organizations can streamline operations, reduce lead times, and improve overall project outcomes.

In this section, it has been examined the relationship between the improvements implemented and the gains achieved relative to the investment costs. This involves a detailed analysis of cost-benefit relationships, where the effectiveness of each improvement is measured against its financial outlay. Understanding this relationship is crucial for determining the viability and sustainability of the enhancements.

A feasibility analysis was conducted for each scenario by calculating the payback period, which determines how quickly the investments would amortize. The payback period is a critical metric in financial analysis, providing insights into the time required for an investment to generate returns equivalent to its initial cost. This analysis offers a comprehensive understanding of the cost-effectiveness and potential return on investment for the proposed enhancements, enabling informed decision-making. Analyzing costs in a country like Turkey, where inflation is significantly high, presents certain challenges. High inflation can distort cost projections and affect the accuracy of financial forecasts. Therefore, it is essential to incorporate inflation-adjusted metrics to ensure realistic assessments. The costs and delays associated with projects were calculated based on the period under consideration, and other cost components were assessed accordingly. This approach ensures that the financial analysis remains relevant and accurate despite economic fluctuations.

Table 6.29 ROI Calculation for Scenarios

	Cost (\$)	Performance Increase	Saving (\$)	Annual Saving (\$)	Return on Investment (year)
Scenario 1	0	29%	1.682	403.680	-
Scenario 2	600.000	46%	2.668	640.320	0,94
Scenario 3	1.800.000	63%	3.654	876.960	2,05
Scenario 4	1.530.000	58%	3.364	807.360	1,90
Scenario 5	1.350.000	44%	2.552	612.480	2,20
Scenario 6	3.500.000	73%	4.234	1.016.160	3,44

Table 6.29 provides information on the return on investment for each scenario, offering valuable insights into the financial viability of the improvements. By presenting ROI data, stakeholders can evaluate the potential benefits of each scenario, facilitating strategic planning and resource allocation. This comprehensive analysis not only highlights the financial implications but also underscores the strategic importance of targeted improvements in enhancing operational efficiency.

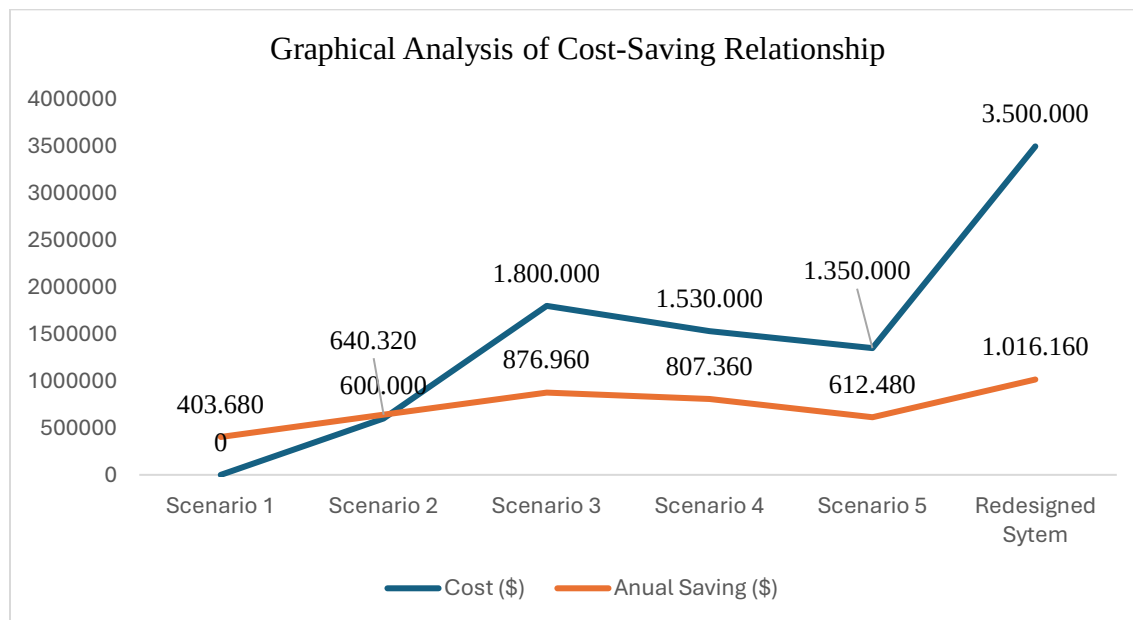


Figure 6.49 Graphical analysis of cost-saving relationship

Figure 6.49 presents a graphical representation of the financial savings achieved in relation to the costs incurred for each scenario. This visual depiction elucidates the cost-benefit relationship, providing a comparative analysis of the economic efficiency across the various proposed interventions.

