DEVELOPMENT OF A MULTI-SCENARIO SIMULATION MODEL FOR SPARE PARTS INVENTORY OPTIMIZATION IN MINING OPERATIONS

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ABSTRACT

DEVELOPMENT OF A MULTI-SCENARIO SIMULATION MODEL FOR SPARE PARTS INVENTORY OPTIMIZATION IN MINING OPERATIONS

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The growing market competition compels many industries to change their operational structures at strategic and operational levels dramatically. It has been recognized that inventory management requires continuous monitoring and improvement and it is vital for businesses to ensure smooth operations by avoiding production loss and reducing the overall cost of inventory. For various production companies operating in different industries, inventory is considered as one of the most expensive assets. Among different inventory types, the spare parts inventory is of great importance for production management in ensuring high equipment availability at a minimized operating cost.

In the mining industry, mass and continuous production should be sustained with an incontrovertible contribution of high-capacity equipment. Due to the high operational loads, complexity, and cost of the mining machines, unplanned downtimes resulting from spare parts' unavailability may cause a great financial loss. Among different types and classifications of spare parts available in a mining spare parts warehouse, tires are significant for operations where wheel machineries are used. In open-pit operations where trucks with varying capacities are extensively employed for material hauling operations, tires can account for up to 20% of the total operating costs. In addition, any tire shortage in a warehouse may lead to tremendous production loss. In this regard, the current study intends to develop a discrete-event simulation algorithm for optimizing spare parts inventory problems in various inventory systems, giving the cost-wise best output among all the scenarios by utilizing Arena® Software. Within the scope of generating these scenarios, different parameter combinations of four inventory policies, namely (s, Q), (s, S), (R, Q), and (R, S), are utilized.

The proposed algorithm is implemented for the tires of a truck fleet, which covers seven identical trucks with six tires each and operates in a surface coal mine in Turkey. In this study, four well-known inventory policies are utilized to evaluate both continuous and periodic inventory review approaches. For the continuous reviewing approach, (s, Q) and (s, S) policies are identified, while (R, Q) and (R, S) policies are discussed for the periodic reviewing approach. On this basis, a total of 637 scenarios are generated from the inventory policies built based on different reviewing and triggering mechanisms, and each scenario is simulated for five years. The results show that the most optimal scenario for continuous review inventory policy is observed to be (s=9, S=49), where spare parts are ordered up to an inventory level of 49 whenever the number of components in the inventory drops to 9. Similarly, the most optimal scenario for periodic review policy is observed to be (R=6480, Q=45), where the fixed batch size of 45 is ordered every 6,480h. Accordingly, the annual system cost is observed as $2,604,032 and $2,608,617 for the best-case scenarios of continuous and periodic review policies, respectively. Besides, it was observed from both policies that the model is capable of ensuring the balance between the cost items by allowing stock-out to a certain extent in the best-case scenarios.

Keywords: Inventory Management, Spare Parts Inventory, Mining Trucks, Tire Inventory, Discrete-Event Simulation

ÖZ

MADEN İŞLETMELERİNDE YEDEK PARÇA ENVANTER OPTİMİZASYONU İÇİN ÇOKLU SENARYOYA SAHİP BİR BENZETİM MODELİ GELİŞTİRİLMESİ

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Artan pazar rekabeti, birçok endüstri için operasyon yapısını stratejik ve operasyonel seviyelerde önemli ölçüde değiştirmeye zorlamaktadır. Operasyonların sorunsuz bir şekilde yürütülmesini sağlamak için, fırsat kaybını önleyip toplam envanter maliyetini azaltarak, verimli bir envanter yönetimi elde etmenin hayati önem taşıdığı kabul edilmektedir. Envanter, çeşitli sektörlerde faaliyet gösteren birçok şirket için en maliyetli varlıklardan biri olarak düşünülmektedir. Farklı envanter türleri arasında yedek parça envanteri, minimum işletme maliyeti ile yüksek ekipman kullanılabilirliğini sağlama hedefine ulaşmada büyük önem taşımaktadır.

Madencilik sektöründe, karşılanması gereken seri ve sürekli üretim gereksinimi, yüksek kapasiteli makinelerin yadsınamaz katkısıyla sağlanmaktadır. Maden makinelerinin büyük operasyonel yükleri ve pahalılığı nedeniyle, yedek parça bulunamamasından kaynaklanan plansız duruşlar büyük maddi kayıplara neden olabilmektedir. Bir madenin yedek parça deposunda bulunabilecek farklı yedek parça türleri arasından lastikler, tekerlekli makinelerin kullanıldığı operasyonlar için büyük önem bir önem arz etmektedir. Hafriyat ve nakliye operasyonları için çeşitli kapasitelere sahip kamyonların yoğun olarak kullanıldığı açık ocak işletmelerinde,

lastikler, toplam işletme maliyetlerinin %20'si kadarını oluşturabilmektedir. Ayrıca, ihtiyaç olduğu anda depoda yeterli sayıda lastik bulunmaması da kayda değer bir üretim kaybına, dolayısıyla ek maliyetlere yol açabilmektedir. Bu bağlamda, mevcut çalışma Arena® yazılımı kullanarak, bir yedek parça envanter optimizasyonu problemi için çok senaryolu bir ayrık olay simülasyon algoritması geliştirmeyi amaçlamaktadır. Bu senaryoların oluşturulması kapsamında, (s, Q), (s, S), (R, Q) ve (R, S) olmak üzere dört farklı envanter politikası ve bu politikaların farklı parametre değerleri kullanılmaktadır.

Geliştirilen algoritma, Türkiye'de bir açık ocak kömür madeninde faaliyet gösteren, her biri altı lastiğe sahip yedi kamyondan oluşan bir kamyon filosunun lastik envanteri için uygulanmıştır. Bu çalışmada, hem sürekli hem de periyodik gözden geçirme yaklaşımlarını kapsayacak şekilde, iyi bilinen dört envanter politikası kullanılmıştır. Buna göre, sürekli gözden geçirme politikası kapsamında (s, Q) ve (s, S) politikaları, periyodik gözden geçirme politikası kapsamında (R, Q) ve (R, S) politikaları belirlenmiştir. Farklı çalışma dinamiklerine sahip dört envanter politikasından, toplam 637 senaryo oluşturulmuş ve her bir senaryo beş yıllık bir süre için simüle edilmiştir. Elde edilen sonuçlara göre, sürekli gözden geçirme envanter politikası için, envanter seviyesi 9'a düştüğünde, bu seviyeyi 49'a çıkaracak kadar yedek parçanın sipariş edildiği, (s=9, S=49) senaryosunun en iyi senaryo olduğu gözlemlenmiştir. Benzer şekilde, periyodik gözden geçirme politikası için, her 6,480 saatte bir 45 adet yedek parçanın sipariş edildiği, (R=6,480, Q=45) senaryosunun en iyi senaryo olduğu gözlemlenmiştir. Buna göre, sürekli ve periyodik gözden geçirme politikalarının en iyi durum senaryoları için yıllık sistem maliyeti sırasıyla 2,604,032$ ve 2,608,617$ olarak elde edilmiştir. Bunlara ek olarak, her iki senaryoda da, maliyet kalemleri arasındaki dengenin, sistemin envanter yetersizliğinden kaynaklanan duruşlara belirli bir ölçüde izin vermesiyle sağlandığı gözlemlenmiştir.

Anahtar Kelimeler: Envanter Yönetimi, Yedek Parça Envanteri, Maden Kamyonları, Lastik Envanteri, Ayrık Olay Simülasyonu

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CHAPTER 1

INTRODUCTION

1.1 Background

Globalization and the increasing competition lead various industries to change their strategical and operational policies. The competitive elements of adapting to the dynamic industrial environment, improving responsiveness to the consumer market, and maintaining the market share can be mitigated with powerful technical strategies (Guo *et al.*, 2019). Operations management has long recognized that efficient inventory management has great importance on businesses for ensuring the smooth running of operations, avoiding opportunity loss on sales, and reducing the overall cost of inventory. For many companies, the inventory which may represent as much as 50% of the total invested capital, is considered as one of the most expensive assets (Heizer *et al.*, 2017).

Inventory is the number of items kept in the stock by a business organization to meet the customer demand and/or satisfy the spare part requirements of the machinery-based operations. Several functions can be served by the inventory that provides flexibility to the organization activities. Inventory management covers the optimization of inventory ordering and holding decisions considering customer satisfaction, supplier capability, and production schedules, such that the total inventory-related costs will be minimized. Customer demand is the starting point of the inventory management, which can be internal for a spare part and/or not completed product, or external for a finished product. In either case, achieving proactive, accurate, and efficient inventory management is crucial. There is a trade-off between the service level and the investment in the inventory that should be optimized in such problems. There are four common types of inventories that organizations maintain to serve the functions of inventory (Heizer *et al.*, 2017).

Three of them, which concern raw material, work-in-process, and finished goods are generally related to the organizations supplying products to customers. On the other hand, operating supply/maintenance inventory type is generally associated with the organizations demanding necessary parts to keep machinery and processes in an operable state. In this sense, the inventory problem can be handled in two separable perspectives, depending on whether the organization is a supplier or a demander. There is a third category fitting into both perspectives and is called a multi-echelon system.

For the organizations, whose aim is to ensure mass and continuous production by achieving a high equipment availability with a lower cost, the management of operating supply/maintenance inventory, also called spare parts inventory, becomes a major challenge. Spare parts are indicated as common inventory stock items, essential for maintaining the equipment (Hu *et al.*, 2018). Spare parts management is inclusive of various research areas, which can be specified as, inventory control, supply chain management, and demand forecasting (Rosienkiewicz *et al.*, 2017). Although various models have been developed for the spare parts inventory management problem regarding the different inventory policies built based on different review and triggering mechanisms, ensuring the continuous improvement of these models has always been a necessity.

In this sense, the current study intends to develop a simulation algorithm to optimize the spare parts inventory problem, which can be experienced in different inventory systems ensuring the mass and continuous production by high equipment availability in an operating environment with high uncertainty. The developed algorithm is also implemented for the tire spare parts of a truck fleet in a coal mine by using different inventory policies, and investigating their effects on equipment availability and total inventory related costs.

1.2 Problem Statement

With the growing competition on market share, inventory management representing as much as 50% of the total invested capital has become of great importance, especially for companies playing a crucial role in the national economy and carrying on a business with sophisticated technologies (Balakrishnan *et al.*, 2013). For many industries, the uncertainty at the operational level is quite high, and the machine-intensive operating systems are required to ensure the intended production rate and high equipment availability at a minimized operating cost. Indeed, for such systems, operations may be performed in very challenging working environments holding high stochasticity to forecast the failure profiles of machinery components and the resultant spare part requirements. On this basis, large operational loads and operational complexity may lead to unplanned downtimes with tremendous production loss. One of the main reasons for unplanned downtimes is the unavailability of spare parts when required in maintenance activities (Qarahasanlou *et al.*, 2017). On the other hand, overstocking may cause inadequate storage space and deterioration of parts as well as high capital expenditures which is vital for the companies using sophisticated technologies in large-scale operations. Therefore, developing new technological and managerial methods is crucial to control the spare parts inventories efficiently.

Among various spare parts available in mining warehouses, tires have an essential effect, especially on loading, hauling, and auxiliary activities where wheel machineries are operated extensively. A tire may experience different failure modes throughout its lifetime and its ownership cost may variate depending on its active operating time and purchase price. Along with fuel cost and operator salaries, tires have a great share in expenditures and can account for 20% of the total operating cost in the mining industry (Meech and Parreira, 2013). Having an efficient tire spare parts inventory management can result in observable savings, considering that tires used in mining may cost up to $45,000 (Carter, 2007). In addition, since tires are structured with a series configuration in machinery, any downtime due to both maintenance and tire stock-out conditions may cause financial consequences generally higher than the physical cost. In this sense, implementing a multi-scenario simulation model for the optimization of the tire spare parts inventory problem has the potential to reduce the operating cost flow by minimizing the unexpected halts of machinery-based operations, and developing a trade-off between physical and non-physical cost items.

1.3 Objectives and Scopes of the Study

The main objective of this study is to develop a multi-scenario simulation model for the optimization of spare parts inventory problems that can exist in various inventory systems considering different inventory policies. Sub-objectives of this research study can be summarized as i) identifying inventory management system characteristics, ii) developing mutual mathematical interactions among inventory and maintenance dynamics, iii) pre-processing of the data and assessing parameters, iv) executing the simulation model in a discrete-event simulation (DES) environment, v) analyzing effects of the inventory policies on the equipment availability and total system cost, and vi) determining the cost-wise best output among all the scenarios.

Within the research scope, the multi-scenario structure of the system is considered to be built as a function of different inventory policies, which are (s, Q), (s, S), (R, Q), and (R, S) policies, and the policy parameters holding different decision dynamics. In addition, random lifetime, random repair time, and the random lead time of the spare parts construct the stochastic structure of the simulation model. For the implementation of the algorithm, the tire spare parts of a truck fleet operating in a surface coal mine is taken as the target component. At this point, five-year dataset of seven 177 tonne trucks between 2015 and 2019 is processed and introduced to the algorithm.

1.4 Research Methodology

This research study utilizes a stochastic structure to analyze a multi-scenario inventory management system behavior. The research methodology carried out in this study is illustrated in Figure 1.1.

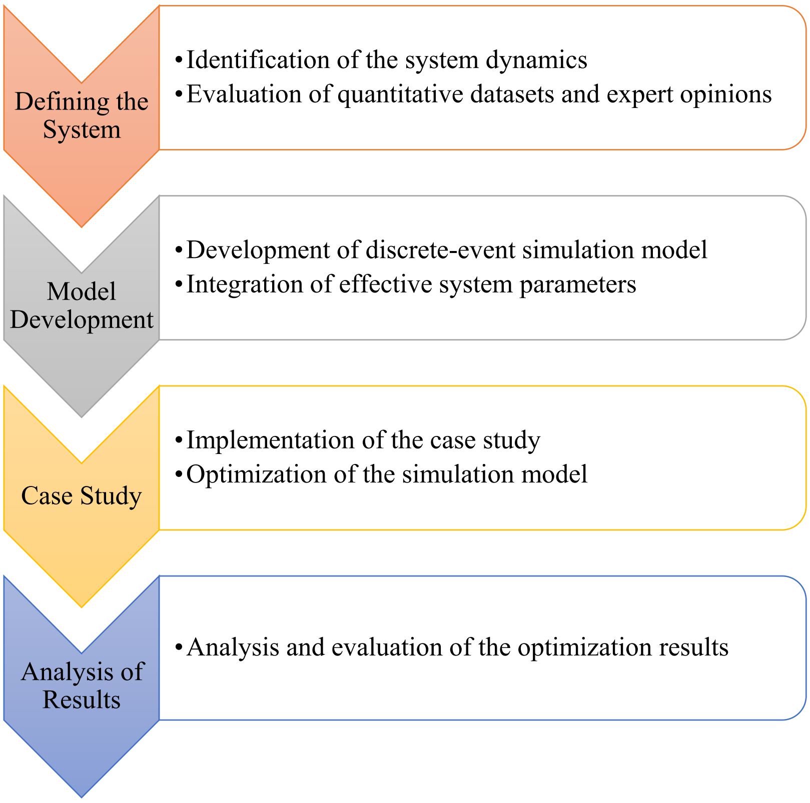


Figure 1.1 Research Methodology of the Thesis Study

The main research methodology steps are given as follows:

i. Identification of system's structure, functional dependencies and boundaries with decomposing the system into its components, depending on the evaluation of quantitative failure, repair datasets and expert opinions.

ii. Development of a simulation algorithm in discrete-event simulation environment by introducing the system configuration, failure-specific maintenance actions, and indicated inventory policies.

iii. Implementation of the case study and optimization of the introduced inventory policies and their parameters with monitoring and reporting the random operating hours, repair times, and production loss times as well as total inventory related system cost.

iv. The output analysis of the system under different scenarios which consist of different inventory policies having varying parameters, and evaluating the sensitivity of the total inventory related system cost to changing system decisions.

1.5 Significance and Expected Contributions of the Thesis Study

Despite that various studies have been performed about inventory management, multi-scenario simulation modeling of spare parts inventory management has not been studied in detail. Moreover, the implementation of spare parts inventory management in mining is highly limited. Indeed, the related studies in mining industry covering the tire management concept mostly focus on analyzing the factors affecting tire management and improving the tire lifetime. In this regard, although it may have a remarkable effect on unplanned production halts, the tire spare parts inventory problem has not been attracted enough attention in the previous studies. In this sense, the current study intends to develop a simulation model for optimizing spare parts inventory problems in various inventory systems, considering different inventory policies with random component lifetimes, repair times, and lead times. It also covers the implementation of the developed model for a tire spare parts inventory management system. Hence, this study enables a detailed evaluation to reveal the effects of different inventory policies on the total inventory related costs and the equipment availability.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This section explains the terms related to inventory management, and the classification and working principles of the inventory policies to constitute a broad base of knowledge on the topic. In addition, it reviews the previous spare parts inventory studies applied in the mining industry. Lastly, tire management and event simulation concepts are extensively discussed.

2.2 Inventory Management Concept and Classification

As mentioned in Section 1.1, the inventory problem can be handled in two main perspectives, according to the system dynamics associated with the inventory type managed by the organizations, indicating whether the organization is a supplier or a demander. Also, there is a concept called a multi-echelon system that covers both supplier and demander perspectives.

Inventory problems in the perspective of a supplier are generally referred to as lot-sizing problems, which can be described as production planning problems having a structure with setups between production lots. Generating few setups by producing large quantities to satisfy the demand leads to high inventory holding costs. On the other hand, generating setups too often with producing fewer quantities leads up to the risk of unfulfilled demands, so the costs of stock-out as well as high setup costs. This situation creates a trade-off between inventory holding cost arisen to satisfy the demand and the costs that are incurred as a result of running out of stock. For a supplier, stock-out costs can be expressed as either a lost sale reflecting the risk of losing the competition in the market, or a back-order causing additional costs.

Therefore, the objective is to achieve effective utilization of resources, enhancing consumer satisfaction by minimizing all related expenses. In addition, multi-echelon inventory systems are evaluated in terms of the effective coordination between the procurement planning, which decides when and how much raw material is to be procured from the suppliers, and the production planning, which decides when and how much end product is to be produced to send to the customers. This coordination is achieved by multi-echelon supply chain management. As it is shown in Figure 2.1, multi-echelon inventory systems have multiple stages, such as raw materials supplier, distributor, manufacturer, retailer, end product supplier, and final customer, in which each stage has one or more members. The objective is to enhance the performance of the entire chain through the joint optimization of procurement and production planning in such a way that the related costs are minimized.

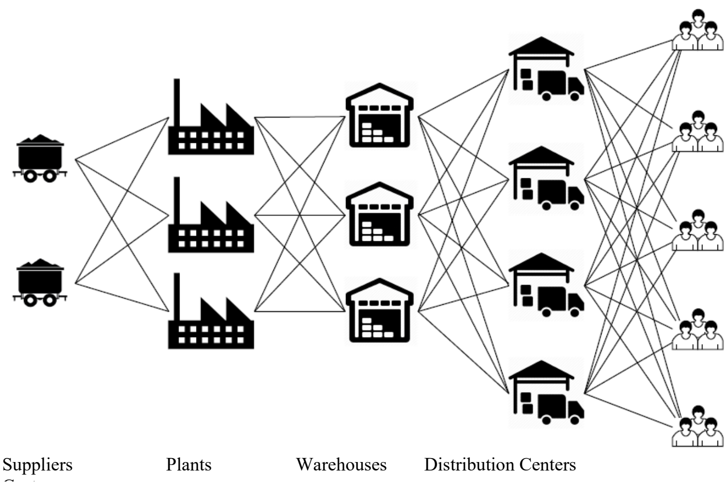


Figure 2.1. Multi-echelon Supply Chain Network

Inventory problems in the perspective of a demander are generally referred to as spare parts inventory management problems. In practice, spare parts inventory management is strongly interconnected with maintenance management. While the need for corrective or preventive maintenance generates the demands of the spare parts, maintenance activities are carried out relying on the availability of the spare parts. Thus, the spare parts inventory problems have usually been studied as the joint system of inventory and maintenance management in the related literature. Dynamics of the spare parts inventory management differ from other manufacturing inventory managements, which are work-in-process and finished products. Firstly, system functions and purposes are different. Work-in-process inventories are designed for smoothing out all forms of irregularities in a production flow, and finished product inventories are designed for protecting the system from all types of abnormalities in delivery flow. On the other hand, spare parts inventories are not intermediate products to be processed or final products to be delivered to a customer. They ensure that machine components are available in warehouses in case of any maintenance requirement. Secondly, management strategies are different for inventory policy applications. Work-in-process and finished product inventory levels can be changed depending on the operational decisions such as production rates, schedules, product quality, and service level. However, the inventory levels of spare parts are determined as a function of the maintenance activity applied and the deterioration mechanism of the operating system (Kennedy *et al.*, 2002). Finally, most of the spares required for maintenance works are slow-moving parts that need high investment. Thus, unlike fast-moving manufacturing inventories, spare parts are generally characterized by intermittent or lumpy demand.

Spare parts management is crucial in terms of preventing significant economic losses by ensuring continuous production with high efficiency. At this point, placing few orders with large quantities to satisfy the demand leads to an over-storage problem, which may cause inadequate storage space, deterioration of parts, high inventory holding costs, and high capital investment flow. Managing capital flow is of vital importance, especially for companies carrying on a long-running business with sophisticated technologies. On the other hand, placing orders too often with fewer quantities leads to the risk of unfulfilled demands, so the costs of stock-out as well as high ordering costs. For a demander, stock-out costs can be expressed as production loss, damage in production scheduling, and the penalty costs, due to extended equipment downtime or equipment unavailability or plant shutdown. Indeed, although the decisions on operational risk appetite can be changeable depending on the unit value of production as well as severity and occurrence likelihood of stock-out condition, the unavailability of spare parts can cause vital consequences, particularly for the companies that need to satisfy mass and continuous production. As a consequence, this situation creates a trade-off between overstocking costs arisen to satisfy the demand and the costs incurred as a result of running out of stock. The detailed cause-effect diagram for overstocking and understocking spare parts from the perspective of a demander is shown in Figure 2.2. The main target of the spare parts inventory management problems is generally to optimize the inventory and the maintenance of the operating system, such that the joint cost of the system is minimized.

There are two approaches used to maintain the inventory levels in joint systems, which are continuous review policy and periodic review policy. In the continuous review policy, the inventory levels are continuously checked to determine whether a particular condition is met, which is required to order the spares. There are two well-known continuous inventory review policies: the (s, Q) and the (s, S) policy. In the (s, S) inventory policy, whenever the inventory level drops to the value of s, spare parts are ordered up to inventory level S. Despite that the inventory is triggered based on the same condition, in the (s, Q) policy, the order quantity of spares is equal to the fixed batch size of Q. In addition, these two policies work identically if Q is equal to (S-s) when there is a per-unit demand. In the periodic review policy, the inventory levels are checked at regular time intervals. If there is no additional condition to satisfy, spare parts are ordered at the beginning of each time interval. One of the commonly-used periodic review inventory policies is (R, s, S) policy. Inventory level is reviewed for every R period; spare parts are ordered up to inventory level S if the inventory level drops below s. When s is not specified, (R, s, S) policy becomes (R, S) policy where spare parts are ordered up to inventory level S in every R review period. Another well-known periodic review inventory policy is (R, Q) policy, where the spare parts of a fixed batch size of Q are ordered in every R review period. Boundaries and scopes of these inventory policies highly depend on business type, sector dynamics, and the corporate structure, where the work packages of the maintenance activities are established considering machinery usage and the financial

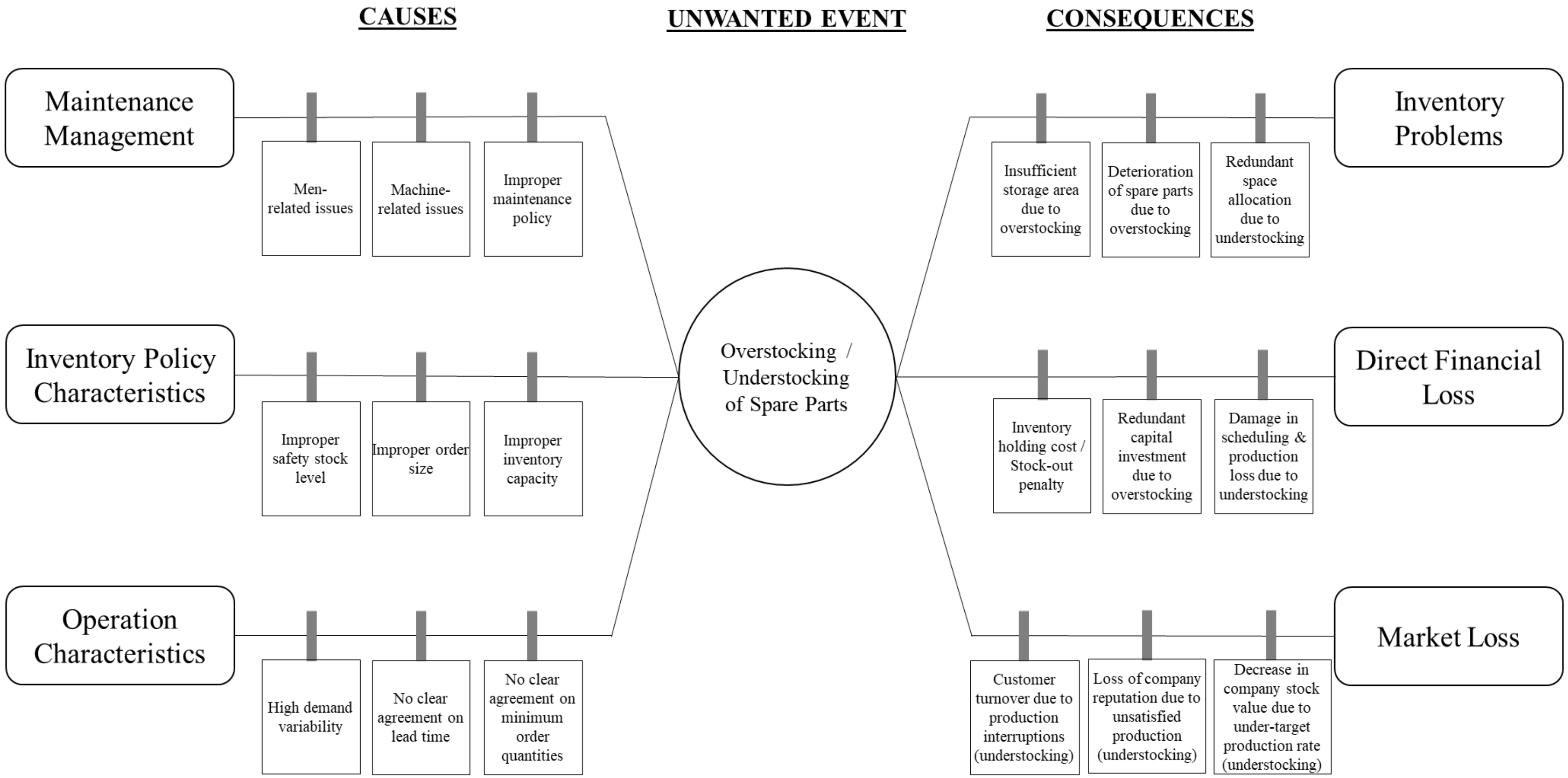


Figure 2.2. Cause-Effect Diagram of Overstocking and Understocking of Spare Parts

risk appetite of the company. Maintenance activities are categorized mainly into corrective maintenance (CM) and preventive maintenance (PM). Corrective maintenance is defined as restoring a randomly failed component to its operational state by a repairing or replacement activity. Immediate CM and deferred CM are the two types of corrective maintenance, and they are implemented depending on the criticality of the failed component. On the other hand, preventive maintenance is defined as the process of detecting and fixing major defects that have the potential to turn into a failure soon if not intervened. Preventive maintenance can be classified as predetermined, condition-based and opportunistic maintenance. Predetermined maintenance is carried out at pre-arranged times depending on time and/or usage. In condition-based maintenance, maintenance activities are initiated when a measurable parameter representing the system state reaches a determined threshold limit value. Opportunistic maintenance is performed when a component failure results in the opportunity to preventively maintain another component, which is deteriorated but non-failed (Ben-Daya *et al.*, 2016). Besides, preventive maintenance is referred to as preventive replacement, especially for non-repairable components since repairing is not an option. Similarly, a preventive replacement can also be applicable for a repairable component if its deterioration level is so high that any repairing activity cannot restore the component to an operationally-efficient level. The well-known and often used preventive replacement types can be categorized as age-based, block-based, condition-based, and group replacement. In age-based replacement, the component is replaced either when it reaches the predetermined age or fails, whichever of these occurs first. Block-based replacement is initiated at pre-determined times regardless of the component's failure history. In condition-based replacement, a component is replaced when a measurable parameter representing the system state reaches a determined threshold limit value. Group replacement occurs when a group of components is replaced at a fixed time and/or when the system reaches a certain age (Horenbeek *et al.*, 2013).

At this point, the previous works on inventory management, which can be classified under three different organization structure as supplier, multi-echelon, and demander, will be discussed in Section 2.2.1 to Section 2.2.3.

2.2.1 Inventory Management in the Perspective of a Supplier

The objective of inventory problems in the perspective of a supplier is generally to achieve effective resource utilization, ensuring the optimal inventory and the steady production flow, to enhance customer satisfaction and to minimize the costs of setup, production and inventory so that the market share can be sustained in an effective and feasible way. In production planning, inventory management is generally adopted to production scheduling, quality management, capacity management, equipment, and supply management. The structure of lot-sizing problems can be examined in several different aspects. Planning horizon, number of production stages, number of products in the system, demand-type, and resource capacity constraints are the factors that affect the complexity of the problem (Suwondo and Yuliando, 2012). In this regard, Lu and Qi (2011) studied a single-stage dynamic lot-sizing problem for a system with a multi-product, in which the replenishment of the inventories depends on a particular production output ratio determined for each product. Considering that the demand is deterministic dynamic and demand rejection is allowed, they proposed two heuristic algorithms for minimizing the total cost of total production, inventory, and lost sales costs. Noblesse *et al.* (2014) examined the lot-sizing problem in a capacitated single-stage and single-item production-inventory system where the production lead time is stochastic and depends on the orders placed in the inventory model. Assuming a continuous review inventory policy, they developed a model to minimize the expected ordering and inventory costs per unit time to obtain optimal inventory parameters.

In addition, setup cost and production schedule structures can characterize the problem. You *et al.* (2019) presented a mixed-integer linear programming model for the capacitated multi-stage lot-sizing problem under dynamic, time-varying production environment. By considering the time-varying setup cost and dynamic capacity constraint and defining the lead time as the preparations of subsystems, the production schedule is optimized so that the total cost, including production setup cost and the inventory-holding cost, is minimized over the planning horizon. Lot sizing problems may also consider the decisions on the product quality to determine whether the deteriorated products will be remanufactured or not. In this point, Sonntag and Kiesmüller (2018) studied a single-stage and single-product production system considering random yield losses caused by stochastic proportional yield. It is assumed that the production quantity is determined by the order quantity required in the inventory to be refilled up to a level so that the stochastic customer demand can be satisfied. They developed a mathematical model to obtain the optimal base-stock level in a way that average inventory holding and back-ordering costs are minimized in a production environment where disposing and reusing decisions of defective items are included. Brulard *et al.* (2019) represented a mixed-integer linear optimization model combining a multi-dimensional and multiple-choice knapsack problem with a two-stage lot-sizing problem. The model integrated strategic and tactical decisions for a multi-technique, multi-product, and multi-client production system to maximize the economic revenue under some considerations such as deterministic dynamic demand, capacitated resources, and short-time perishability of products.

Besides, decisions on the back-ordering concept may shape the problem structure, where an additional cost is incurred for each back-ordered unit per period. Li and Hu (2017) examined a single-machine, multi-product lot-sizing, and scheduling decision-making problem by proposing a two-stage stochastic programming model. By including stochastic workforce efficiency and stochastic demand with the allowed back-ordering, production sequence and lot sizes were optimized by minimizing the total expected system costs over the planning horizon. Altendorfer (2019) investigated a single-stage production/inventory system with stochastic advance demand information and limited capacity to simultaneously optimize the planning parameters, such as planned lead time, lot size, and safety stock. A heuristic optimization model applied to minimize inventory and back-order costs showed that the specific trade-off of the system is created by the demand information quality.

2.2.2 Inventory Management in the Perspective of a Multi-Echelon System

In the literature, procurement policies for raw materials and production planning systems, which are related to lot-sizing decisions, were often studied separately so that the complexity of the integrated problem dimensions such as procurement, inventory, production, and scheduling can be reduced. However, in the recent studies, it has been observed that the coordination between procurement and production planning can be achieved by multi-echelon supply chain management concept (Song *et al.*, 2014). Such problems generally have multiple objectives, but the primary aim is to improve the overall performance of the chain through the integrated optimization of procurement and production control for all stages, such that related costs are minimized by achieving a certain level of customer satisfaction. At this point, Song (2009) studied a joint optimization of ordering and production control in a chain of three entities. Considering stochastic demand arrivals, processing times, and replenishment lead times, the ordering and production policies were optimized by minimizing the cumulative of material and product holding costs and demand back-ordering costs subject to capacitated warehouses for both raw materials and finished goods. Taleizadeh *et al.* (2011) studied a supply chain problem including a multi-product, multi-vendor and multi-buyer parameters, where each vendor has warehouse capacity while each buyer uses (R, Q) inventory control policy to order with a limit to purchase products. The objective was to determine safety stock levels, reorder points and number of the shipments by minimizing the total cost of the supply chain, considering stochastic demand and variable lead time. Sana (2011) examined a supply chain problem for the supplier, manufacturer, and retailer, and proposed an integrated inventory-production model including product quality. An analytical method was implemented to determine optimal raw material order size and the production rate by considering the negligible lead time and constant demand, in order to maximize the total expected profit of the supply chain. Sana (2012) proposed an integrated model for a single-product supply chain system consisting of manufacturer, vendor, and retailer by considering the economic order quantity and economic production quantity model. The objective was to maximize the expected average profit by detecting optimal order quantities, number of the shipments, and production rate of the joint system. Pal *et al.* (2012) proposed an integrated inventory-production model for a multi-echelon, multi-item supply chain system involving a manufacturer, multiple retailers, and multiple suppliers. It is considered that each end product is generated by combining raw materials at a certain percentage and delivered to the retailers where these products are sold based on the demand in the market. Song *et al.* (2014) developed an integrated inventory management policy for raw material procurement and production control in a manufacturing supply chain with multiple system uncertainties such as random customer demands, stochastic production times, and uncertain material supplies, in such a way that the expected total cost is minimized. Wang *et al.* (2015) modeled a joint lot-sizing and pricing problem in a two-echelon supply chain which includes a supplier manufacturing the products and a retailer selling them in the market. The objective was to optimize the selling price, order quantity, and lot size by maximizing the system-wide profit, considering the supplier's finite production rate with price-sensitive deterministic demand. Hlioui *et al.* (2015) studied a three-stage supply chain problem consisting of integrated production, replenishment, and quality decisions by regarding imperfect delivered lots and random lead time. A response surface methodology and a simulation model were applied to obtain the optimal parameters of a production strategy and a replenishment strategy, in such a way that the long-term expected total cost is minimized. Tewary *et al.* (2017) studied a four-echelon inventory system consisting of a manufacturer, two warehouses, three distributors, and four retailers and framed a reorder interval based mixed integer non-linear programming problem, where customer demand and lead times were considered as constant. The objective was to satisfy the customer demand and optimize the order lot size, production batch size, reorder interval and interval of production for manufacturer so that inventory cost through whole system is minimized. Mokhtari (2018) designed a solution algorithm for a defective manufacturing system in which the number of defective items and demand rate parameters were considered to be uncertain. The objective of this study was stated as to jointly optimize the order lot sizes and production by achieving the minimization of the total cost of the system. Das *et al.* (2019) extended this deterministic modeling technique to a stochastic model for a multi-echelon distributive system with a continuous review inventory policy in order to determine the optimal values of the reorder point, safety stock quantity, order quantity, and service level in each stocking point.

2.2.3 Inventory Management in the Perspective of a Demander

In the perspective of a demander, the common objective is to develop optimal policies for timely and adequate procurement and stocking of spare parts inventories and the maintenance of the operating system, so that the joint cost of holding, ordering, stock-out of spare parts, and maintenance is minimized (Samal and Pratihar, 2015). In practice, spare parts inventory management problem can be characterized by several aspects relying on the type of the preventive maintenance policy applied, individual characteristics of inventory policy, the number of operating parts, and the deterioration characteristic of the system (Panagiotidou, 2014). The related studies in the literature have implemented the inventory control policy along with the preventive maintenance policy and considered the optimization of policy parameters jointly. Some researchers have considered the simultaneous optimization of inventory control and age-based preventive replacement, in which a part is replaced at a particular age or a failure, whichever occurs first. Armstrong and Atkins (1996) examined a system consisting of a single component with a random failure rate, where only one spare component is allowed to be kept in stock. The objective was to obtain a joint optimization model of spare ordering policy and age-based replacement policy, in such a way that the long-run average cost including replacement, shortage, holding, and breakage costs were minimized. Xu *et al.* (2011) proposed a joint optimization model of spare part inventory control policy and age replacement policy for a single unit system. In the study, optimal values of the maximum stock level, the inventory replenishment cycle length, and the preventive replacement interval parameters are established, by minimizing the total cost. Gan *et* *al.* (2015) performed a mathematical analysis for a production system comprised of two serial machines, an intermediate buffer, and a spare parts inventory. In order to minimize the long-term expected cost rate, a genetic algorithm was utilized and the optimal values of the control parameters consisting of the initiating time of buffer accumulation, the buffer size, the spare parts arrival time, and the preventive maintenance age were obtained. Panagiotidou (2019) studied a joint optimization of preventive replacement time and spare parts ordering policy, for systems with multiple identical operating items under an (s, S) continuous review inventory policy and age-based preventive replacement policy. The model represents the analytical interrelationships between the ordering policy and the replacement and jointly optimizes the values of continuous review policy parameters and preventive replacement age so that the expected total cost per time unit is minimized.

Some other researchers have studied the joint optimization of inventory policy and block-based preventive replacement, where a part is replaced at pre-arranged times regardless of the failure history. Huang *et al.* (2008) studied a generalized joint optimization policy of block replacement and periodic review spare inventory with random lead time. Nguyen and Bagajewicz (2010) investigated a system to jointly optimize the spare parts inventory policy, the preventive maintenance frequency, and labor allocation by utilizing a genetic algorithm. Kader *et al.* (2013) studied an integrated spare parts inventory and block type preventive maintenance problem for non-self-announcing manufacturing systems of one type of product, which is subjected to the random failure rate. Considering system degradation and an inventory policy of (s,Q) where s equals to zero, a mathematical model was developed based on cost criteria. It was aimed to determine the optimal preventive replacement period and the optimal order quantity of spare parts, in a way that total operating costs, including maintenance and spare parts cost, is minimized over a finite horizon. Jiang *et al.* (2015) investigated a multi-unit system with inventory deterioration and proposed a joint optimization model of periodic review inventory and block replacement policies. In the study, the total expected cost rate of the system was minimized where decision variables are defined as maximum inventory level and preventive replacement interval. Samal and Pratihar (2015) developed a novel approach for joint optimization of spare parts inventory and preventive maintenance problems, which determines the optimal spare parts ordering and preventive maintenance intervals jointly. The optimal time interval values were obtained by utilizing non-traditional optimization tools so that the cumulative cost rate of spare parts inventory and preventive maintenance was minimized under an (R, S) inventory policy where R is the block preventive maintenance cycle.

In some studies, the spare parts inventory problem has been considered together with condition-based preventive replacement, in which the replacement is performed when the system state reaches a pre-determined threshold. Vaughan (2005) presented a stochastic dynamic programming model to determine an optimal inventory policy of spare parts considering random failure and preventive maintenance as two sources of demand. An optimal spare parts inventory control policy was developed to minimize the total expected cost of the inventory system over periods by managing the non-stationary demand, under the assumption of no backlogging and one-period of replenishment lead time. Wang (2012) studied a joint optimization problem covering preventive maintenance inspection interval, spare parts inventory control, and the delay-time concept connecting the inspection interval with the failure numbers. A stochastic dynamic programming was employed to minimize the total system cost by assuming a periodic review and (S, Q) ordering policy under a fixed order lead time. Panagiotidou (2014) a studied the joint model of spare parts ordering and maintenance for multiple identical operating items, which are periodically inspected and can be preventively maintained, repaired, or replaced depending on their conditions. The optimization was performed by giving ordering decisions for spare parts and maintenance activities jointly. A real case was implemented and determined the optimal spare parts ordering quantity, time and inspection interval by minimizing the total cost values regarding two ordering policies which are a continuous review policy (s, S) and a periodic review policy (R, S). Keizer *et al.* (2017) studied an integrated problem of inventory and condition-based maintenance for a system containing multiple components with a shared pool of spares. Assuming that the system is monitored through periodic inspections and lead time is fixed, the model is formulated as a Markov Decision Process where the inventory policy parameters are determined through minimizing long-run average cost. The performance of the model was compared by applying an (s, S) policy to a single component system. Zhang and Zeng (2017) utilized semi-regenerative process theory to determine a joint strategy to optimize periodic condition-based opportunistic preventive maintenance and a spare parts provisioning policy. A multiunit system with multiple identical units could be optimized by minimizing the expected cost rate considering constant order lead time and (R, s, S) inventory policy.

2.3 Spare Parts Inventory Problem in the Mining Industry

Management of demand intervals and quantities of spare parts correlated with the frequency and profile of maintenance activities applied in a production area is called spare parts inventory policy. How to establish the boundaries and scope of such a policy depends on the sector dynamics in terms of machinery usage and the company's financial risk appetite. On this basis, the unit economic value of a mining operation variates largely depending mostly on the related commodity prices, periodical production rate of the company, demand level in the market, and the customer mass and available gaps in the sales potential. Spare parts inventory policies, as an integral part of maintenance policies, are of capital importance, especially in machine-intensive sectors such as mining, where uncertainty in the operational level is quite high and should be managed carefully not to interrupt the resultant turnover of production.

In one of the related studies, Ghodrati and Kumar (2005) examined the effect of the operating environment on inventory stock levels of replaceable components. In the study, how the factors related to operator efficiency, maintenance crew efficiency, quality of hydraulic oil, climate conditions, and operating environment may affect the inventory decisions of the hydraulic brake pump of wheel loaders in a mining company was investigated. Ghodrati *et al.* (2007) developed an event tree diagram to visualize and estimate multiple possible combinations of the decisions that can be effective in the success of spare parts inventory management. In this sense, probabilistic consequences of sequential inventory decisions were considered in an application conducted for the loaders in an iron mine. Wang *et al.* (2009) investigated how condition monitoring indicators can be integrated into an inventory policy by applying the developed methodology to the motors of haul trucks in a mine. At this point, aggradation of iron and sedimentation levels in the motor oil were considered to be valid indicators of motor deterioration and the resultant spare part requirement. Louit *et al.* (2010) developed a dynamic control model of the service rate in a single-server queuing system to optimize the inventory policy of critical repairable spare components for a fleet of mobile mining equipment. The policy was defined in the form of (S,χ), where S is the optimal stock size and χ is the optimal expedited repair trigger level, under the consideration of minimization of expected cost per unit time for the inventory system in the long run. Louit *et al.* (2011) built up a multi-objective inventory optimization model where the model objective could be switched as minimizing cost, maximizing simultaneous reliability, maximizing reliability in a time-interval, and maximizing availability. The developed model was applied to a repairable component of haul truck in a mine. Martinez *et al.* (2016) constructed an integrated inventory model where insurance policy against production loss due to the stock-out condition of spare parts was included. The model was implemented for an unrepairable component of a hydraulic excavator in a mine. Rosienkiewicz *et al.* (2017) investigated the problem of lumpy demand forecasting that is typically observed in heavy machinery spare parts business. The research conducted in the paper pointed out that spare parts in the mining industry have a characteristic of lumpy demand, where it is vital for the inventory management because of the difficulties in modeling and forecasting such type of demand. The goal of the study was to develop a new hybrid spare parts demand forecasting method, which can be used in the mining industry, by combining artificial neural networks and regression models. The proposed model was applied to forecast the future demand for three spare parts of a haulage vehicle, based on real data from a copper mine. Zhang *et al.* (2018) developed a cost-minimization model of a shared-inventory problem where multiple companies use a common spare parts inventory. The model was applied for a shared-inventory of three gold mines in such a way that the total cost of procurement, stocking, and production loss was minimized. Gölbaşı (2019) developed a simulation algorithm to measure the impact of the applied spare parts policy on the production loss, also referred as system availability. The algorithm was applied for a dragline employed in a coal mine, and quantitatively verified with a numerical example. Şenses, Gölbaşı and Bakal (2021) presented a mixed-integer mathematical model to optimize the order lot sizes and the schedule of the lubricating oils used in a mining company to minimize the total inventory cost. The model was implemented to a multi-item and multi-supplier system under block-based preventive maintenance and continuous review inventory policy. The optimization results revealed that the model can improve the company's current lubricating oil inventory policy by yielding a total saving up to ₺18,566.