Scenario 1: No cost, 29% performance increase, \$403,680 annual saving. ROI not applicable.

Scenario 2: \$600,000 cost, 46% performance increase, \$640,320 annual saving. **Quickest ROI at 0.94 years**, highly cost-effective.

Scenario 3: \$1,800,000 cost, 63% performance increase, \$876,960 annual saving. ROI of 2.05 years, substantial gains.

Scenario 4: \$1,530,000 cost, 58% performance increase, \$807,360 annual saving. ROI of 1.90 years, balanced approach.

Scenario 5: \$1,350,000 cost, 44% performance increase, \$612,480 annual saving. ROI of 2.20 years, longer payback.

Scenario 6: \$3,500,000 cost, 73% performance increase, \$1,016,160 annual saving. **Highest performance increase** but longest ROI at 3.44 years.

The scenario analysis presents a spectrum of investment options with varying levels of cost, performance enhancement, and return on investment (ROI). Scenario 1 offers a unique proposition with no implementation cost and a 29% performance increase, resulting in \$403,680 annual savings, though ROI is not applicable due to the absence of initial investment. Scenario 2 demonstrates high cost-effectiveness with a \$600,000 investment yielding a 46% performance increase and \$640,320 annual savings, boasting the quickest ROI at 0.94 years. Scenarios 3 and 4 represent substantial investments of \$1,800,000 and \$1,530,000 respectively, with corresponding performance increases of 63% and 58%, and annual savings of \$876,960 and \$807,360. Their ROIs of 2.05 and 1.90 years respectively suggest a balanced approach between investment and returns. Scenario 5, with a \$1,350,000 investment, offers a moderate 44% performance increase and \$612,480 annual savings, but has a longer ROI of 2.20 years. Finally, Scenario 6 presents the most

ambitious option, requiring a \$3,500,000 investment for the highest performance increase of 73% and annual savings of \$1,016,160, albeit with the longest ROI period of 3.44 years.

This comprehensive analysis provides decision-makers with a nuanced understanding of the trade-offs between initial investment, performance enhancement, and time to recoup costs, facilitating strategic decision-making aligned with organizational priorities and risk tolerance. Scenario 2 is the most attractive for immediate gains due to its quick ROI. Scenario 6 offers the highest performance increase but requires significant investment and has a longer payback period. Decision-makers should consider the trade-offs between cost, performance, and ROI.



CHAPTER SEVEN

CONCLUSIONS

This thesis presents a comprehensive analysis of operational process improvement and project delay minimization in a manufacturing company. The research, grounded in advanced simulation modeling techniques and cost-benefit analysis, has successfully addressed the three primary objectives established at the outset of the thesis. The findings demonstrate significant advancements in the company's pursuit of operational excellence and contribute valuable insights to both academic literature and industrial practice.

Related to Objective 1: Reduction of project delays in order to minimize the economic impact of penalties on project profitability, the first objective of thesis focused on reducing project delays and minimizing their economic impact. Through systematic analysis, the research identified root causes of delays and proposed strategic interventions. The study developed six scenarios, each offering unique combinations of investment, performance improvement, and financial returns:

Scenario 1: This scenario stands out for its exceptional value proposition. With no investment cost, it achieves a 29% performance improvement and \$403,680 in annual savings. This finding is particularly significant as it offers an immediately implementable solution with substantial benefits. It likely involves process optimizations or policy changes that don't require capital expenditure, making it an ideal starting point for improvement initiatives.

Scenario 2: Requiring a modest \$600,000 investment, this scenario yields a 46% performance increase and \$640,320 in annual savings. With the quickest ROI at 0.94 years, it provides a compelling short-term strategy for delay reduction. This option is highly attractive for companies seeking significant improvements with limited capital outlay and rapid returns.

Scenario 3: This more ambitious scenario involves a \$1,800,000 investment, resulting in a 63% performance increase and \$876,960 annual savings. With an ROI of 2.05 years, it offers substantial gains for companies willing to make a larger initial investment. This option is suitable for organizations with a slightly longer-term perspective on returns and the capacity for more significant capital expenditure.

Scenario 4: Presenting a balanced approach, this scenario requires a \$1,530,000 investment, delivering a 58% performance increase and \$807,360 annual savings. Its ROI of 1.90 years makes it an attractive middle-ground option, offering substantial improvements without the highest levels of investment or risk.

Scenario 5: With a \$1,350,000 investment, this scenario achieves a 44% performance increase and \$612,480 annual savings. However, its longer ROI of 2.20 years may make it less attractive compared to other options unless there are additional non-financial benefits not captured in these metrics.

Scenario 6: The most ambitious option, this scenario requires a significant \$3,500,000 investment but promises the highest performance increase of 73% and annual savings of \$1,016,160. Despite offering the greatest long-term benefits, its 3.44-year ROI is the longest among all scenarios. This option would be suitable for companies with substantial capital, looking for transformative changes and willing to wait longer for returns.