2.4 Evaluation of Tire Component as a Critical Spare Part

This section explains the evaluation of a tire component as a critical spare part. First, the structure of a tire component, the classification and working principles are explained. In addition, the terms related to tire management in mining and tire failure types are comprehensively discussed. Last, the previous tire management studies applied in mining industry are reviewed.

2.4.1 Structure of a Tire

A tire is the part of a vehicle that is fitted on the rim and filled with compressed air, ensuring contact with the ground. Besides providing and maintaining the traction, braking, and direction of travel, tires also maintain load carry-ability of vehicles and absorb vibrations and shocks caused by contact with the ground. Tires are mainly divided into radial and bias tires depending on the belt construction leading to changes in the contact surface with the ground. Tire types can also be categorized by i) the inner tube construction as tubeless and tube-type tires, ii) the season as summer, winter, and all-season tires or iii) the application as passenger car, light truck, and off-the-road tires. Tires have a composite structure consisting of steel synthetic reinforcements, rubber compounds, and textile (Goodyear, 2010). The main components of radial and bias tires are shown in Figure 2.3.

Figure 2.3 Structural Diagram of Radial Tire (a) and Bias Tire (b) (Yokohama Rubber Co., 2021)

For radial tires, the cords constructing the carcass are arranged perpendicularly to the centerline of the tread, while they are intersected at a diagonal approximately 40 degrees from the centerline for bias tires. The radial tires ensure more contact with the ground transferring more power, more stability at speed, lower friction, and lower heat comparing to bias tires. On the other hand, bias tires allow more compliant ride off-highway, and are typically less expensive. The functions of radial and bias tires are briefly explained as follows (Yokohama Rubber Co., 2021):

i. Belt - With multiple steel cord layers, provides strength to the tire, stabilizes the tread, and protects the carcass from penetrations.

ii. Carcass - Transmits the steering and braking forces between the road and the wheel and carries the load of the tire under operating pressure.

iii. Inner Liner - Inner walls of tubeless tires are lined with a layer of rubber constructed to prevent the air loss.

iv. Bead - Fixes the tire on the rim properly and maintains it in position.

v. Bead Wire – A ring-shaped steel wires to reinforce the material in the tire.

vi. Chafer - A layer of hard rubber protecting the bead zone from erosion caused by rim chafing.

vii. Sidewall - Protects the carcass and provides resistance to weathering and flexing.

viii. Tread - Outermost part of the tire that contacts with the road surface and provides traction while protecting the tire body.

ix. Breaker - Protects the carcass from the cuts in the tread and helps to absorb shocks.

2.4.2 Tire Management in Mining

Tires of material excavation and hauling vehicles used in several types of operations, including agricultural, forestry, and mining industries, are usually subject to harsh environmental conditions. Purchasing costs of these tires, which need to meet the safety requirements in the field and can reach up to 4m in diameter based on the application, are extremely high. Therefore, tire failure, besides being a safety hazard, is indeed a costly event resulting in loss of production and time (Kotchon *et al.*, 2012).

In the mining industry, tires are frequently-used spare parts for wheel machinery employed in material loading, material hauling, and auxiliary operations in demanding mining environment. Tires can account for 20% of the total operating costs, such that the tire-related costs of a truck throughout its lifetime may exceed the truck's initial purchase price (Meech and Parreira, 2013). The effect of premature tire failure on the direct cost is evaluated based only on its remaining lifetime. However, there are also some indirect costs incurred, such as the additional labor cost and the lost production time, considering that a tire replacement can take up to 8 hours depending on the waking conditions (Kagogo, 2014). Therefore, a tire inventory policy applied in a mining area should consider various factors such as, characterization of equipment fleet, production rate, equipment availability, and tire failure frequencies. A tire inventory policy should be constructed in such a way that direct and indirect cost flows related to tire inventory and tire unavailability should be minimized.

Fluctuations in the numbers of spare parts available in a warehouse depend on the failure modes spare parts are exposing to, their frequencies, and maintenance work packages applicable to each failure mode. On this basis, tire failure levels variate, from slight damage to a hazardous one that can threaten driver safety. Three major types of tire failures are generally observed in mining areas, which are cuts and punctures, impact damage, and irregular wear. Any of these failure modes can occur single or multiple times throughout a tire’s lifetime with varying frequencies. At this point, 80% of large tires is detected to have at least one failure before their wearing out where cuts are responsible for about 45 percent of these failures (Cat Global Mining, 2007). Cuts and punctures are caused by external factors such as unfavorable road conditions and sharp objects on the road that can pierce through the tire's surface. Although a tire may lose air pressure due to cuts or punctures, it might still be repairable if the damage is under a certain tread thickness. On the other hand, an impact break is usually caused by driving over potholes or obstacles on the road at excessive speed or wrong angles. Consequently, the tire sidewalls may disintegrate or the tread and plies may delaminate. In addition, the bulge incurred on the tire may weaken tire structure and increase the likelihood of failure occurrence (Continental, 2020). Moreover, irregular tire wear can occur in several ways during rolling and sliding contact of tires with the ground through abrasion and ablation mechanisms, mainly caused by fatigue. These mechanisms may cause different wearing formations on the tire surface, so the tire wear classification is closely related to the formation of the worn surface (Klüppel, 2014). The most typical forms of irregular tire wear are illustrated in Figure 2.4.

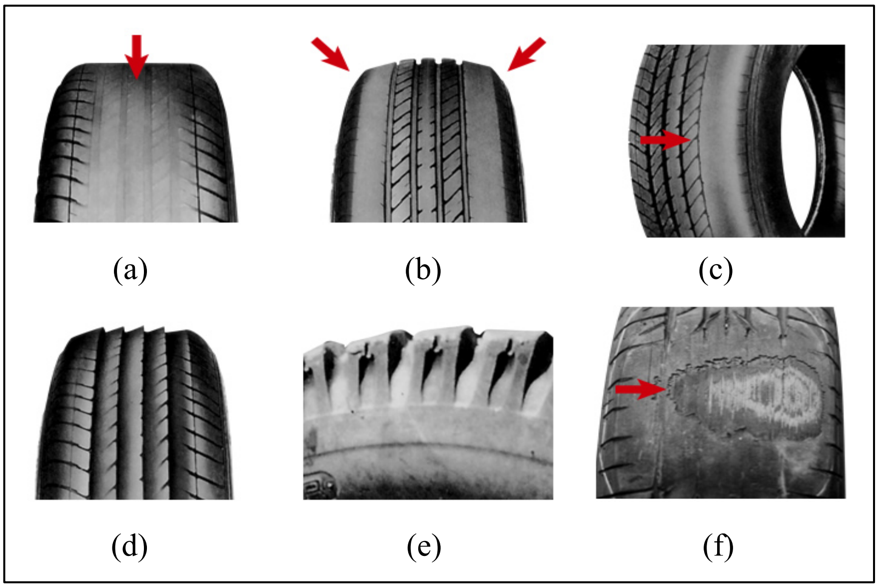


Figure 2.4 Tire wear types – Center wear (a), Shoulder wear (b), One-sided wear (c), Feather Edge wear (d), Heal and Toe wear (e), Spot wear (f) (Yokohama Rubber Co., 2020)

Due to inherent complexity of operations, tire performance can be measured depending on various internal and external factors. The factors affecting tire performance in a mining area can be explained in four categories: machine parameters, maintenance practices, operating practices, and site conditions (Carter, 2007). Machine parameters are referred as truck design parameters such as steering geometry and brake heat dissipation. Maintenance practices cover both machine and tire maintenance activities, where tire maintenance includes the preventive maintenance of tire rotation, tire alignment, and tire inflation pressure. Tire rotation here indicates the changing positions of tires on the vehicle periodically to maximize the tire life by spreading the tire wear to each tire evenly. Proper inflation pressure mitigates tire heat levels and improves flexibility and ground contact. Over-inflation results in higher operating temperatures, while under-inflation results in reduced tire circumference, so both adversely affect tire tread wear (Meech and Parreira, 2013). Operating practices point to dynamic operational parameters such as work cycle, payload, and speed. Truck overloaded and/or traveling at high-speed lead to increased stress in treads, weakening bonding, and generating excessive heat in tires, making the tire more susceptible to failure (Carter, 2007). Site conditions imply climatic factors such as temperature, rain, and snow, and haul road design and maintenance. A well-designed haul road can be explained by integrating safety berms, drainage ditches, straight sections, and super-elevated curves. Due to super-elevation, trucks can operate at more consistent speeds generating less heat with less braking. In addition, maintaining road surface and drainage control are essential to eliminate the effects of sharp loose rocks, tire slippage, and wet/muddy roads to tire wear (Cat Global Mining, 2007). A detailed cause and effect diagram showing the factors affecting tire wear is shown in Figure 2.5.

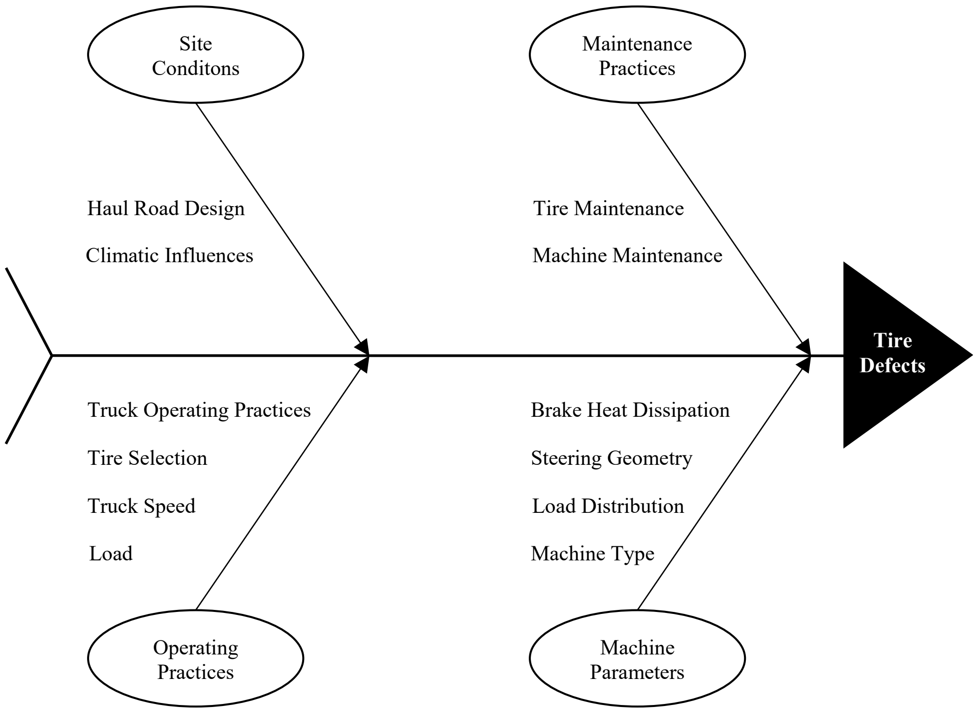


Figure 2.5 Cause and Effect Diagram Showing the Factors Affecting Tire Wear (Carter, 2007)

Tire condition control is typically carried out via visual inspection by technicians or operators, who then decide if any tire needs further testing and/or maintenance. However, this procedure cannot be performed practically if there is internal damage, which cannot be detected through a visual inspection. In addition, based on the availability and allocation of the maintenance personnel at the site, inspection might not be conducted with required frequency to detect the tire defects before these defects turn to major and irreparable failures. Besides, despite that some temperature and pressure monitoring systems are implemented to preventively detect tire failure, it is likely that they may not notice highly localized damages (Kotchon *et al.*, 2012). Thus, developing a suitable maintenance plan that can mitigate and control tire failures, provides an early detection of failure and eventually extents the tire lifetime. By this way, safety and financial considerations arising from tire usage can be controlled and monitored effectively.

2.4.3 Tire Management Studies in Mining

In today's mining industry, tire management strongly related to truck performance has become a critical topic since hauling operations can be interrupted to a great extent in cases where stochastic nature of failure modes, new tire requirement frequencies, and supply-chain conditions are not considered at a desired level when constructing a tire management policy. In this sense, some researchers have been performed in the literature to reveal the dynamics and factors of tire usage and management in mining.

Zhou (2007) carried out an analysis to determine the optimum tire rotation practices such as rotation time and rotation sequence and review the effect of some factors on off-the-road tires operating in two different mines. A statistical approach was applied to determine the optimum tire air pressure setting and the tire rotation time, while tire rotation sequence acronyms were generated to determine optimum rotation sequence. The study outputs show that when tire rotation is used, the tire life increases in both mines. Morad and Sattarvand (2013) developed a method using neural networks to estimate the tire wear rate of dump trucks operating in a copper mine and calculate the residual service lifetime based on the consumed tread depth. For the hauling operation where a total of 56 tire were captured in a database, three input parameters were identified which are initial tread depth, consumed tread depth, and the inspection time. Then, a simulation study showed that the estimated values represents the real values, having a correlation coefficient of 96.6%. It was concluded that artificial neural networks could be an effective method to estimate the lifetime of the tires. Meech and Parreira (2013) developed a model to investigate the tire wear of an autonomous haulage truck fleet by comparing with the manual fleet employed in an open-pit mine. There are nine trucks in the mine operating with two shovels. A simulation-based model using fuzzy logic, capable of introducing the tire wear as a function of truck velocity and payload where both affect the tire temperature, was designed and implemented. Study results showed that tire temperature has an impact on tire wear up to 15%, considering an ambient temperature of 35°C. Also, an improvement by 8% was achieved on the tire wear of autonomous haulage fleet comparing with the manual fleet. Kagogo (2014) investigated the effectiveness of the tire management for trucks operating in an open-pit mine. The study intended to evaluate the factors affecting the performance of haul truck tire, types of failures, and their impact on the related cost and improve the management system by increasing the tire life. The mine is observed to experience that 49% of the tires prematurely failed mainly due to cut separation. A more aggressive approach on the pit maintenance or identifying red zones in the site, were stated to be useful to improve the tire management system. Lindeque (2016) introduced a new tire management strategy indicating how to integrate the proposed improvements into the system. The study was carried out for a haul fleet covering 12 CAT 777 and 17 Komatsu 730 haul trucks, operating in an open-pit iron mine where, in 2014 alone, it was reported that 61% of operating tires failed prematurely and 41% of them were due to wearing out. A sensitivity analyses was conducted in the study and the results highlighted the importance of remedial actions on tire life. At this point, the proposed tire management strategy improved tire life by 105% and 41% for CAT 777 and Komatsu 730 trucks, respectively. Qarahasanlou *et al.* (2017) developed an approach by applying a covariate-based reliability analysis to predict tire spare parts behavior of a dump truck fleet operating in a copper mine. The aim of the study was to forecast the required number of tire spare parts based on the reliability estimations of the component using a historical failure dataset of 11 years. The technical characteristics of tire, machine parameters, and the operating environmental conditions were introduced as covariates in the model. It was inferred that temperature, rainfall, and the position of the tires on the axles have an important impact on the operating behaviors of the tires. By both including and excluding the covariates, economic order quantity and reorder point were calculated for the fleet covering 10 trucks, and the required number of tire spare parts were predicted for the following two years. The outputs pointed out that the spare part management may significantly be improved by re-evaluating the covariate effects.

Although tires are extensively used and consumed in mining operations under harsh environmental conditions, it is observed from the literature that tire spare parts inventory management has not attracted enough attention previously.

2.5 Event Simulations

This section firstly explains the simulation concept, its classification, pros and cons, and the related terms to constitute a broad knowledge on the topic. In addition, the previous simulation studies on inventory management applied for both mining industry and other production industries are addressed, respectively.

2.5.1 Simulation Concept and Classification

Simulation is the imitation of a real-world system, which can be done by hand or on a computational environment. The main purpose of the simulation is to get a better understanding and/or improve the system, by drawing inferences about the operating characteristics and the performance measures of the real system (Banks *et al.*, 2010). Since World War II, incorporating simulation in system-related activities has become indispensable for various business areas including manufacturing, project management, logistics, transportation, military, and health care (Altiok and Melamed, 2007).

In general, a system is defined as a set of components interacting with each other and organized to accomplish a common purpose. In order to get a better understanding of a system, some basic system components need to be defined. The entity is defined as the object of interest in the system, while an attribute represents a property of the entity. An activity indicates the period of time with a specified length. System-state is defined as the description of the system condition at any time, through the collection of variables related to the assigned objectives. In addition, event is a term representing an instantaneous occurrence which may change the system-state. Typically, a system requires inputs processed by these internal components to produce some outputs. Changes occurring in the system environment, defined outside of the system, often affects the system dynamics. Hence, in the modeling phase, system boundaries and the effective environment should be defined attentively in accordance with the study objectives (Banks *et al.*, 2010). Conceptualization of a system is shown in Figure 2.6.

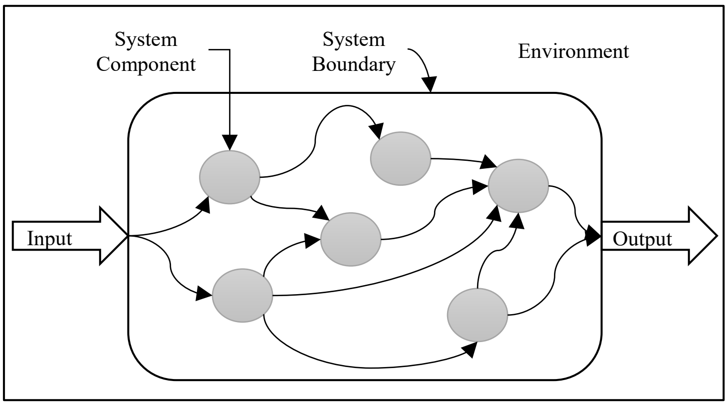


Figure 2.6 Conceptualization of a System (Rossetti, 2016)

A simulation model typically consists of a set of assumptions regarding to the system conditions, which are constructed using symbolic, logical, and mathematical interactions between the system entities. After development and validation stages, the simulation model can be used to design new systems considering its performance measures and analyze the performance of existing systems under varying circumstances (Banks *et al.*, 2010).

System or simulation models can be characterized as stochastic or deterministic, static or dynamic, and discrete or continuous. The models that include random input variables are classified as stochastic models, while the deterministic models consist of a known set of inputs, without randomness or with negligible randomness. The static simulation models do not consider the effect of time on system state, while dynamic models define and include time as a significant factor or indicator of system behavior. A system is also classified with a discrete model if the system-state changes at the discrete set of points in time or with a continuous model if the system-state changes continuously in time (Rossetti, 2016). A system can be defined using multiple of these types. Branching of system types can be seen in Figure 2.7.

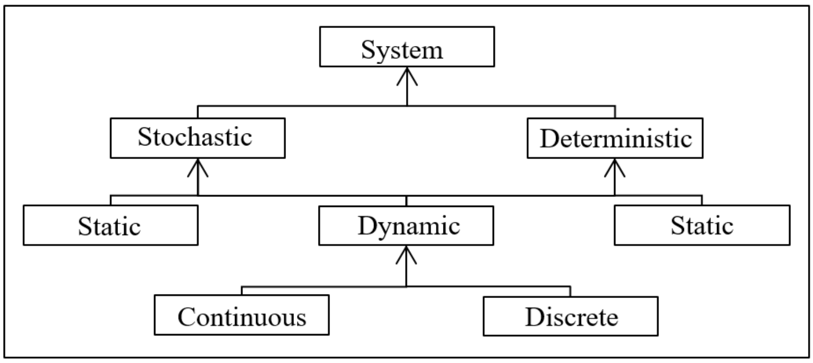


Figure 2.7 General Types of Systems (Rossetti, 2016)

Dynamic simulation, which can be classified as continuous and discrete, is frequently used in system modeling. In a discrete-event simulation, observations are collected at certain points in time called events, when any change occurs in the system-state. On the other hand, observations are gathered continuously through observation periods in a continuous simulation (Rossetti, 2016). State variables of discrete and continuous systems are presented in Figure 2.8.

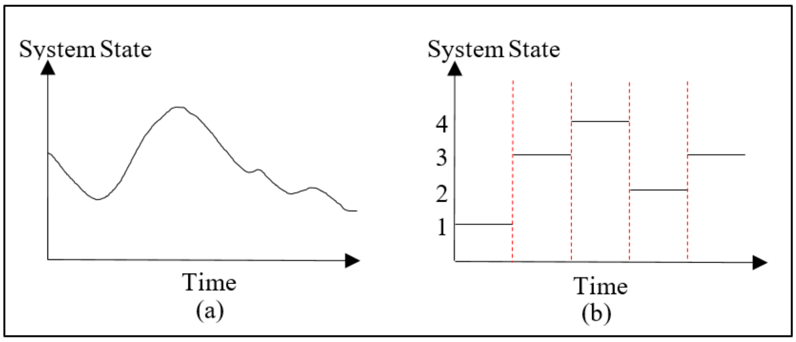


Figure 2.8 State Variables of a Continuous (a) and a Discrete (b) System (Banks *et al.*, 2010)

Simulation has many advantages and also some shortcomings/limitations. In this regard, advantages of a simulation model are listed below (Banks *et al.*, 2010).

i. Without committing resources for their acquisition, simulation allows to test every aspect of a proposed change and/or correction in a system.

ii. Simulation enables to speed up or slow down the phenomena which is investigated, by expanding or compressing the time.

iii. Simulation answers how and/or why certain phenomena occur by taking a detailed examination of the system.

iv. New methods, decisions, operating policies, or procedures can be examined practically without causing any interruption or expense in the real system.

v. Simulation enables to diagnose the problems by giving an insight about the interactions between system components, their importance and impacts on the overall system performance.

vi. By performing bottleneck analysis, the reasons behind the excessive delays in materials, information or any process can be discovered.

vii. Simulation helps to understand how the system actually operates.

viii. In redesigning existing systems or designing new systems, simulation helps to specify the requirements and answers all of the "what-if" questions.

In addition, some shortcomings/limitations of a simulation model are mentioned as follows:

i. Building a model requires experience and special training. In addition, models constructed for the same system by different individuals are unlikely to be the same despite of having some similarities.

ii. Interpretation of the simulation outputs may be difficult in distinguishing the way an observation occurs caused by either randomness or interrelationships of the system.

iii. Model building and analysis may be expensive and time-consuming. In addition, if any of the resources for model building and analysis are skimped, insufficient simulation models can be developed without representative outputs.

iv. Inappropriate usage of simulation can take place when an analytical solution is possible or preferable for the related case.

The main steps of a simulation model are listed below (Banks *et al.*, 2010) and the schematic view representing these steps is shown in Figure 2.9.

i. Identification of the problem statement

ii. Identification of the objectives and required dataset

iii. Conceptualization of the model

iv. Data collection

v. Construction of the conceptualized model

vi. Verification and validation of the model

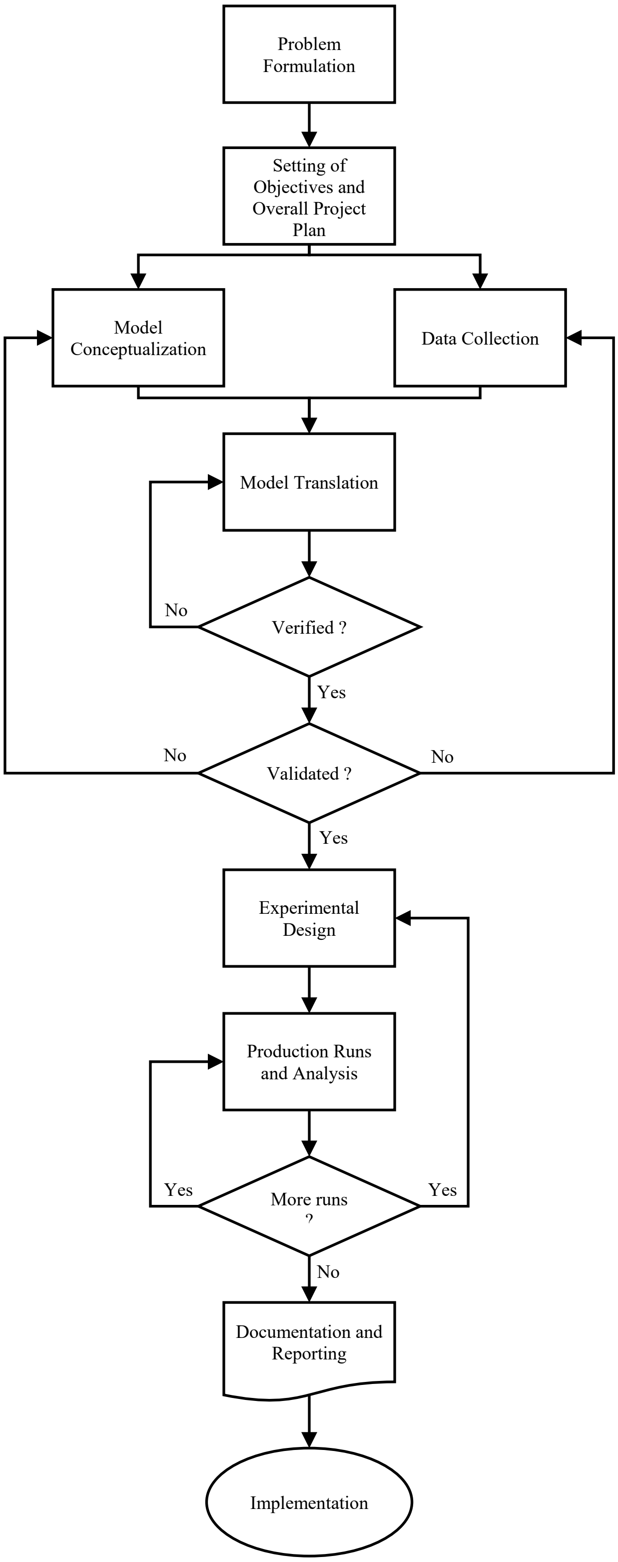


Figure 2.9 The Schematic View Representing the Steps in Modeling (Banks *et al.*, 2010)

2.5.2 Simulation Applications in Mining

The first simulation model for the mining operations was developed by Rist in 1961 and aimed to optimize the number of trains in a haulage operation of an underground molybdenum mine, using Monte Carlo simulation technique (Sturgul, 2001). Over the past few decades, various simulation and simulation-based optimization approaches have been developed to evaluate dispatching policies, short-term and long-term production scheduling, equipment selection and sizing for both open-pit and underground mines.

Among the recent studies, Hashemi and Sattarvand (2015) designed a simulation model for loading and hauling equipment operating in an open-pit copper mine. Productivity assessment scenarios were implemented by modifying the number of trucks and the results showed that the overall mine production can be improved by 40%. Then, a dispatching simulation model was developed to minimize truck waiting times and improve the production rate. An improvement in the total production by 7.8% was achieved compared to the fixed assignment system. In addition, an ore blend control model was developed based on the monitoring of the excavation system, and a stable ore grade level was maintained. Dindarloo *et al.* (2015) investigated a truck-shovel selection and sizing problem for open-pit mines, by proposing a comprehensive simulation framework regarding stochasticity in the mining operations. This model was built including system uncertainties caused by material loading and haulage operations. Then, the model was computed by using discrete-event simulation, and the results were verified via implementing the model for a large open-pit mine. Que *et al.* (2016) presented a simulation-based optimization approach by utilizing discrete-event simulation to improve the operational performance of a continuous transport system operating in a mine. A case study was conducted to investigate the interactions between a shovel and the ground articulating pipeline mining system and maximize the system efficiency. Park *et al.* (2016) proposed a simulation model for a haulage system consisting of trucks and loaders employed in an underground limestone mine. The objective of the study was to optimize the number of trucks by simulating the dispatching system with three loading points. Upadhyay and Askari-Nasab (2018) presented a simulation-optimization framework, which utilizes a discrete-event simulation model interacting with goal-programming, to develop a short-term production plan including uncertainties in mining operations. The model was ensured an efficient short-term production plan by analyzing the effect of different dispatching strategies, traffic congestion, and haul road designs on the mining operations. The proposed model was verified by applying to an iron mine with scenario analysis. Ozdemir and Kumral (2019) proposed a two-stage dispatching system for surface mining operations to maximize the equipment utilization regarding time and operational capacity limitations. A discrete-event simulation model was used for allocation of trucks in the production points by maximizing the mine throughput, whereas linear programming was used for simultaneously truck and shovel matching by minimizing the truck waiting times. The case study presented in the article showed that 7.7% increase in productivity can be achieved. Shishvan and Benndorf (2019) combined a stochastic simulation model and a deterministic optimization model to solve the job-shop scheduling problem and the transportation problem experienced in coal mines. The system was computed by a discrete-event simulation. The proposed approach was applied to a large-scale mine, and the dispatch decisions were optimized. Manríquez *et al.* (2020) presented a simulation–optimization framework to improve the short-term production scheduling program of an underground mine. In each iteration, a mixed-integer linear programming model was utilized to construct a single production schedule. Then the schedule was simulated by a discrete-event simulation model considering the system uncertainties and reconstructed into a better schedule after the evaluation. A case study was conducted by implementing the proposed framework to a real-scale Bench and Fill mine.

In addition, some researchers have been focused on the asset maintenance/reliability and its impact on production, availability, and equipment utilization. In this regard, Louit and Knights (2001) developed a discrete-event simulation model which investigates the impact of various management actions on improving the efficiency of the mine maintenance system. By implementing different scenarios, it was aimed to reduce the repair times and the unplanned failure frequencies, so to increase the fleet availability. Gilardoni *et al.* (2016) proposed a dynamic policy, where the optimal preventive maintenance times continuously were updated based on the failure history to determine an optimal preventive maintenance policy for the repairable systems considering the imperfect maintenance concept. Utilizing the simulation model, the dynamic model performance was compared with the periodical preventive maintenance policy in terms of the expected cost. The model was applied to off-road engines of a mining company, and the study results presented that the dynamic model can ensure lower operating cost per unit of time. Gölbaşı and Demirel (2017) developed a simulation algorithm to determine the optimal inspection intervals of a mining machinery by using the delay-time approach. The maintenance mechanism was designed to minimize the expected maintenance cost of the system by achieving the correlations between machinery performance and the production. The proposed model was applied to two draglines operating in a coal mine, and the simulation results pointed out implementing the optimized inspection intervals can reduce the total maintenance costs by 5.9% and 6.2% for the given machines. Sembakutti *et al.* (2018) presented an approach to optimize the preventive replacement times of shovel teeth. The risk-quantification approach was developed based on Monte Carlo simulation and Markov chain Monte Carlo simulation to investigate the uncertainties of the policy and obtain confidence intervals for the replacement times of shovel teeth. The study results showed that a proper replacement policy can enable to manage the system uncertainties and to improve the operational efficiency. Ugurlu and Kumral (2020) presented an approach to evaluate the performance and the reliability of drilling machines and drill bits. The study intended to determine the optimum drill bit replacement time using the reliability analysis and simulate the drilling interactions in a discrete-event environment. A case study was performed for an open-pit mine operating ten rotary drilling machines. The simulation results revealed that the proposed approach can be used effectively for asset management and production scheduling. Gölbaşı and Ölmez Turan (2020) developed a multi-scenario discrete-event simulation algorithm to optimize the maintenance policy specific to the system by using the stochastic interactions between preventive, corrective, and opportunistic maintenance actions for different inspection intervals. Two case studies were conducted for multi-system earthmoving operations with the optimization criteria of system availability maximization and single-system earthmoving operation where the optimization was achieved by the minimization of total maintenance cost. The results showed that a remarkable improvement in the system availability and the total maintenance cost could be achieved.

2.5.3 Simulation Applications in the Other Production Industries

In the past few decades, simulation has been widely used in the field of inventory management. Simulation is a more powerful technique than analytic models in terms of its representative structure of the real world and its ability to simplify the modeling of complex problems (Hu *et al.*, 2018). When an inventory management is addressed as spare parts management, which is generally subject to the joint optimization of complex maintenance and inventory policies, simulation models may bring a great benefit to reveal the mutual and complicated interactions between maintenance and inventory policy dynamics.

A simulation-based joint optimization model of spare provisioning and age-based preventive replacement was studied for i) single-unit systems assuming a continuous review ordering policy (Kabir and Al-Olayan, 1994), ii) systems with multiple parts assuming a continuous review ordering policy (Kabir and Al- Olayan, 1996) and iii) systems with multiple parts assuming a periodic review ordering policy (Kabir and Farrash, 1997). In addition, Ilgin and Tunali (2007) examined an integrated optimization of spare provisioning and preventive maintenance policies of a manufacturing system with a multi-component and presented a simulation-optimization approach combined with genetic algorithms. To be able to capture all stochastic and dynamic characteristics of the system, the simulation model of the manufacturing line was employed as a fitness function evaluator. Hu *et al.* (2008) proposed a general optimization approach that integrates discrete-event simulation with a genetic algorithm for a spare part ordering policy under age-based maintenance. Wang *et al.* (2015) established a spare parts support probability model to determine the optimum stock of spare parts. Accordingly, a comprehensive decision-making simulation model was developed for joint optimization of the equipment maintenance and spare parts ordering under condition-based maintenance policy, based on random equipment deterioration level and total operating cost of the system. The model was employed for a single equipment system under (S-1, S) inventory control strategy and random lead time for evaluating the cost rate, system availability, and the stock-out probability of spare parts. Mardin and Dekker (2016) established a simulation model for joint optimization of spare parts ordering and block replacement schedule in an identical multi-component system, where the spare parts ordering model was separated into a stochastic model for failure replacement and a deterministic model for planned block replacement, under the inventory policy of (s, S), and deterministic lead time. The proposed model was developed to find out the optimum block replacement interval, the optimum reorder point, and the optimum maximum stock level to minimize the total long-run average cost related to maintenance and inventory activities. Nguyen *et al.* (2017) presented an integrated predictive maintenance and inventory strategy for non-identical multi-component systems with complex structures, where both predictive maintenance and spare parts provisioning operations are handled jointly. By using Monte Carlo simulation techniques, the optimal decision parameters were determined such that the total cost rate is minimized considering age-dependent failure rate, constant lead time, and (R, s, S) inventory policy. In the model, R equals to inspection interval, and both reorder level (s) and inventory position up to level (S) depend on the maintenance plan. Yang and Kang (2017) proposed a joint optimization policy of spare parts inventory strategy with block preventive replacement in a system consisting of multiple components by applying the Monte Carlo simulation-optimization approach. By minimizing the total cost, their objective was to determine the optimal parameters of maximum inventory level and the replacement interval, under the assumption of zero lead time and (R, S) inventory policy where R is the preventive maintenance cycle. Chen *et al.* (2017) introduced a novel degradation prediction approach and developed a new failure probability estimation function considering component service time and degradation extent simultaneously. A simulation algorithm was designed to determine the optimal replacement and spare part ordering times jointly for a single component, in such a way that the expected long-run cost rate is minimized under fixed lead time and (R, Q) inventory policy. In the policy, R is taken as decision variable and Q is equal to one.

2.6 Summary and Study Motivation

Within the scope of this study, a broad base of knowledge is constituted by developing a background on the related topics, and the related studies in the literature are comprehensively reviewed. Firstly, the inventory management concept is introduced and the classification of the inventory management problems is explained. Based on the system dynamics associated with the inventory type managed by the organizations, the inventory problem may be handled in three perspectives, which are supplier, multi-echelon, and demander. Inventory problems in the perspective of supplier and demander are generally considered as lot-sizing problems and spare parts inventory management problems, respectively. On the other hand, multi-echelon inventory systems are typically discussed as the coordination between procurement and production planning which is achieved by multi-echelon supply chain management. A detailed literature review covering these three inventory management approaches is carried out. Then, since this study focuses on the spare parts inventory problem, the importance of the spare parts inventory problem addressed in the mining industry is explained and the related studies in the literature are examined. Since the uncertainty in the operational level is quite high and the inventory should be managed carefully not to interrupt the resultant turnover of production, it is emphasized that spare parts inventory policies are of great importance. In addition, tire management concept, the structure of a tire component, the tire classification, working principles and tire failure types are explained since the tire is considered as the target component for the implementation of the inventory management model developed in this study. At this point, the fact that tires may be accounting for 20% of the total operating cost and the indirect costs may be incurred due to lost production time highlights the importance of the tires for sustainability of the operations. Lastly, the related terms regarding simulation, the classification and pros and cons of the simulation are explained to constitute a broad knowledge on the topic. Some simulation studies in the mining and other production industries are examined.

It is observed that multi-scenario simulation model for spare parts inventory management has not been studied in detail in spite that various studies have been performed on inventory management. Moreover, the spare parts inventory management studies in the mining industry are considerably limited despite that the spare parts may have a significant impact on unplanned production halts. In addition, tires are extensively used in mining operations under harsh environmental conditions, still tire spare parts inventory management has not been attracted enough attention in the previous studies. In fact, the studies including tire management in mining industry generally focus on improving the tire lifetime by analyzing the factors affecting tire management. In this sense, the current study intends to develop a multi-scenario simulation model for optimizing spare parts inventory problem which can be encountered in different inventory systems. In addition, a case study expressing the implementation of the developed model into a tire spare parts inventory management system is included.

CHAPTER 3

DEVELOPMENT OF A SPARE PARTS INVENTORY OPTIMIZATION ALGORITHM

3.1 Introduction

Especially in machine-intensive sectors where the operational uncertainties are quite high, there is also another risk of forecasting the failure profiles of machinery components and the resultant spare part requirements. The demand of the spare parts is basically generated by corrective and/or preventive maintenance activities and generally characterized by intermittent, i.e. lumpy, demand. Components with intermittent demand have occasional demand arrivals having long time intervals in which no demand occurs. High variability in demand patterns leads to considerable difficulties in terms of inventory control. In addition, the uncertainty in lead time, which is the time between placing of an order and the acquisition of the product, and the uncertainty in maintenance plan may increase randomness and complexity in the problem. Thus, in this study, random lifetime, random repair time, and the random lead time of the spare parts will be considered when constructing the stochastic structure of the simulation model.

At this point, a discrete-event simulation, which aims to determine the optimal spare parts inventory policy giving the cost-wise best output among all the scenarios, will be developed with a dynamic and stochastic structure. Using the principles of the inventory policies and analyzing their effects on the equipment availability, the developed algorithm is expected to improve the operating cost flow by minimizing the unexpected halts of the operations. The algorithm can be adapted to different inventory systems where the uncertainty in the operational level is quite high and the machine-intensive operating systems dominate the production that should be above particular amounts for a period so that machine availability should be satisfied at a minimized operating cost.

The simulation algorithm, logic and the steps will be explained in detail in Section 3.2, where the Arena® implementation and modeling steps will be highlighted in Section 3.3.

3.2 Simulation Algorithm and Effective Parameters

As mentioned in Section 2.2, continuous and periodic inventory review policies are the two approaches for the inventory review used in joint systems. In this study, four well-known inventory policies including continuous and periodic review characteristics will be examined. For the continuous review policy, where the inventory levels are continuously checked, the (s, Q) and the (s, S) policies were taken into consideration. On the other hand, the (R, Q) and the (R, S) policies were introduced to the model as the periodic review policy, where the inventory levels are checked at regular time intervals. Table 3.1 summarizes those inventory policies and their decision variables defined in the simulation model.

Table 3.1. *Spare Parts Inventory Policies Included in the Model*

Inventory Policy	**Decision Variables**
(s, Q)	s: Triggering inventory level Q: Fixed batch size
(s, S)	s: Triggering inventory level S: Maximum inventory level
(R, Q)	R: Review period Q: Fixed batch size
(R, S)	R: Review period S: Maximum inventory level

Each inventory policy has different working mechanisms, as illustrated in Figure 3.1, which affect the decisions on spare parts inventory. In the (s, Q) inventory policy, whenever the inventory level drops below s, spare parts of fixed batch size of Q is ordered. Although the inventory is triggered based on the same condition, spare parts are ordered up to inventory level S, in the (s, S) policy. Besides, in every R review period, spare parts of a fixed batch size of Q is ordered in (R, Q) policy, while spare parts are ordered up to inventory level S in (R, S) policy. In this study, parameters of each policy were addressed both individually and collectively to allow the simulation model to evaluate multiple scenarios for the stochastic operating environment of the system to be analyzed.

Inventory decisions are triggered by maintenance actions which are basically preventive and/or corrective maintenance for repairable components and preventive and/or corrective replacement for non-repairable components. Inventory position changes with removing components needed in replacement actions from the inventory and adding components in incoming orders to the inventory. For each inventory policy, there is a stock-out risk that the system may encounter, arising due to the random characteristic of both demand and the lead time. The demands of the spare parts are generated depending on the need for maintenance actions covering non-repairable operations, which are based on uptime and downtime behaviors of the component. Thus, this algorithm requires introducing time between failure (TBF) and time to repair (TTR) characterization functions for the component(s). This process will be explained in Section 4.2.1.

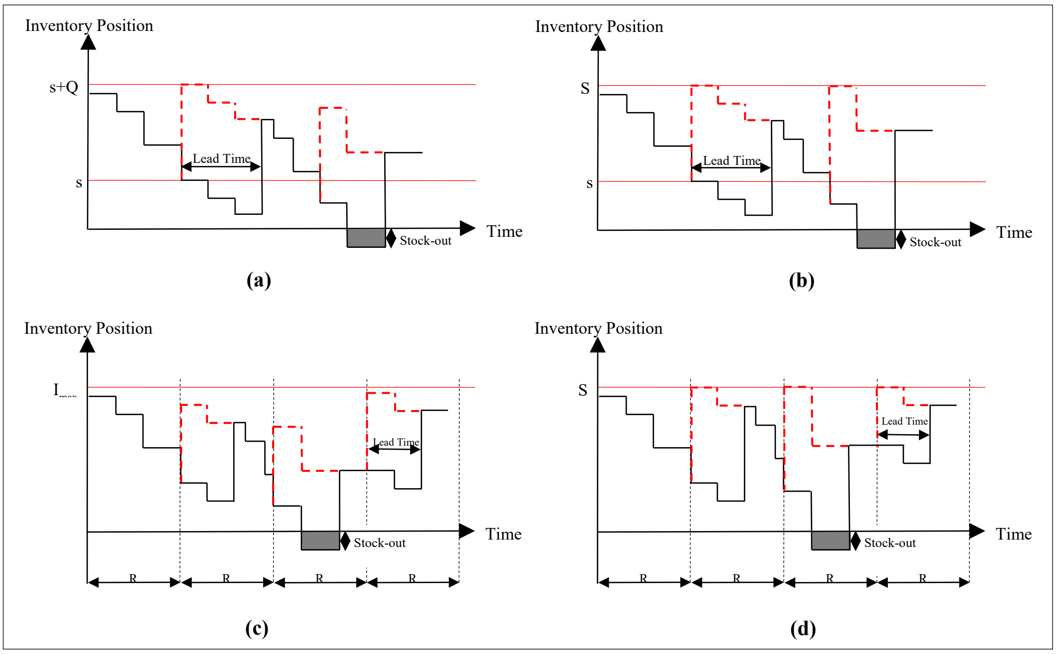


Figure 3.1 Working Principles of Inventory Policies - (s, Q) policy (a), (s, S) policy (b), (R, Q) policy (c) and (R, S) policy (d)

In addition, the initial inventory level, which is determined by multiplying a coefficient, n, specified for each policy by a certain policy parameter, is defined separately for each scenario. In this sense, initial inventory level is considered as ns for (s, Q) inventory policy; nS for (s, S) inventory policy; nQ for (R, Q) inventory policy; and nS for (R, S) inventory policy.