These results not only validate the achievement of the first objective but also offer practical, data-driven solutions for project management in manufacturing environments. The aim of thesis to delay minimization contributes to the broader field of project management, offering insights into how companies can mitigate the financial risks associated with project delays through strategic operational improvements.

The range of scenarios presented provides decision-makers with a comprehensive toolkit for operational improvement, catering to different risk appetites, investment capabilities, and desired outcomes. Scenarios 1 and 2 stand out for their immediate or quick returns, making them particularly attractive for initial implementation. Scenarios 3 and 6, while requiring larger investments, offer the most substantial long-term improvements for companies with the capacity to make significant capital expenditures.

The second objective aimed to identify and address inefficiencies and bottlenecks in supply and production processes. Utilizing advanced simulation modeling, the study conducted a detailed analysis of resource utilization and efficiency within the existing system. This analysis revealed critical insights, such as the identification of high wait times for resources including Machine 2, Supervisor, Technician 4, Purchasing Agent, and Trucks.

The development of the six distinct scenarios for efficiency optimization represents a significant contribution to the field of operations management. Each scenario offers a different approach to addressing the identified inefficiencies, with varying levels of investment and expected returns. This range of options allows companies to choose the most appropriate strategy based on their specific constraints and goals.

The third objective involved evaluating the feasibility of relocating the workshop to the factory. This aspect of the study demonstrates the integration of strategic decision-making with operational analysis. The comprehensive assessment of the relocation's impact on efficiency, coupled with a detailed ROI analysis, provides a model for how companies can approach significant structural changes in their operations.

The conclusion that the relocation project aligns with the company's strategic goals and promises long-term operational efficiency improvements illustrates the importance of linking operational decisions to broader organizational strategies. This finding contributes to the literature on strategic management and operational alignment in manufacturing contexts.

In terms of methodological contributions and broader implications, one of the most significant contributions of this study is its demonstration of a generalizable methodology for process improvement. The research shows that regardless of the sector or specific process, the steps outlined in this study can be followed to model and improve operational processes using advanced simulation techniques. This finding has broad implications for the field of operations management, offering a versatile approach that can be adapted to diverse industrial contexts.

The study also highlights the critical importance of process mapping and modeling in project-based firms, despite the inherent challenges. This insight is particularly valuable for project

management literature, emphasizing the link between detailed process understanding and overall system efficiency and profitability.

The integration of simulation modeling with cost-benefit analysis in a high-inflation economic environment represents a methodological advancement. This approach provides a more robust framework for decision-making under economic uncertainty, contributing to the literature on financial modeling in operations management.

In terms of practical implications and future research directions, the six scenarios presented in this study offer a range of strategic options for short, medium, and long-term planning. This variety of options, each with detailed performance and financial implications, provides decision-makers with a comprehensive toolkit for operational improvement. The study thus bridges the gap between academic research and practical application, offering immediately actionable insights for industry professionals.

Future research could extend this work in several directions:

- Cross-industry application: Testing the generalizability of the methodology across different industrial sectors to validate its broad applicability.
- Long-term impact assessment: Conducting longitudinal studies to evaluate the long-term effects of the implemented improvements on organizational performance and competitiveness.
- Integration with emerging technologies: Exploring how emerging technologies such as artificial intelligence and Internet of Things (IoT) can be incorporated into the simulation models to enhance predictive capabilities and decision support.
- Sustainability focus: Expanding the model to include environmental and social sustainability metrics, aligning operational improvements with broader sustainability goals.
- Human factors analysis: Incorporating a more detailed analysis of human factors and their impact on process efficiency and project delays.

In conclusion, this thesis not only achieves its stated objectives but also makes significant contributions to the fields of operations management, project management, and decision

science. By providing a robust methodology for process improvement and demonstrating its application in a real-world manufacturing context, the study offers valuable insights for both academic researchers and industry practitioners. The range of scenarios presented, from no-cost improvements to significant capital investments, provides a comprehensive framework for decision-making in operational excellence initiatives. The findings underscore the importance of data-driven decision-making in operational excellence and provide a foundation for future research in process optimization and strategic operational management.

7.1. Implications and Ramifications of Application

The findings of this thesis, particularly concerning the objective of relocating the workshop to the automation factory, were presented to the company's senior management team, leading to significant real-world applications. This presentation marked a crucial juncture where academic research directly influenced corporate decision-making, bridging the often-perceived gap between theoretical studies and practical business operations. Based on comprehensive analysis, which included detailed simulations, financial projections, and operational assessments, the company decided to implement the workshop relocation project in 2023. This decision was not taken lightly and involved multiple stakeholders, including operations managers, financial analysts, and strategic planners. The decision was predicated on two key factors:

The study's projection of meeting expected performance improvements: The simulation models and data analysis indicated substantial enhancements in operational efficiency, production capacity, and overall system performance.