The target observation period is defined as a simulation period, where the maintenance and inventory decisions are allowed to be given randomly and interactively for a period of machine operation. It is a case-specific value determined in a way that the characteristics of all failure modes should be represented in the system. Any downtime due to maintenance and/or stock-out condition is valued in terms of production loss, depending on the unit-time production value of the target system. In the model, the involvement of a spare machine in the operation is neglected, in case of an unexpected downtime. Moreover, component rotation, which can be considered under preventive maintenance actions, is also neglected in the model. While shortage and back-ordering are allowed in each inventory policy, it is assumed that the deterioration of components, imperfect maintenance, and quantity discounts are not possible. Under the required order principles in the policy, it is assumed that an order is placed only if there is no order already placed, and the order quantity is received in a single delivery. In addition, inventory capacity and the number of maintenance crew are not considered as a constraint in the current model even though they can be adapted practically in future studies.

In this regard, the flowchart of the developed algorithm is illustrated in Figure 3.2. There are a main module and two separate but mutually-interactive sub-modules in the algorithm, which are inventory cost and inventory review modules. In brief, the algorithm logic can be explained as follows:

i. System management is provided in the main module. First, an inventory policy and a corresponding simulation scenario are assigned to the system. Then, machine entities are created and introduced into the algorithm. Time between failure (TBF) values of each failure mode and the corresponding repair times (TTR) spent in the maintenance activities are assigned to each component of each entity according to the components' failure and repair characterization.

ii. For each entity, component IDs that will be exposed to any failure, and the corresponding maintenance activities are decided, considering failure detection periods and failure mode superiorities together with the assigned TBF values. Then, it is decided whether the failure mode will cause a repairable or a non-repairable failure condition. If there is a repairable failure, the machine entity proceeds to the maintenance section.

iii. If there is a non-repairable failure and the related inventory level is enough for replacement of the failed component(s), then the machine entity proceeds to the maintenance section after the inventory level (I) is updated. In the case of any stock-out in the inventory, the machine entity waits until a signal, indicating the order has arrived, is received from the inventory review sub-module. Then, after the inventory level is updated regarding the order arrival depending on the lead time (t_{lead}) assigned, the machine entity proceeds to the maintenance section. Then, production loss in terms of time and the corresponding cost value are cumulatively calculated.

iv. The entities arriving at the maintenance section are maintained according to the maintenance activity assigned. The time between failure values, and the corresponding repair times are updated considering the applied maintenance type and the component ID, which failed. Due to stock-out and maintenance activities, production loss values are calculated as indirect operational costs and added to the total system cost (C_t).

v. The inventory cost sub-module evaluates the components in the warehouse and calculates the inventory holding cost at the end of each 24 hours. On the other hand, the inventory review sub-module checks the inventory level and takes action in compliance with the inventory policy available for the operation. Ordering cost, unit purchase cost, and inventory holding cost are calculated as direct operational cost items and added to the total system cost (C_t). These sub-modules and their working principles will be explained in detail in Section 3.3.

vi. When the active observation period (t_a) reaches target observation period (t_t), all machines are withdrawn from the system regardless of the ongoing processes, and all the values assigned specifically to each machine are reset. According to the specified inventory policy, the next simulation scenario is assigned to the system by converting all entities, attributes, and variables into their default and initial positions in the main module. If there is still an ongoing operation of an entity in the system by the time that the target observation period has reached, time interval the entity spent in operation until that moment is calculated and included into the related cost item.

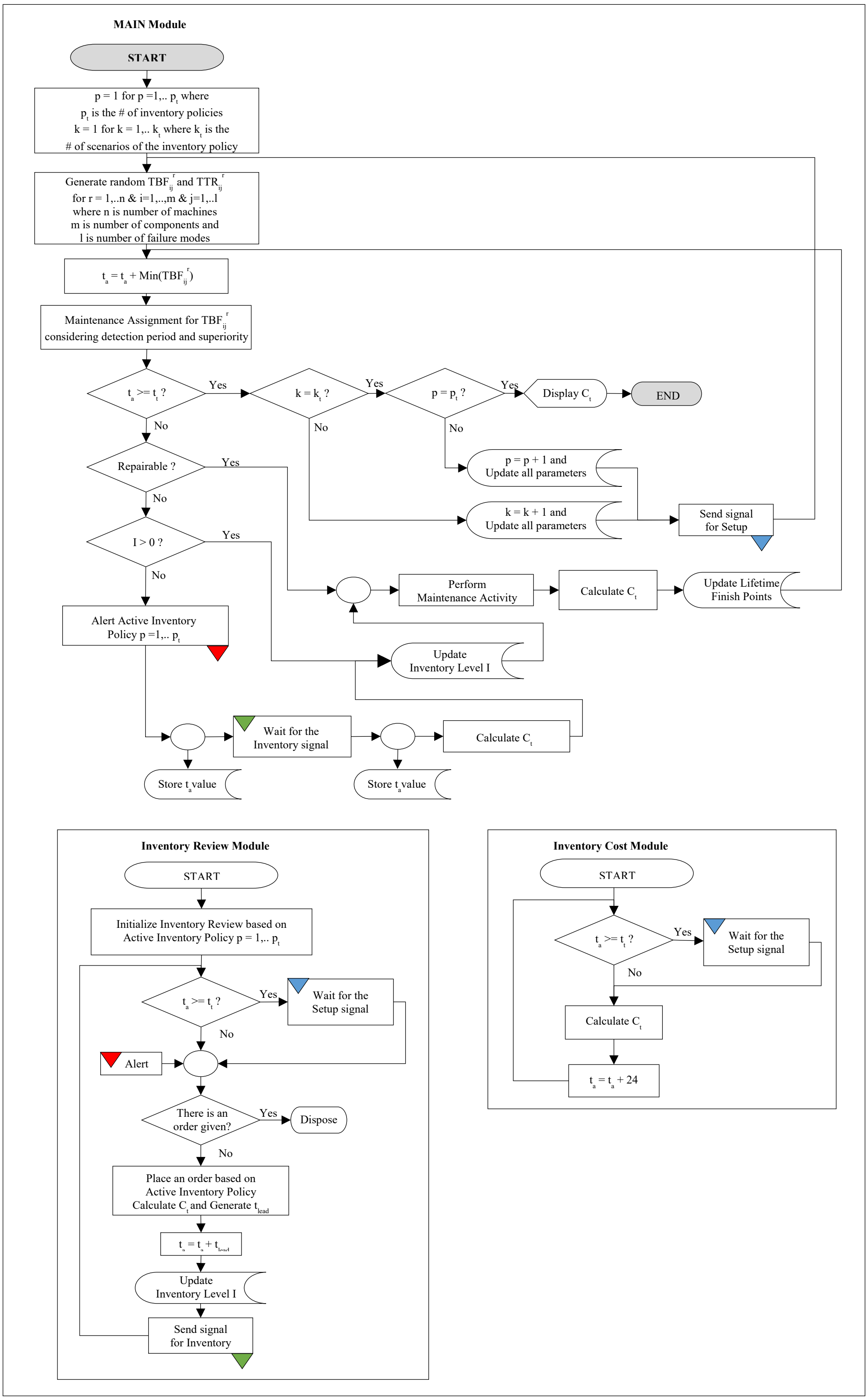


Figure 3.2 Algorithm of the Simulation Model

3.3 Simulation Modeling in Arena

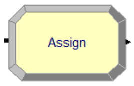
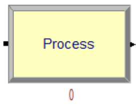
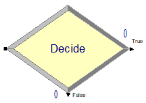
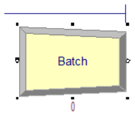
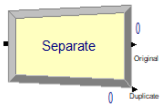
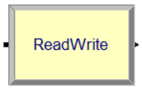
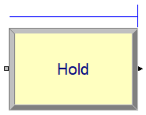
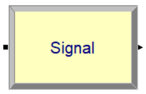
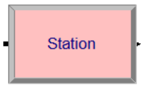
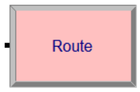
As mentioned in Section 2.5.1, simulation models can be characterized in several aspects. In this study, the developed simulation model is defined as a dynamic, stochastic, and discrete-event model since the system includes random input variables and the system-state changes at a discrete set of points in time. Arena®, a general-purpose simulation software built upon a simulation language called SIMAN, allows simulating discrete, continuous and combined discrete/continuous systems. It has been widely used in various businesses because of ensuring flexibility in modeling and application of complex systems. In this regard, Arena® Software was utilized to develop and execute the multi-scenario inventory simulation model to determine the optimal spare parts inventory policy and parameters.

In Arena®, data modules and flowchart modules are basically used to generate the simulation models. Modules are set of objects storing the information required to simulate a system. Flowchart modules describe the simulation process, while data modules define the characteristics of process elements. Among all the data and flowchart modules, the fundamental ones used in the development of the inventory simulation model are described in Table 3.2 and Table 3.3, respectively.

Table 3.2. *Data Modules and Descriptions in Arena®*

Data Modules	Description
Entity	Defines dynamic objects which are active in the system throughout the simulation.
Attribute	Defines individual characteristics of the entities.
Variable	Defines overall system specifications regardless of the entity attributes.
Expression	Defines mathematical expressions which will be re-evaluated at every new call in the model.
Queue	Defines waiting point for the entities due to any constraint on the resources.
Resource	Defines resources utilized by the entities, such as equipment and people.

Table 3.3 *Flowchart Modules and Descriptions in Arena®*

Flowchart Modules		Description
Create		Creates entities used in the model.
Dispose		Destroys the entities entering the module.
Assign		Assigns any valid expression to a specified attribute or variable.
Process		Defines a particular action, which includes seize, delay, and release processes.
Decide		Directs flow of entities depending on specified conditions.
Batch		Forms a temporary or permanent entity set.
Separate		Duplicates incoming entity or splits entities from an existing temporary entity set.
Record		Records statistics specified in the model.
Read/Write		Reads data from an input file and writes data on an output file.
Hold		Keeps entities in the preceding queue until a prespecified signal received.
Signal		Sends a prespecified signal when entity enters the module.
Station		Represents the entrance point of a station which entities are transferred.
Route		Transfers the entities to the specified station.

In the inventory simulation model, target systems whose components are exposed to failures are introduced as the main entities. There are also two different entity types defined in the model: i) a worker who reviews the inventory level based on the inventory policy, and ii) another worker who calculates the daily inventory holding cost according to the inventory level. Moreover, TBF and TTR expressions are defined initially and their random values are assigned to attributes defined for each component of each machine in the model. Since attributes are unique for each entity, machine IDs, and production loss times are also introduced as attributes, in addition to the assigned TBF and TTR values. Besides, policy type, scenario number, policy parameters, inventory level, inventory capacity, lead time, total production loss time, the target observation period, and all cost items are defined as system variables. Maintenance crew is the only resource in the model. In the model, three types of queues are defined where the machines wait for an order to arrive and the workers wait for the next setup in each sub-module.

The main module, where the system management is achieved by operating the inventory and maintenance decisions for the assigned properties of machines, can be examined in four parts. The first part of the main module, illustrated in Figure 3.3, covers creating entities, assigning system properties to these entities, and giving all the decisions related to inventory and maintenance parameters. First, an inventory policy and a corresponding simulation scenario are assigned to the system. Then, the simulation starts with creating and numbering the entities. The time between failures (TBF), and time to repair (TTR) values of each failure mode are assigned to each component of each machine, according to the components' failure and repair characterizations. The algorithm checks whether the target observation period for the current scenario will expire following the first failure. In that case, the entities are sent to the last part of the main module, where the setup for the new scenario takes place. Otherwise, the failure mode and component ID of the first failure to be experienced are identified, then the corresponding maintenance activity is assigned to the defective component. If there are multiple failures expected to occur at the same time, maintenance operations are scheduled as if a different maintenance activity will be performed for each failure. Then, maintenance plan is updated by considering the failure mode superiorities for the maintenance activities scheduled to be performed. Superiority is a condition observed when a maintenance work being performed also eliminates the other failure for the same component. For instance, replacement of a tire due to impact damage eliminates the cumulative effect of irregular wear available on the component. For this case, failure mode of impact damage is superior to the failure mode of irregular wear. If a superiority condition exists in maintenance activities, then maintenance plans are updated. Considering the maintenance plan updated, repair times for each active maintenance work are identified. Among these repair times, the one with the highest value is defined as the repair time of the current maintenance plan of the machine.

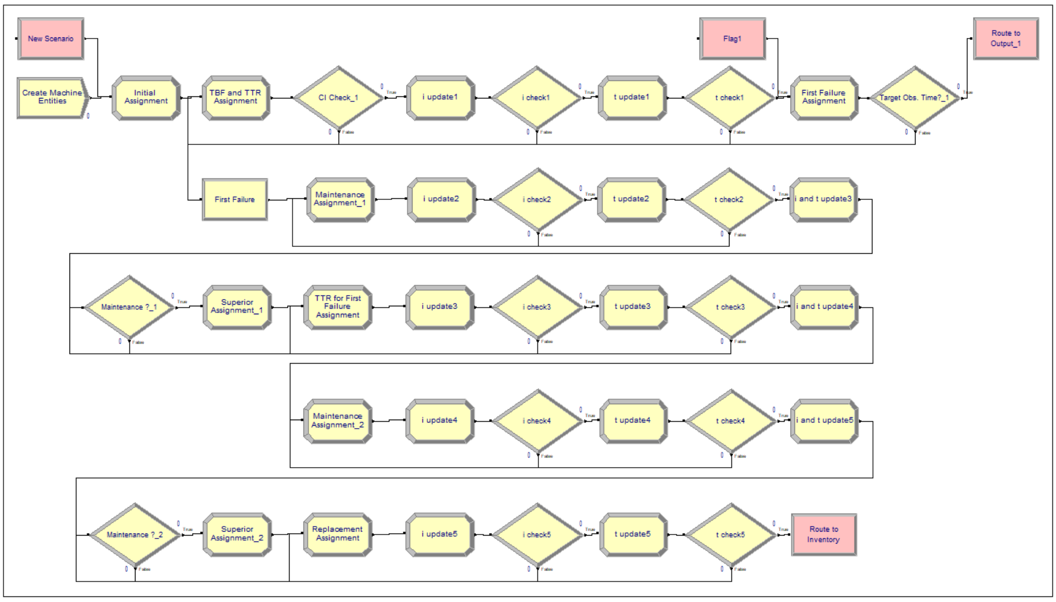


Figure 3.3. Main Module – Part 1

Subsequently, the maintenance plan is updated again considering the failure mode detection periods. If a failure has not yet occurred but is within a failure detection period, during which deterioration can be observed, and if its potential repair time is lower than the repair time of the current maintenance plan multiplied by a certain coefficient, then a maintenance activity is assigned preventively for that failure. The coefficient here is decided administratively. At this point, if the coefficient is taken as one, deteriorated but non-failed component cannot be maintained preventively if its expected maintenance duration is more than the active maintenance duration. This number can be given higher than one if there is any tolerance time additional to the active maintenance duration. Thereafter, considering the failure mode superiorities once again, the maintenance plan is updated one last time and it takes its final form. Finally, the number of components that need replacement is determined for each machine and the machines are transferred to the inventory section.

The second part of the main module, illustrated in Figure 3.4, operates the inventory decisions assigned to each machine. The machines that do not need a component replacement bypass the inventory section and proceed directly to the maintenance section. If there is a non-repairable failure that requires component replacement, inventory level is checked to find out whether there is sufficient inventory or not. If there is enough number of spare parts available, the inventory level is updated regarding the number of components removed from the inventory for maintenance. Then the machine proceeds to the maintenance section. In the case of any stock-out in the inventory, a signal is sent to the inventory review sub-module forcing the inventory to place an order regardless of the working principles of the policy. Activation of this signal requires that there is no order already being waited to arrive. Then, the machine waits in a queue until another signal indicating the order has arrived is received from the inventory review sub-module. Based upon the order arrival, the machines are released one by one from the queue, where they are sorted according to the required component numbers from the lowest to highest. The inventory level is updated considering the number of components removed from the inventory. If the component requirement of all the machines waiting in the queue cannot be met with this fresh lot-order, another signal is sent to the inventory review sub-module. The machines whose spare parts requirements are not met continue to wait in the queue. The algorithm checks whether the target observation period has expired after a machine is released from the queue. In that case, the machines are sent to the last section of the main module, where the setup for the new scenario takes place. Otherwise, for the machines released from the queue, the entrance and exit times are recorded, and the time spent in the queue is calculated in terms of production loss. Considering that the downtime events caused by a stock-out condition may overlap with the planned administrative breaks such as shift and lunch breaks, these downtimes are deducted from the stock-out downtimes to reveal the pure stock-out effect. Hence, production loss cost is calculated as an indirect operational cost item and added to the total system cost. If there is a maintenance scheduled for a repairable failure, it is assumed that this maintenance work is initiated during the production loss period of the machine spent in the queue. Therefore, repair times assigned for these maintenance activities, which are already started, are updated.

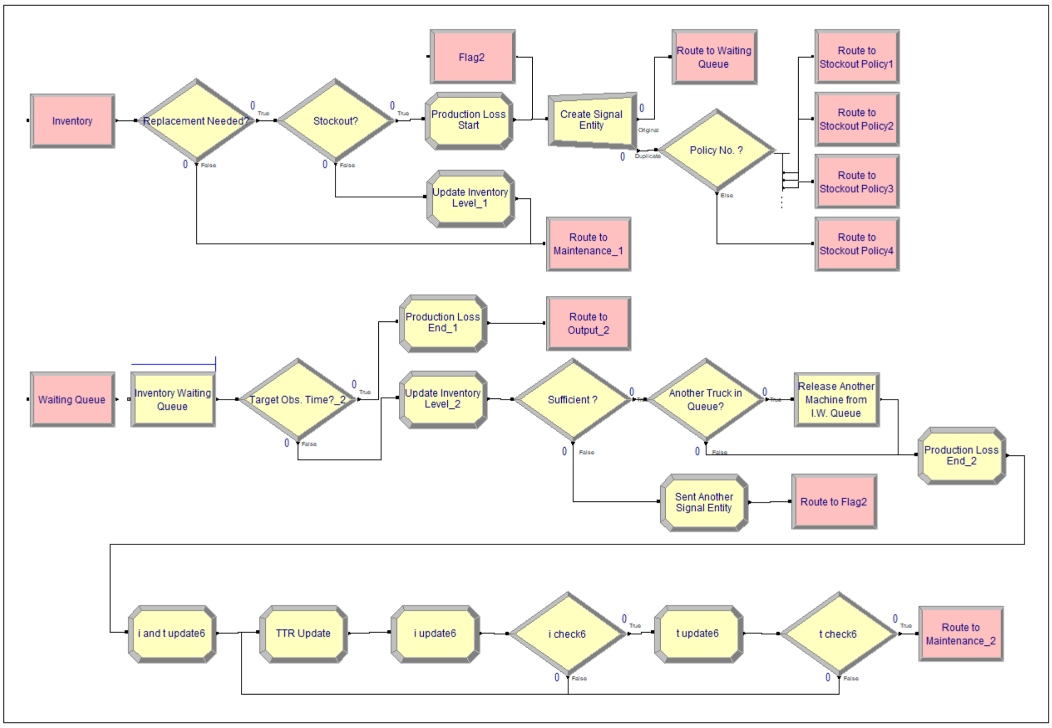


Figure 3.4 Main Module – Part 2

The third part of the main module, illustrated in Figure 3.5, operates the maintenance decisions assigned to each machine. Among the repair times assigned for the active maintenance works, the one with the highest value is defined as the repair time of the current maintenance plan for the machine. The algorithm checks whether the target observation period will expire after the maintenance activity. In that case, the machines are transferred to the last section of the main module, where the setup for the new scenario takes place. Otherwise, the maintenance plan is achieved, and the production interruption during maintenance activities is calculated as production loss time. Since the maintenance downtimes may overlap with the planned administrative breaks, i.e. shift and lunch breaks, these downtimes are reduced by considering the administrative availability of the system. Thus, production loss cost is calculated and added to the total system cost as an indirect operational cost item. Thereafter, time between failure values and the corresponding repair times are updated considering both the active maintenance works and the maintenance works activated due to failure mode superiority. Finally, after the related system variables and attributes are reset, machines are transferred to the first section of the main module where the component ID that is expected to experience the incoming failure, and its failure modes are identified.

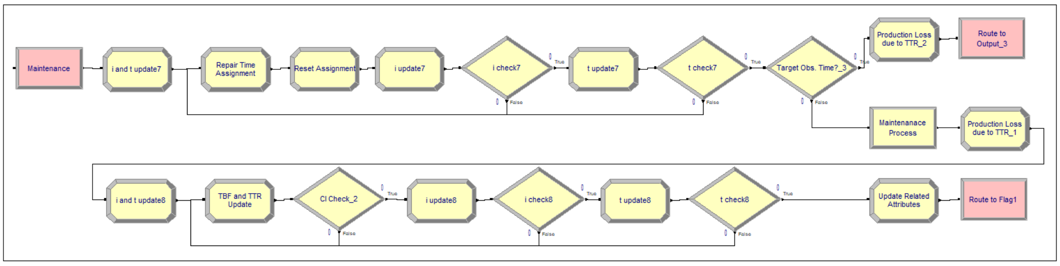


Figure 3.5 Main Module – Part 3

The last part of the main module, illustrated in Figure 3.6, operates the setup decisions taken based on the target observation period. When the target observation period defined for a scenario is over, all machines are withdrawn from the system regardless of the ongoing processes, with a signal to the main module. If there is a machine still being on hold for an order to arrive when the target observation period has expired, this waiting time is calculated and included in the production loss. Similarly, if there is an ongoing maintenance activity when the target observation period expires, the time between the maintenance start time and the last observation time is calculated and included in the production loss. Then, all system variables and attributes of entities are reset. According to the specified inventory policy, the next simulation scenario is assigned to the system, and the target observation period is re-started for the new scenario. Besides, the simulation is replicated until the initial bias is eliminated where a balance point is reached. At the end of each simulation replication, all the cost items calculated for each scenario are recorded as an output data file.

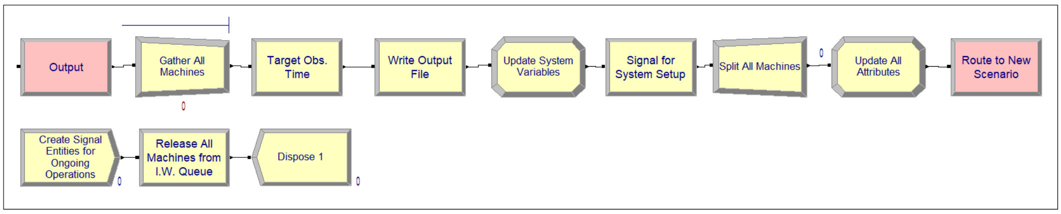


Figure 3.6 Main Module – Part 4

The inventory cost sub-module, illustrated in Figure 3.7, serves for evaluating the cost of the inventory kept. At the end of each day, the inventory records of the component is kept by a worker. Based on the number of components kept in the inventory, the inventory holding cost is calculated as a direct operational cost item and added to the total system cost. When the target observation period has expired, it is waited until the setup of the new scenario is completed.

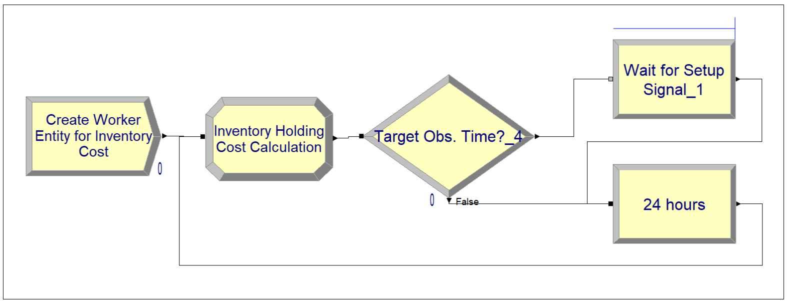


Figure 3.7 Inventory Cost Sub-Module

The inventory review sub-module, where the inventory reviews and the ordering operations are performed based on the working principles of the active inventory policy and corresponding simulation scenario, can be examined in three parts. The first part of this sub-module, illustrated in Figure 3.8, starts with creating worker entities that will perform the reviewing job and the ordering decisions on a continuous or a periodic basis, depending on the active reviewing application under the inventory policy. Then, these entities are sent to one of the four inventory policy sections considering the available inventory policy.

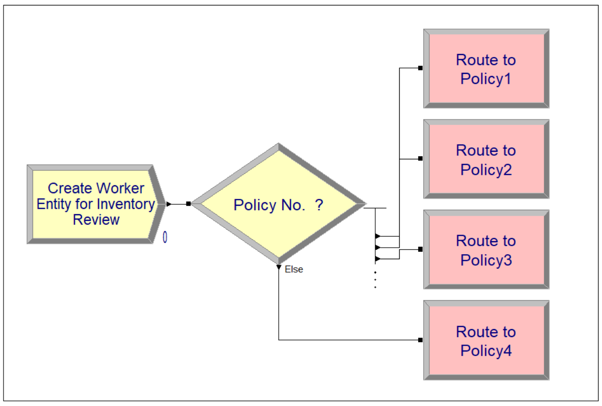


Figure 3.8 Inventory Review Sub-Module – Part 1

The second part of the inventory review sub-module, illustrated in Figure 3.9, operates the inventory review and ordering decisions based on the working principles of the continuous review inventory policies, (s, Q) and (s, S) policies. The inventory level is continuously reviewed depending on a scenario-specific reorder level that triggers the system to place an order. When the inventory level drops below the reorder level s, an order is placed immediately, unless there is an order already being waited to arrive. In addition, receiving a signal from the main module due to machines having a stock-out condition also triggers the system to place an order. Once the ordering process is initiated, the order quantity is determined based on the active inventory policy and the inventory capacity. If the active inventory policy is the (s, Q) policy, the spare parts of a fixed batch size of Q is ordered. On the other hand, if the (s, S) policy is active, the spare parts are ordered up to inventory level S. Herein, it is ensured that the order quantity placed does not exceed the inventory capacity. Then, the ordering and unit purchase costs are calculated as direct operational cost items and added to the total system cost. Thereafter, the lead time of the order in process is assigned to the system. Lead time is considered as the time between creation of a need for placing an order and acquisition of the product. Once an order is received, the inventory level is updated regarding the number of components added to the inventory. Then, a signal indicating that the order has arrived is sent to the main module to release the machines from the inventory waiting queue. When the target observation period has expired, it is waited until the setup of the new scenario is completed. Then, the same operations continue depending on the inventory policy parameters introduced for the new scenario.

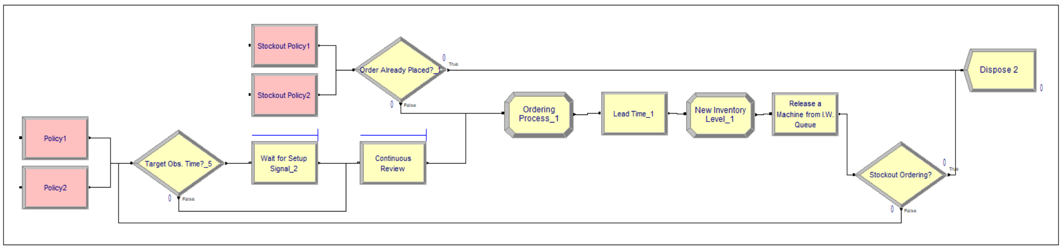


Figure 3.9 Inventory Review Sub-Module – Part 2

The third part of the inventory review sub-module, illustrated in Figure 3.10, operates the inventory review and ordering decisions based on the working principles of the periodic review inventory policies, (R, Q) and (R, S) policies. The inventory level is reviewed at regular time intervals depending on the scenario-specific review period that triggers the system to place an order. When the inventory review period is arrived, an order is placed immediately, unless there is an order already being waited to arrive. In addition, receiving a signal from the main module due to any stock-out condition also triggers the system to place an order, regardless of the review period intervals. These types of orders out of the regular review period in stock-out periods lead to a re-arrangement in the policy. These policies can be called induced periodic review policies. Once the ordering process is initiated, the order quantity is determined based on the active inventory policy and the inventory capacity. If the active inventory policy is the (R, Q) policy, the spare parts of fixed batch size of Q is ordered. If the (R, S) policy is available, then the spare parts are ordered up to inventory level S. Again, it is ensured that the order quantity placed does not exceed the inventory capacity. After this point on, system decisions regarding cost calculation, lead time assignment, and inventory level update are made by following the same track as the second part of the inventory review sub-module. When the target observation period has expired, it is waited until the setup of the new scenario is completed. If the last review period scheduled in the previous scenario is extended to the new scenario, it is eliminated. At this point, a new review period adjustment is ensured for the new scenario. Then, the same operations continue depending on the inventory policy parameters defined for the new scenario.

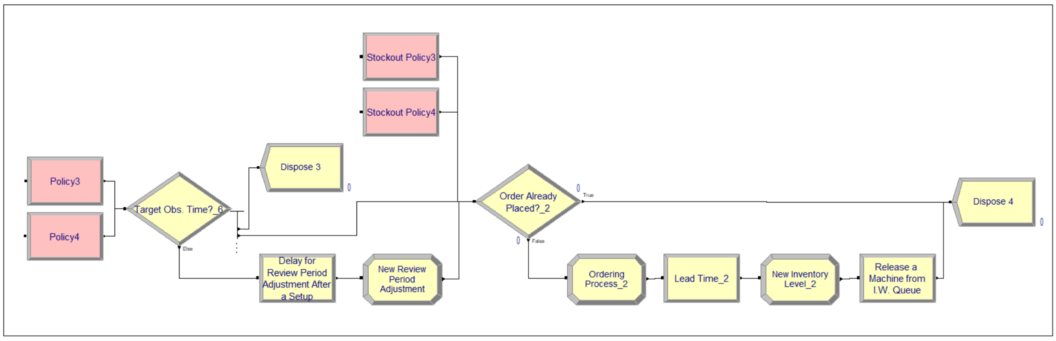


Figure 3.10 Inventory Review Sub-Module – Part 3

CHAPTER 4

ALGORITHM IMPLEMENTATION FOR THE INVENTORY POLICY OPTIMIZATION OF HAUL TRUCK TIRES

4.1 Introduction

In this section, the implementation of the developed simulation model to a tire spare parts inventory system of a truck fleet is represented. On this basis, a real dataset acquired from a surface coal mine and some expert opinions are processed and used as input in the algorithm to reveal the applicability and capability of the model. Input dataset and optimization results will be discussed in detail in Section 4.2.

4.2 Case Study

The proposed discrete-event simulation model was applied to the tires of a truck fleet operating in an open-pit coal mine in Turkey. An identical truck fleet consists of seven trucks having six tires each, as illustrated in Figure 4.1. The dataset covering objective and subjective maintenance data of trucks was provided by the mining company. The inputs derived from the provided dataset, conducted surveys with the experts, and the related machinery catalogues are explained in Section 4.2.1. Finally, the results of the implementation are discussed in Section 4.2.2.

Figure 4.1 Schematic View of Front (a) and Rear (b) Tires of a Truck

4.2.1 Input Dataset of the Algorithm

The quantitative dataset provided by the company consists of maintenance records on truck breakdowns regarding failure occurrence times, repair times, and their brief explanations for a period between 2015 and 2019. The time between failure occurrences include active operating time as well as operational and administrative breaks, such as refueling times, shift changes, and lunch breaks available for the trucks employed in three shifts. There are seven 177 tonne CAT 789C, fifteen 78 tonne Komatsu HD785-1 and twelve 91 tonne Komatsu HD785-7 dump truck records in the dataset. Moreover, maintenance records hold 4,154 and 3,450 different maintenance activities for the CAT and Komatsu trucks, respectively. In the mining industry, tires are frequently used as spare parts in material loading, material hauling, and auxiliary operations under harsh environmental conditions. As mentioned in Section 2.4.1, tires have one of the most noticeable impacts on mining haulage economics as they can account for up to 20% of the operating costs (Meech and Parreira, 2013). Therefore, tires are considered as the target component for the implementation of the inventory management model developed in this study. Due to a lack of sufficient amount of data and explanation in the tire maintenance records of Komatsu dump trucks, the fleet of CAT dump trucks is addressed as the target entity in the case study. Therefore, the fleet included in the model is composed of seven identical trucks having six tires each. CAT 789C trucks are operated with standard 37.00-R57 tires (Caterpillar, 2007), an important element of the inventory management problem since they are capital intensive and may have a great influence on the total operating cost of the haulage operation. The earthmover tires used in this study are radial type tires having 37 in. section width and 57 in. rim diameter (Goodyear, 2016). Typical dimension designations for earthmover tires are illustrated in Figure 4.2.

Before processing of the maintenance data, the human errors covering typing errors and duplicated records were removed from the dataset. Then, considering the failure descriptions in the dataset and the literature review conducted in Section 2.4, tire breakdowns were divided into sub-categories representing four different failure modes, which are deflation, cuts and punctures, impact damage, and irregular wear.

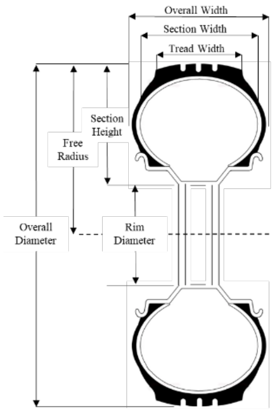


Figure 4.2 General Size Designations for Earthmover Tires

Each failure mode was assigned to different work packages of maintenance activities, established considering the nature of the failure, machinery usage, and the financial risk appetite of the company. For instance, deflation, and cuts and punctures failure modes can be repaired correctively, while the other failure modes require replacement. In this regard, failure modes to be analyzed in this study, their descriptions and typical maintenance actions can be investigated in Table 4.1.

Table 4.1 *Failure Modes and Their Descriptions*

Failure Mode	Code	Failure Description	Maintenance Type
Deflation	F01	Air leaking at the valve core, the valve stem or the bead	Corrective Maintenance
Cuts and Punctures	F02	Piercing through the tread area due to sharp objects	Corrective Maintenance
Impact Damage	F03	Disintegrated tire sidewalls, or delaminated tread and plies	Corrective Replacement
Irregular Wear	F04	Worn out tire surface	Preventive Replacement

Four main failure modes that requires three different maintenance actions are detected as shown in Table 4.1. Corrective maintenance refers to that failed components can be recovered with a repairing activity, without requiring replacement with a new component from inventory. On the other hand, corrective replacement is applied just after failure for the failures where replacing with a new component is the only option and the failed component is not safe or practical to be repaired. Last, preventive replacement is applied before any failure if there is any indicator(s) showing that operating the related component is not safe. Here, irregular wear failure mode will be estimated using suggested formulations where the other failure modes will be characterized using the dataset. Hence, the failure and repair data were assigned to each related failure mode, which are F01, F02 and F03. In this sense, the total maintenance numbers, and the total maintenance durations of each failure mode in the dataset covering a period between 2015 and 2019 are shown in Figure 4.3.

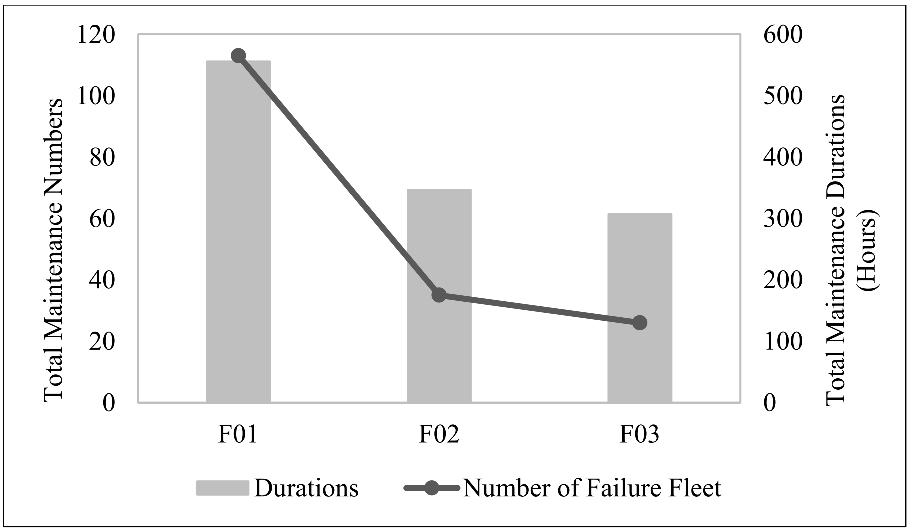


Figure 4.3 Maintenance Numbers and Durations in the Data of F01, F02 and F03

In a 5-year period, the total numbers of failures are observed as 113 for F01, 35 for F02, and 26 for F03. In addition, the total system halts due to maintenance activities are observed as 555.75, 346.75, and 307 hours for the F01, F02 and F03 failure modes, respectively. It is revealed that F03 requiring a component replacement in case of a failure has the lowest occurrence frequency, and total maintenance duration compared to the other two failure modes, for which corrective maintenance is applied.

First, the clustered data is pre-processed to eliminate the outlier values, and evaluate time-dependency, and autocorrelation. Then, each data group is analyzed to determine their representative best-fit distributions or regression equations so that they can be introduced to the algorithm for generating random uptime and downtime values. At this point, allocation and clustering data into groups to be analyzed is performed considering failure modes without considering truck and tire IDs since they are assumed to be identical. Once any random failure occurrence is generated, which truck and tire ID will expose to that failure is determined randomly with uniform (homogeneous behavior) distribution. In this sense, it is assumed that each tire of each individual truck displays the same failure behavior for a certain failure mode, in case that there is no change in maintenance department work intensity in a 5-year period.

In this regard, lifetime and repair time datasets were allocated to the failure modes of the fleet. These datasets were primarily subjected to statistical tests to detect outlier occurrences, independency, autocorrelation, and trend since a non-stationary time series in the analysis affects the uptime/downtime characterization method.

Outliers are extreme and inconsistently very high or very low values, compared to the general behavior of the related dataset. Therefore, elimination of the outlier values is essential to prevent unfavorable deviations that may be encountered in analysis results (Rossi, 2010). Box plots, which are non-parametric tests, indicate the minimum and maximum data values, as well as the 25th (Q_1), 50th (median) and 75th (Q_3) percentile points in the data distribution. The area between Q_1 and Q_3 values of these plots is called the interquartile range (IQR), and any data having a value less than $Q_1 - 1.5xIQR$ or more than $Q_3 + 1.5xIQR$ is generally labelled as outlier. In this sense, box plots were utilized to detect outlier occurrences in lifetime and repair time datasets for each failure mode of the fleet. Hence, the outliers observed in the lifetime dataset of F01, F02, and F03 and labeled as dot symbols can be observed in Figure 4.4.

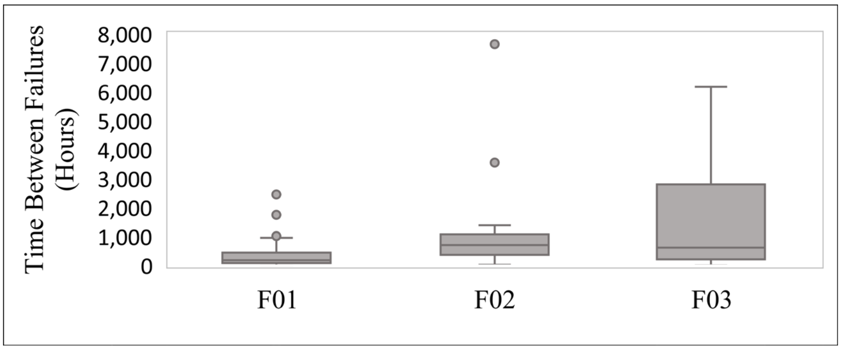
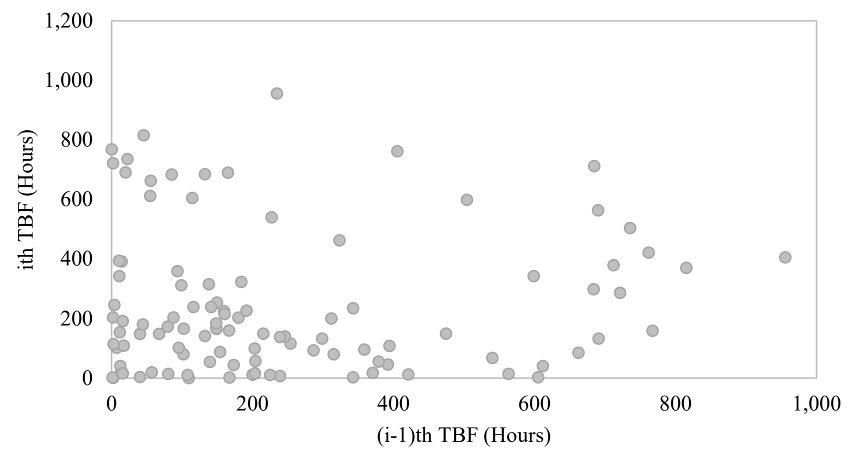


Figure 4.4 Box Plot for Outlier Detection in the Lifetime Data of F01, F02 and F03

After detecting and eliminating the outlier values from the datasets, the Pearson correlation test, and Lag-1 scatter plot were examined to analyze the correlation between the sequential data values. In this sense, the Lag-1 scatter plots were generated using i^{th} and $(i-1)^{th}$ values of the lifetime and repair time datasets for each failure mode of the fleet. The plots, following any particular pattern, can be qualitatively interpreted as an indicator of possible data dependency. Moreover, the Pearson correlation tests where the data typically represents a strong correlation if the coefficient value lies between ± 0.50 and ± 1 were utilized to verify these qualitative observations. As an example, Figure 4.5 shows the Lag-1scatter plot and Pearson correlation test results for the lifetime dataset of F01.



	Pearson Correlation Coefficient	P-value
Lag-1:	0.039	0.694

Figure 4.5 Data Independency Test for the Lifetime Data of F01

The illustrations for the lifetime datasets of F02 and F03 can be viewed in Appendix A. As a result of the independency tests conducted on all lifetime datasets, no data dependency was detected.

Following the independency tests, the stationarity of the datasets was tested for uptime and downtime data behavior in time. Lifetime datasets having a trend behavior indicate that the components are subject to an observable increase or decrease in time between failures data in time. Such a deduction is valid for repairable failure modes, since non-repairable failure modes do not induce aging or improvement conditions in time intervals. If a failure mode is non-repairable or repairable with non-trend behavior, the datasets representing such failure modes are considered as stationary and not subjected to time-dependency. For the stationary datasets, descriptive parameters can be estimated using best-fit distributions. On the other hand, a stochastic process, which can measure increasing/decreasing lifetime trend in the sequential data, can be utilized in parameter estimations, for the non-stationary datasets (Gölbaşı, 2015). As observed in Table 4.1, the third failure mode (F03) is the only non-repairable failure mode. Therefore, its lifetime dataset is already considered stationary. In this regard, the trend behaviors of the lifetime datasets were analyzed only for the repairable failure modes (F01 and F02) by utilizing some quantitative hypothesis tests.

The quantitative hypothesis tests used in this study are Crow-AMSAA, Laplace, Lewis-Robinson, and pairwise comparison nonparametric test (PCNT). Crow/AMSAA and Laplace methods check if the data are suitable for the homogenous Poisson process, where Lewis-Robinson and PCNT methods test if the data can be fitted in an ordinary renewal process. In the ordinary renewal process, it is assumed that a failed component is restored to its original state since the maintenance is performed perfectly, and so the aging problem of the component is neglected. Basically, the ordinary renewal process considers homogeneous Poisson process if the data having a constant failure rate fits into exponential distribution (Gölbaşı, 2015; Høyland and Rausand, 2004). Hence, hypothesis tests can provide robust evidence of whether a time-series follow any trend in time or not.