The investment's attractive Return on Investment of 3.44 years for a \$3,500,000 expenditure: This financial metric was particularly compelling, as it promised a relatively quick recovery of the substantial capital outlay. This favorable ROI indicated that the investment would be amortized rapidly, typically faster than many large-scale industrial projects. Furthermore, the analysis projected that the relocation would subsequently contribute a direct 73% increase to the company's profitability in the following years. This significant boost to profitability was a major factor in convincing the management to proceed with the project. The implementation of this investment

decision yielded numerous tangible and intangible benefits, transforming various aspects of the company's operations:

- **Elimination of material transportation costs:** The physical integration of the workshop and automation factory removed the need for inter-facility transportation, resulting in substantial savings in vehicle expenses, fuel costs, and associated maintenance.
- **Human resource optimization:** The consolidation of operations led to more efficient utilization of human resources, reducing overtime, improving scheduling, and enhancing overall labor productivity.
- **Time efficiency:** The elimination of transportation between facilities significantly reduced lead times, improving overall production cycle times and enhancing the company's responsiveness to market demands.
- **Direct integration of production components:** This streamlined the production process, eradicating losses stemming from transportation delays, handling damages, and material tracking inefficiencies.
- **Improved quality control:** The closer proximity of all production stages allowed for more immediate and effective quality checks, reducing defects and rework.
- **Enhanced communication:** The physical consolidation fostered better communication between different departments, leading to improved problem-solving and innovation.

Data collected in 2024, a year after the implementation, demonstrated a 65% improvement in the factory's system efficiency. This substantial increase encompassed various metrics, including production output, energy efficiency, and resource utilization. While this figure does not precisely align with the initial projections, which may have been more optimistic, it nevertheless evidences a significant correlation between the simulation model's predictions and actual outcomes. This alignment validates the robustness of the simulation methodology employed in the study.

The successful implementation of this project has provided several insights into organizational decision-making processes:

- **Validation of Simulation-Based Planning:** The close correlation between projected and actual efficiency improvements underscores the value of system simulation in strategic planning. It demonstrates that well-constructed simulation models can provide reliable forecasts for complex industrial processes.
- **Risk Mitigation in Capital Investments:** The accuracy of ROI and performance projections demonstrates the efficacy of simulation-based analysis in mitigating investment risks. By providing a more accurate picture of potential outcomes, such analyses can help companies make more informed decisions about large capital expenditures.
- **Strategic Alignment:** The decision to proceed with the relocation project highlights the importance of aligning operational improvements with long-term strategic objectives. It shows how tactical decisions, when properly aligned with overall strategy, can drive significant organizational growth and efficiency.
- **Change Management:** The successful implementation underscores the importance of effective change management in large-scale organizational transformations. It likely involved careful planning, stakeholder engagement, and ongoing communication to ensure smooth execution.
- **Interdepartmental Collaboration:** The project's success likely required strong collaboration between various departments, including operations, finance, human resources, and IT, highlighting the importance of cross-functional teamwork in major organizational initiatives.

The successful application of this research has broader implications for industry practices:

Academic-Industry Partnership: This case study illustrates how academic research can enhance industry applications, providing a model for future collaborations between universities and corporations.

Data-Driven Decision Making: The project promotes the importance of data-driven decision-making in industrial settings, showing how empirical evidence and statistical analysis can guide major strategic decisions.

Holistic Approach to Efficiency: It emphasizes the importance of a holistic approach to efficiency assessment, considering not just individual processes but the entire system's performance.

Long-Term Strategic Planning: The case demonstrates the value of long-term strategic planning in manufacturing, showing how initial investments can lead to sustained competitive advantages.

Technology Integration: The success of the automation factory relocation underscores the growing importance of technology integration in modern manufacturing processes.

Although the implementation was largely successful, the minor discrepancy between projections and actual improvements highlights the complexity of real-world systems and the necessity for continuous monitoring and adjustment. This variance serves as a reminder that even the most sophisticated models have limitations, and that real-world implementation often involves unforeseen challenges and variables.

In conclusion, the real-world implementation of the thesis recommendations has not only validated the research findings but also demonstrated the value of integrating academic research with industry practice. This case study serves as a testament to the power of advanced analytical techniques in guiding strategic investments and operational improvements. It highlights the potential for significant organizational transformation when theoretical knowledge is effectively translated into practical application. Moreover, it underscores the ongoing need for rigorous analysis, adaptability, and continuous improvement in the face of evolving industrial landscapes and technological advancements.

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