Crow-AMSAA points to a trend behavior in a dataset if $2N/\hat{\beta} < \chi^2_{2N,1-\alpha/2}$ or $2N/\hat{\beta} > \chi^2_{2N,\alpha/2}$. $\hat{\beta}$ is the expected shape parameter which can be calculated using Equation 4.1, where N is the total failure number, T_i is the arrival time of i[th] failure, $1-\alpha$ is a confidence interval, and $\chi^2_{a,b}$ is the score of chi-square distribution (Gölbaşı, 2015; Wang and Coit, 2005).

$$\hat{\beta} = \frac{N}{\sum_{i=1}^{N-1} \ln\left(\frac{T_N}{T_i}\right)} \tag{4.1}$$

Moreover, in Laplace test, data trend is accepted if $U_L > z_{\alpha/2}$ or $U_L < -z_{\alpha/2}$. U_L is the test statistics and can be calculated using Equation 4.2, where again N is the total failure number, and T_i is the arrival time of i[th] failure (Gölbaşı, 2015; Wang and Coit, 2005).

$$U_L = \frac{\sum_{i=1}^{N-1} T_i - (N-1)\frac{T_N}{2}}{T_N\sqrt{\frac{N-1}{12}}} \tag{4.2}$$

Besides, Lewis-Robinson test points out a trend behavior if $U_{LR} > z_{\alpha/2}$ or $U_{LR} < -z_{\alpha/2}$. U_{LR} is the test statistics and can be calculated using Equation 4.3, where $CV[X]$ is the coefficient of variance, and X is the time between failure data (Gölbaşı, 2015; Wang and Coit, 2005).

$$U_{LR} = \frac{U_L}{CV[X]} \tag{4.3}$$

Finally, pairwise comparison nonparametric test PCNT accepts a trend behavior in a dataset if $U_p > z_{\alpha/2}$ or $U_p < -z_{\alpha/2}$. U_p is the test statistics and can be calculated using Equation 4.4, where N is the total failure number, and U is the number of instances in which $X_j > X_i$ for $j < i$ (Gölbaşı, 2015; Wang and Coit, 2005).

$$U_p = \frac{U - N(N-1)/4}{\sqrt{\frac{(2N+5)(N-1)N}{72}}} \tag{4.4}$$

In the light of this information, the trend behaviors of lifetime datasets for F01 and F02 failure modes of the fleet were analyzed using quantitative hypothesis trend tests with a 95% confidence interval. The test results for the lifetime datasets are shown in Table 4.2. Hence, it was observed that each failure mode has a stationary lifetime dataset with non-trend behaviors.

Table 4.2 *Trend Analysis for the Lifetime Data of F01 and F02*

Test Name	**Test Statistics**	**F01**	**F02**
Crow-AMSAA	$2N/\hat{\beta}$	209.8	55.8
	$\chi^2_{2N,1-\alpha/2}$	171.8	43.8
	$\chi^2_{2N,\alpha/2}$	252.0	88.0
	Decision	No Trend	No Trend
Laplace	U_L	0.05	0.07
	$z_{\alpha/2}$	1.96	1.96
	Decision	No Trend	No Trend
Lewis-Robinson	U_{LR}	0.05	0.11
	$z_{\alpha/2}$	1.96	1.96
	Decision	No Trend	No Trend
PCNT	U_p	0.56	-0.19
	$z_{\alpha/2}$	1.96	1.96
	Decision	No Trend	No Trend

Non-trend lifetime data behavior indicates that failure modes exhibit almost predictable lifetime values within a specific range, without any time effect. Moreover, it was assumed that each tire of each individual truck displays a similar failure behavior for a certain failure mode. This assumption indicates that the identical fleet includes similar-behavior trucks, having similar-behavior tires, which can be represented by same uptime and downtime characterizations. Thus, the datasets were fitted into best distributions to determine the uptime characterizations, using the records of whole fleet jointly for each failure mode. Parametric values of lifetime functions for each failure mode are represented in Table 4.3 and corresponding probability density functions are shown in Figure 4.6.

Table 4.3 *Lifetime Parameters of F01, F02 and F03*

Code	Model	Parameter	P-value
F01	Weibull-2P	$\beta = 0.84$; $\eta = 1437$	0.241
F02	Lognormal-2P	$\mu' = 8.1$; $\sigma' = 1.13$	0.582
F03	Weibull-2P	$\beta = 1$; $\eta = 10025$	>0.25

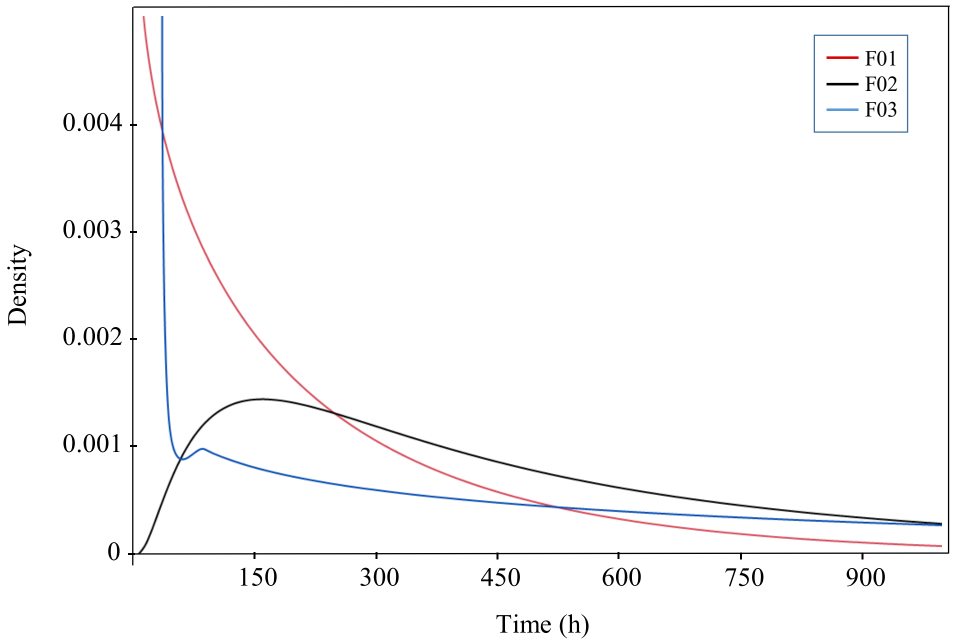


Figure 4.6 Probability Density Functions of Lifetime Dataset for F01, F02 and F03

Considering the statistics in Table 4.3, it is observed that time between failure (TBF) characterization can be qualified using Weibull distribution for the first and the third failure mode, while it can be identified using lognormal distribution for the second failure mode.

In addition, since there was no certain distinction regarding the failed tire position in the maintenance records, the time between failure (TBF) assignments in the model were slightly modified to be compatible with the dataset. In this regard, random lifetime values regarding each failure mode will be generated first, using the lifetime distribution parameters in Table 4.3. Then, a specific tire of a specific truck will be determined randomly using uniform distribution for assigning the incoming failure modes to a certain component. Uniform distribution here shows that each tire in each truck has same probability to be exposed to the failure modes. This process is performed in the same manner for all three failure modes.

After the lifetime parameters were determined, the repair time datasets of each failure mode were processed to detect outlier occurrences, independency, autocorrelation and trend. After the detection and elimination of the outlier values in the datasets, the Pearson correlation test, and Lag-1 scatter plot were analyzed. The independency tests on the repair time datasets of each failure mode show no data dependency. Then, the trend behaviors of the repair time datasets were examined by using quantitative hypothesis tests with a 95% confidence interval. Table 4.4 represents the results of the hypothesis tests. Since the third and the fourth failure modes (F03 and F04) requires a component replacement in case of a failure, TTR of F04 was assumed to be same with F03, since there is lack of enough data for F04 in maintenance records.

Table 4.4 *Trend Analysis for the Repair Time Data of F01, F02, F03 and F04*

Test Name	**Test Statistics**	**F01**	**F02**	**F03**	**F04**
Crow-AMSAA	$2N/\hat{\beta}$	377.2	82.1	44.0	44.0
	$\chi^2_{2N,1-\alpha/2}$	180.8	50.4	32.4	32.4
	$\chi^2_{2N,\alpha/2}$	263.0	97.4	71.4	71.4
	Decision	Trend	No Trend	No Trend	No Trend
Laplace	U_L	-6.31	-1.14	-0.14	-0.14
	$z_{\alpha/2}$	1.96	1.96	1.96	1.96
	Decision	Trend	No Trend	No Trend	No Trend
Lewis-Robinson	U_{LR}	-5.75	-2.12	-0.27	-0.27
	$z_{\alpha/2}$	1.96	1.96	1.96	1.96
	Decision	Trend	Trend	No Trend	No Trend
PCNT	U_p	2.72	1.53	0.51	0.51
	$z_{\alpha/2}$	1.96	1.96	1.96	1.96
	Decision	Trend	No Trend	No Trend	No Trend

Repair time characteristic parameters for the failure mode datasets showing non-trend behavior were estimated via best-fit distributions. On the other hand, F01 showing a trend behavior were processed via a stochastic process called General

Renewal process (GRP) following the assumption of an intervention of maintenance only influence on the time since the last intervention. Observing a trend behavior in the repair time dataset can be caused by having an incapable maintenance crew, employing inadequate number of maintenance crew, improper allocation of the crew into the work packages, and/or increased failure frequency in the operating area. Accordingly, parametric values of repair time functions for each failure mode are represented in Table 4.5 and corresponding probability density functions are shown in Figure 4.7.

Table 4.5 *Repair Time Parameters of F01, F02, F03 and F04*

Code	**Model**	**Parameters**	**P-value**
F01	GRP	β = 0.5; η = 0.16; RF = 0.76	Not iid*
F02	Weibull-2P	β = 2; η = 10.8	>0.25
F03	Lognormal-2P	μ' = 2.15; σ' = 0.5	0.877
F04	Lognormal-2P	μ' = 2.15; σ' = 0.5	0.877

* *Not identically and independently distributed*

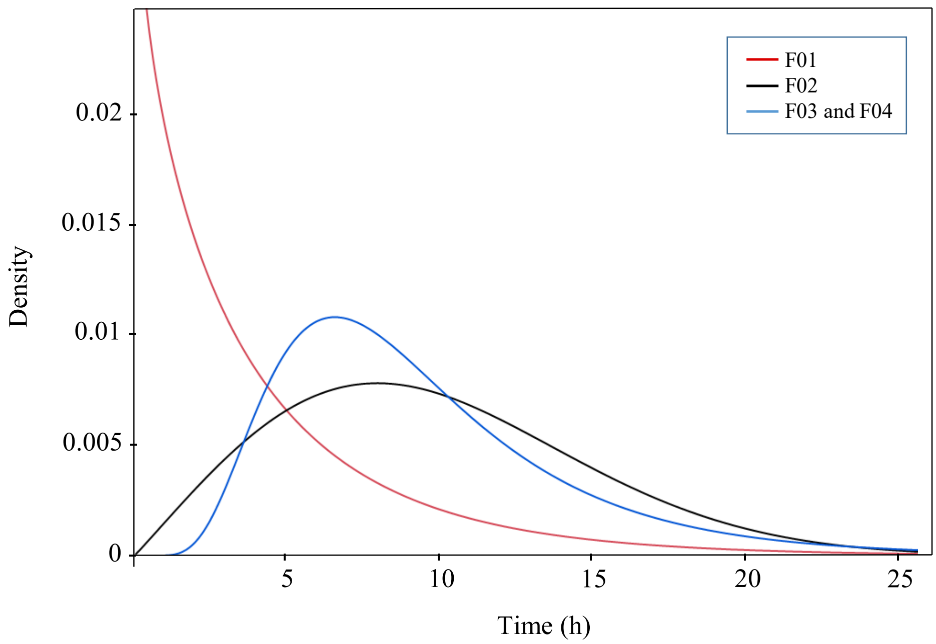


Figure 4.7 Probability Density Functions of Repair Time Dataset for F01, F02, F03 and F04

Considering the statistics in Table 4.5, it is observed that time to repair (TTR) characterization can be identified using Weibull distribution for F02, while it can be qualified using lognormal distribution for F03 and F04. On the other hand, General Renewal Process (GRP) was performed for F01 so that the process allows determining Weibull-2P parameters.

GRP is a stochastic process utilizing consecutive event points of a system in a time period, without considering event frequency used in best-fit distributions. In addition, the ordinary renewal and non-homogenous Poisson processes are also commonly used stochastic methods. In general, the ordinary renewal process assumes that the system is restored to as good as new condition by achieving a perfect repair, while non-homogenous Poisson process considers that the system is restored to as bad as old condition by performing a minimal repair. On the other hand, GRP assumes that the system can be restored to a condition between as good as new and as bad as old. This process utilizes the Kijima's imperfect maintenance parameter using the degree of repair (q) in a range between 0 and 1, or the restoration factor (RF), where RF = 1-q. Thus, if the restoration factor equals to 0 or 1, General Renewal Process turns to non-homogenous Poisson process or ordinary renewal process, respectively. Besides, General Renewal Process is qualified using the parameters of Weibull-2P distribution (Gölbaşı, 2015).

In addition, an auxiliary simulation model was computed to obtain the time between tire wear occurrences for the lifetime characterization of F04, since it is required as an input in the model. This auxiliary model was built up based on a study conducted by Kına (2021) where a truck dispatching algorithm was developed to reveal the dynamic interactions between truck and road to calculate fuel consumption and mine production per period. In the study, different truck characteristics such as truck models, payload capacities, and speed profiles as well as road characteristics such as lengths, grades, and surface conditions were introduced to a discrete-event simulation model (Kına, 2021).

Stochastic processes in the truck dispatching model, related to speed profiles, truck cycle times, and payloads, were converted to a deterministic state considering the operational specifications of CAT 789C used in the inventory management model. In addition, the original model structure estimating fuel consumption and mine production was modified to be able to forecast the tire service life, i.e. the time between the tire wear occurrences. Within its tire life estimating system, Goodyear Tire and Rubber Co. has provided the average tire life estimations based on tire types, as well as the quantitative factors affecting the tire life regarding truck and road specifications (Caterpillar, 2014). Thus, the tire service life estimation was achieved by integrating the related average tire life and factors into the modified truck dispatching model. In this regard, according to the information by Goodyear Tire and Rubber Co., Table 4.6 represents the factor values changing based on the truck and road conditions and Table 4.7 shows the average tire life depending on tire types

Table 4.6 *Tire Service Life Estimation Factors (Caterpillar, 2014)*

Condition	**Factor**	**Condition**	**Factor**
Maintenance		Speeds (Max.)	
Excellent	1.090	16 km/h	1.090
Average	0.981	32 km/h	0.872
Poor	0.763	48 km/h	0.763
Surface Conditions		Wheel Positions	
Soft Earth - No Rock	1.090	Trailing	1.090
Soft Earth - Some Rock	0.981	Front	0.981
Well Maintained	0.981	Driver (Rear Dump)	0.872
Poorly Maintained	0.763	Driver (Bottom Dump)	0.763
Blasted - Sharp Rock	0.654	Driver (Self Propelled Scraper)	0.654
Curves		Grades (Drive Tires Only)	
None	1.090	Level	1.090
Medium	0.981	5% Max.	0.981
Severe	0.872	15% Max.	0.763
Loads		Other Miscellaneous Combinations	
Recommended Load	1.090	None	1.090
20% Overload	0.872	Medium	0.981
40% Overload	0.545	Severe	0.872

Table 4.7 *Base Average Life Depending on Tire Type (Caterpillar, 2014)*

Type of Tire	**Base Average Life**	
	Hours	km
E-3 Std. Bias Tread	2,510	40,400
E-4 Bias Xtra Tread	3,510	56,500
E-4 Radial Xtra Tread	4,200	67,600

Within this context, the tire service life can be estimated by multiplying the base average tire life by the appropriate factors determined for each condition (Caterpillar, 2014). These factors were determined considering the operational specifications of CAT 789C and the road conditions defined in truck dispatching model. In this sense, since the type of tire is E-4 Radial, the base average tire life was indicated as 4,200 hours. Moreover, the excellent road maintenance and the recommended payload were assumed to be achieved, while the other miscellaneous combinations were neglected. In addition, factors related to speed, surface condition, curves and grades were determined separately for each road depending on the road specifications. Finally, the factor regarding wheel position was specified for front and rear tires separately. Thus, the tire service life estimation was achieved by integrating the identified average tire life and the factors into the modified truck dispatching model.

Using the output of the auxiliary simulation model, the lifetime dataset of the fourth failure mode (F04) was generated. In the dataset, the time between failure occurrences include active operating time as well as operational and administrative breaks. In addition, the lifetime dataset was decomposed into tire components with respect to wheel positions, and the uptime characterizations were analyzed for each tire separately. It was assumed that the identical fleet includes identical trucks, but nonidentical tires in terms of F04. Therefore, uptime characterization of F04 was performed considering tire positions.

Since F04 is a non-repairable failure mode, the lifetime datasets of this failure mode was considered as stationary. Therefore, the parameters were estimated using best-fit distributions. Parametric values of lifetime functions of F04 determined for each tire are represented in Table 4.8 and corresponding probability density functions are shown in Figure 4.8. It is observed that time between failure (TBF) characterizations of F04 can be identified using Johnson Transformation with unbounded distribution type for each tire.

Table 4.8 *Lifetime Parameters of F04*

Wheel Position	**Model**	**Parameters**	**P-value**
Left Front	Johnson Trans.	γ=-0.38; δ=0.68; ε=15.8; λ=5001	0.80
Right Front	Johnson Trans.	γ=-0.93; δ=0.43; ε=8.8; λ=4988	0.32
Left Rear Outer	Johnson Trans.	γ=-0.83; δ=0.37; ε=2.9; λ=4895	0.15
Left Rear Inner	Johnson Trans.	γ=-0.35; δ=0.28; ε=8.9; λ=4909	0.16
Right Rear Inner	Johnson Trans.	γ=-0.40; δ=0.37; ε=11.0; λ=4904	0.21
Right Rear Outer	Johnson Trans.	γ=-0.94; δ=0.40; ε=4.5; λ=4895	0.18

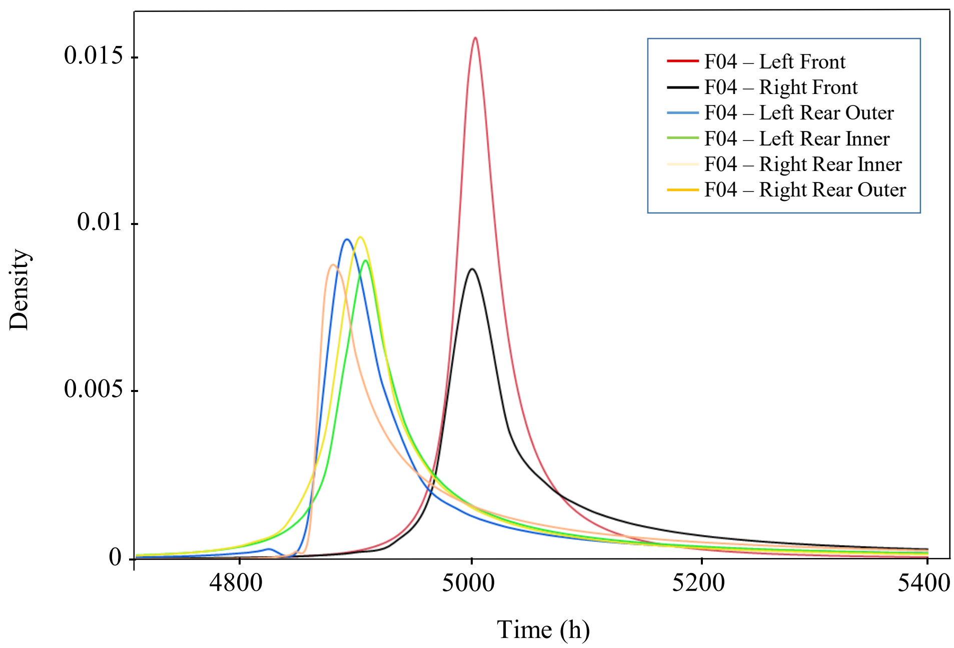


Figure 4.8 Probability Density Functions of Lifetime Dataset for F04

Moreover, the confidence intervals using a 95% confidence level were constructed for each distribution identified in statistical analysis, in order to indicate the upper and lower bounds of TBF and TTR values to be assigned in the model. These bounds representing minimum and maximum values of TBF and TTR can be examined in the table in Appendix B.

Besides the quantitative dataset provided by the company, some subjective data was also acquired covering the expert opinions on the expected inventory cost items. The cost of production loss per hour was considered as the lost revenue of the haulage operations due to system halts, and assumed to be 1.8 \$/bank m^3 material haulage. Estimated values of purchasing cost for Goodyear 37.00-R57 type tire, fixed ordering cost, inventory holding cost, and production loss cost used in the model are summarized in Table 4.9. In addition, lead time was assumed to be uniformly distributed between 20 and 30 days, regardless of the batch size of the order. Herein, lead time was considered as the time between the point where an order needs to be placed, and acquisition of the product, including administrative approval, order placement, and shipping processes.

Table 4.9 *Estimated Cost Values*

Cost Items	**Costs ($)**
Unit purchasing cost of a component	30,000
Ordering cost per order	300
Inventory holding cost per day per item	10
Production loss cost per hour per truck	300

In addition, as mentioned in Section 3.2, the initial inventory level is a scenario-specific value and determined by multiplying a coefficient, n, specified for each policy by a certain policy parameter. Hence, the initial inventory level was considered as ns for (s, Q) inventory policy; nS for (s, S) inventory policy; nQ for (R, Q) inventory policy; and nS for (R, S) inventory policy. In this sense, the coefficient of n was assumed as 2 for (s, Q) and (R, Q) inventory policies, and 1 for (s, S) and (R, S) inventory policies. Moreover, inventory capacity and the number of maintenance crew were not constrained.

Furthermore, the downtimes caused by stock-out and maintenance activities may overlap with the planned administrative breaks, such as shift and lunch breaks. Considering that there are three 30-minute shift breaks and 1-hour lunch break in a day, the trucks are expected to operate for 21.5 hours a day. Thus, the administrative availability of the trucks was calculated as 90%. Therefore, administrative halts are dropped from the downtime for achieving an unbiased downtime calculation caused by maintenance activities and potential stock-out conditions.

As mentioned in Section 3.3, the other input parameters in the algorithm are the failure detection periods, and failure mode superiorities for each failure mode. If a failure has not yet occurred but is within a failure detection period during which deterioration can be observed, a preventive maintenance can be performed for that upcoming failure mode. For such a case, duration of this preventive action should be lower than allowable limits, which is the multiplier of the active maintenance duration. This multiplier can be assigned administratively. In this sense, considering the F02 and F03 cannot be detected in advance of the failure occurrence, failure detection periods were identified only for the F01 and F04. It was assumed that the deterioration due to F01 and F04 can be observed by the operators checking the truck using pre-start checklists just before the shift. Thus, the failure detection period for F01 and F04 was assumed as 8 hours while it was neglected for F02 and F03. In addition, the coefficient utilized to check the failure detection period condition and multiplied by the repair time of the current maintenance plan was assumed as a comparably large value. Besides, recall that superiority is a condition observed when a maintenance operation being performed also repairs some other failure mode(s) inherently for the same tire. In this context, Table 4.10 consisting of binary variables, indicates the superiorities among the failure modes. If a superiority on any failure mode is available, the superior failure mode takes the value of 1. For example, F01 is not a superior to any failure mode, while F02 is a superior to F01. Besides, each failure mode is a natural superior to itself.

Table 4.10 *Failure Mode Superiorities*

Superiorities	F01	F02	F03	F04
$F01_{sup}$	1	0	0	0
$F02_{sup}$	1	1	0	0
$F03_{sup}$	1	0	1	1
$F04_{sup}$	1	0	0	1

4.2.2 Results and Discussion of the Optimization Outputs

After processing and introducing the input dataset, the developed algorithm is computed to find out the most cost-effective inventory policy and its parameters among multiple scenarios, including different inventory policy types with different triggering mechanisms. Due to stochasticity embedded in the algorithm, the model with a 5-year observation period was simulated 500 times for each scenario. As represented in Figure 4.9, the average annual inventory system cost of the scenario of (s, Q) inventory policy, defined as (2, 20), becomes stable after 230th simulation. It means that 230 simulation of a 5-year period is a good representative of the inventory system analyzed using the given dataset.

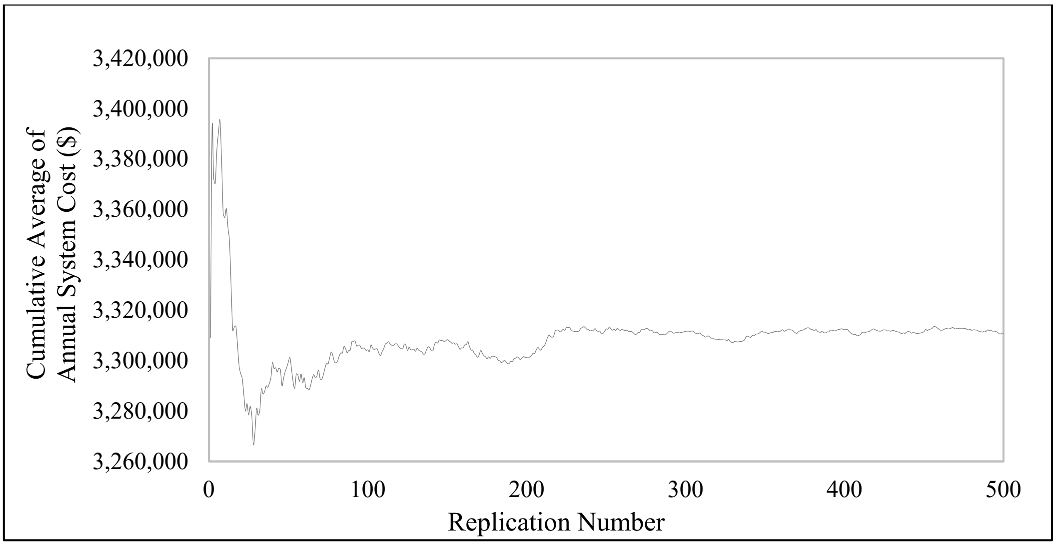


Figure 4.9 Cumulative Average of Annual System Cost Results by Increased Replication Number for the Scenario (2, 20) of the (s, Q) Inventory Policy

The continuous and periodic inventory policies have been analyzed and discussed separately, since their dynamics and implementation principles differ. For each inventory policy, different number of scenarios were defined where the policy parameters vary in the different ranges. Thus, the range of analysis utilized for the case study is summarized in Table 4.11.

Table 4.11 *Range of Analysis*

Inventory Policy	Parameters	Minimum	Maximum	Number of Scenarios
(s, Q)	s	0	10	156
	Q	20	46	
(s, S)	s	5	12	122
	S	25	60	
(R, Q)	*R	2,880	7,200	124
	Q	5	70	
(R, S)	*R	24	3,600	99
	S	20	60	

** in hours* *Total* *501*

The analysis results for the continuous inventory policies in terms of the average annual inventory system cost are shown in Figure 4.10 and Figure 4.11 for the (s, Q) and (s, S) policies, respectively.

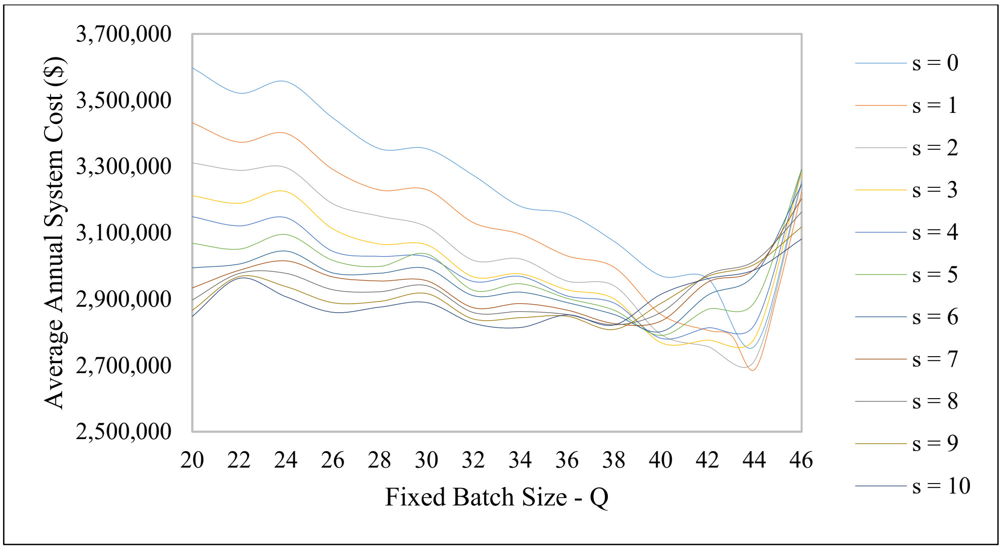


Figure 4.10 Average Annual System Cost Results for the (s, Q) Policies

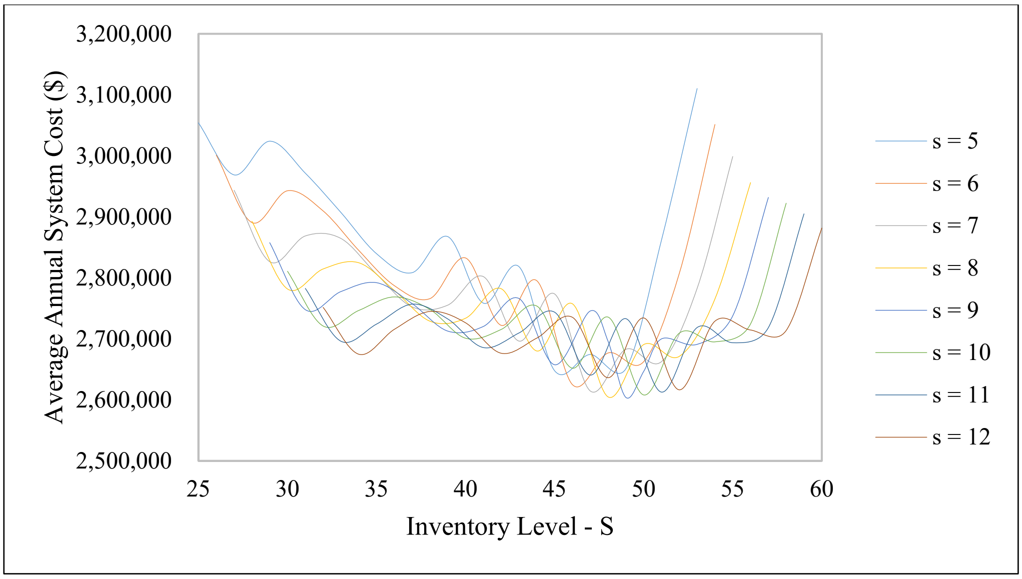


Figure 4.11 Average Annual System Cost Results for the (s, S) Policies

For the (s, Q) inventory policy, fixed batch size Q was incremented by 2 for each safety stock level increased one by one. In addition, fixed batch size Q was incremented one by one for the safety level where the minimum point was achieved so that a total of 156 scenarios was simulated for 5-years period and 500 times each. According to the results, the optimal scenario was achieved as (1, 44) among 156 number of scenarios. Thus, annual system cost of $2,687,958 was reached where the fixed batch size of 44 is ordered whenever the number of components in the inventory drops to 1. On the other hand, for (s, S) inventory policy, different starting and ending points were defined, considering the ranges in which the trade-off of the system can be effectively observed for each scenario. Similarly, inventory level S was incremented by 2 for each safety stock level increased one by one. Again, inventory level S was incremented one by one for the safety level where the minimum point was achieved and an annual system cost value is obtained for the given s and S values each time. According to the results, the optimal scenario was achieved as (9, 49) among 122 different scenarios. Thus, an annual system cost of $2,604,032 was obtained where spare parts are ordered up to inventory level 49 whenever the number of components in the inventory drops to 9. Comparing the best scenarios of these two policies, the scenario defined as (9, 49) of the inventory policy (s, S), observed to be more financially effective, was obtained as the most optimal scenario of the continuous review inventory policies.

Besides, the analysis results for the periodic inventory policies in terms of average annual inventory system cost for each scenario are shown in Figure 4.12 and Figure 4.13 for the (R, Q) and (R, S) policies, respectively.

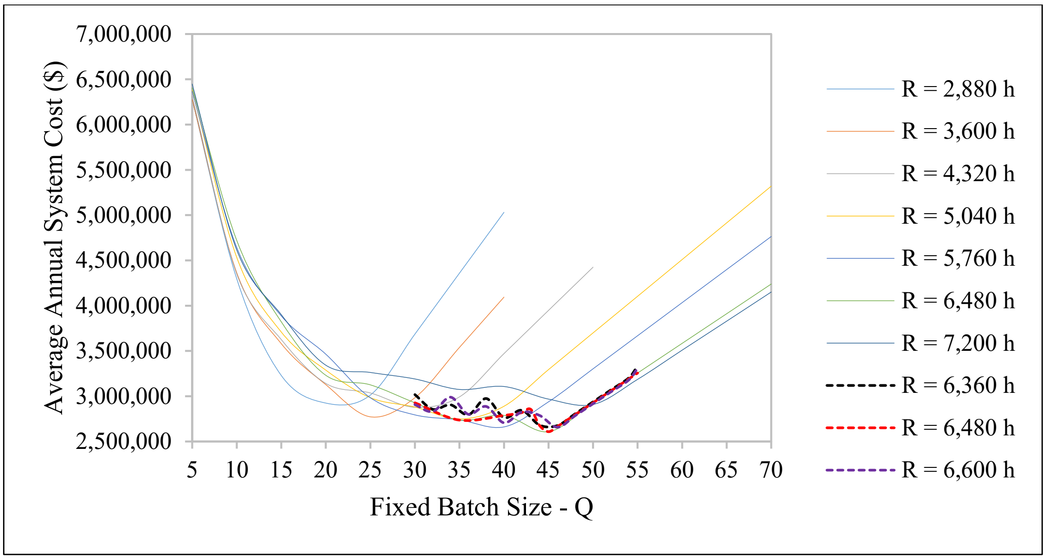


Figure 4.12 Average Annual System Cost Results for the (R, Q) Policies

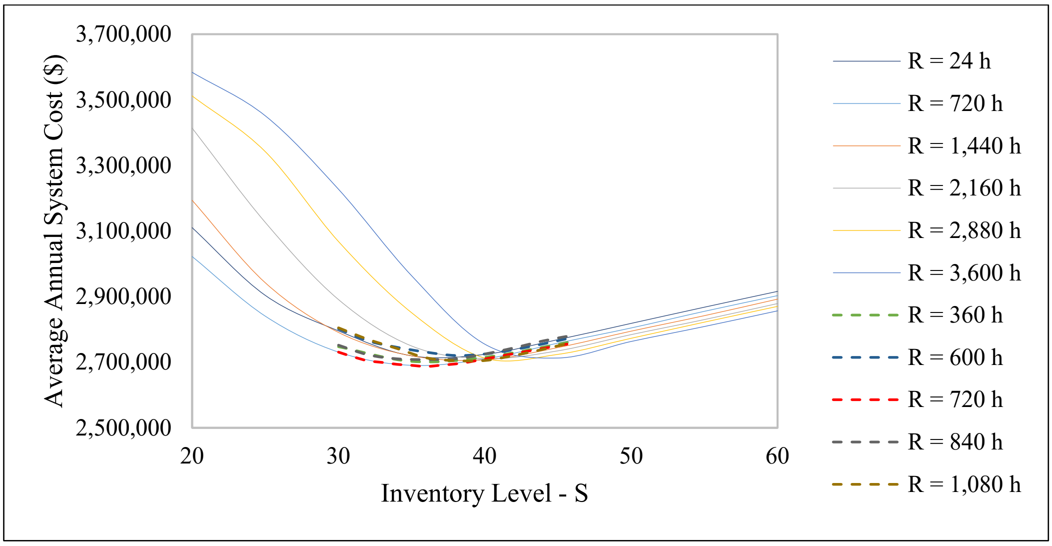


Figure 4.13 Average Annual System Cost Results for the (R, S) Policies

For (R, Q) the inventory policy, the fixed batch size Q was incremented by 5 where the review period R was incremented by one month. The minimum point of the analysis was observed to be the scenario (6,480, 45), and a detailed analysis was performed around the minimum point. At this point, as it is indicated in the dashed lines in Figure 4.12, the fixed batch size Q was incremented by 2, and the review period R was updated as ± 5 days of to the minimum point for a better investigation. According to the results, the optimal scenario was achieved as (6,480, 45) among 124 scenarios. Thus, an annual system cost of $2,608,617 was obtained where the fixed batch size of 45 is ordered in every 6,480h.

On the other hand, for (R, S) inventory policy, the inventory level S was incremented by 5, while the review period R was examined by monthly increments. The minimized value was observed at the scenario (720, 35) and a more detailed analysis was performed around this minimized value. Accordingly, as indicated in the dashed lines in Figure 4.13, the interval increment for inventory level S was taken as 2. Moreover, the review period R was updated to cover fifteen and five days before and after the review period captured at the minimum point. According to the results, the optimal scenario was achieved as (720, 36) among 99 scenarios. Thus, annual system cost of $2,686,966 was observed where the fixed batch size of 36 is ordered in every 720h. Comparing the optimal scenarios of these two policies, the scenario defined as (6,480, 45) of the inventory policy (R, Q), more financially effective, was obtained as the most optimal scenario of the periodic review inventory policies.

As stated in Section 3.3, for periodic review inventory policies, the model may allow an order to be placed when a truck experiences a stock-out condition, even if the next review period has not arrived yet. If such conditions are experienced, these policies can be called induced periodic review policies. Herein, non-induced periodic review policies were defined that neglects this triggering mechanism. Thus, the model has been modified in a way that an order is placed only if the review period has arrived. For these non-induced periodic review inventory policies, investigation ranges and number of scenarios were defined exactly same with the induced periodic review inventory policies, except for the minor scale analyses. The analysis results of non-induced periodic inventory policies in terms of annual inventory cost for each scenario are shown in Figure 4.14 and Figure 4.15 for non-induced (R, Q) and non-induced (R, S) policies, respectively.

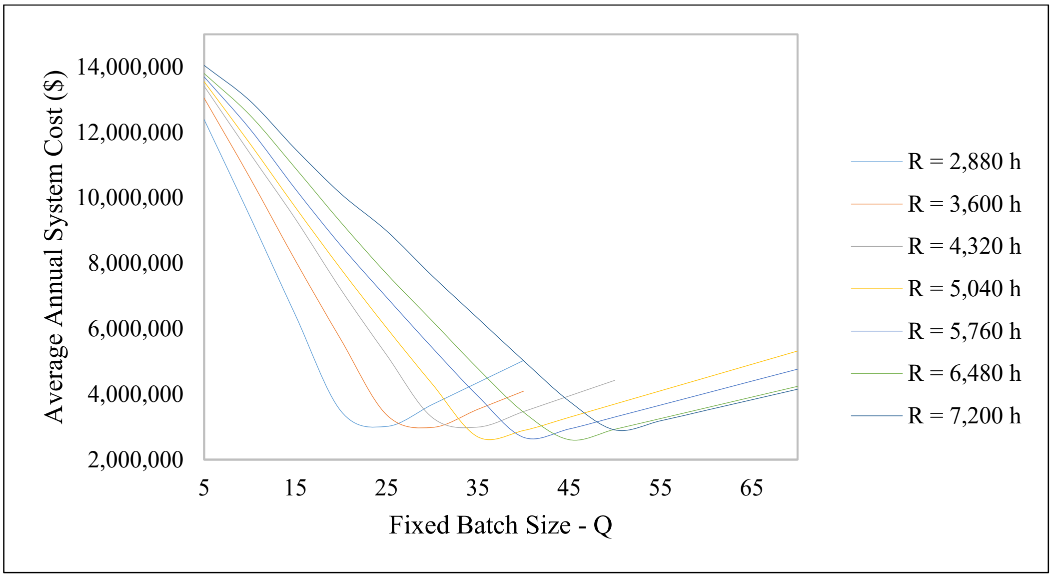


Figure 4.14 Average Annual System Cost Results for Non-Induced the (R, Q) Policies

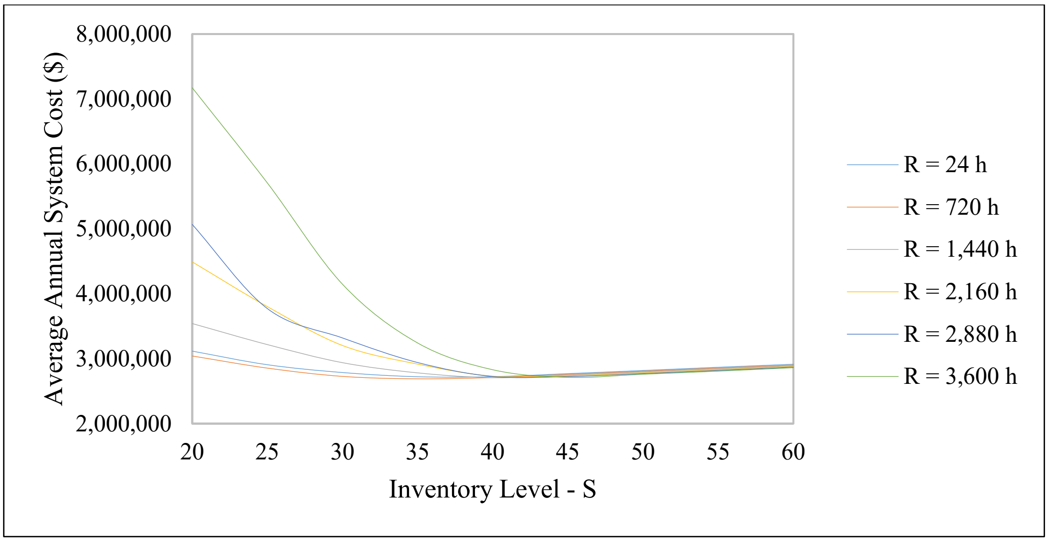


Figure 4.15 Average Annual System Cost Results for Non-Induced the (R, S) Policies

For the non-induced (R, Q) policy, the results show that the optimal scenario was achieved as (6,480, 45) among 82 scenarios. Thus, annual system cost of $2,608,865 was reached where the fixed batch size of 45 is ordered every 6,480h. For the non-induced (R, S) policy, the results reveal that the optimal scenario was achieved as (720, 35) among 54 scenarios. The annual system cost is expected to be $2,690,225 with a fixed batch size of 35 ordered every 720h. Comparing the optimal scenarios of these two non-induced policies, the scenario defined as (6,480, 45) of the non-induced (R, Q) policy, was determined as the most optimal policy of the non-induced periodic review inventory policies. Since there is not any observable difference between the cost values of the optimal scenarios for the induced and the non-induced periodic review inventory policies, it can be inferred that the production loss cost due to stock-out downtime has a balance with the purchasing and holding costs. Hence, comparing the best scenarios of all four periodic review inventory policies, the scenario defined as (6,480, 45) of the induced (R, Q) policy having an annual system cost of $2,608,617 was obtained as the most optimal scenario of the periodic review inventory policies.

In brief, among 637 scenarios in total, the best scenarios for the continuous and the periodic review inventory policy types were indicated as (s=9, S=49) and (R=6,480, Q=45), respectively. For better understanding of the working principles of the algorithm, the optimal scenarios identified for each review policy together with their two extreme scenarios were analyzed in detail. In this sense, for the continuous review policy of (s=9, S=49), two extreme scenarios were identified as (s=9, S=29) and (s=9, S=449). Thus, detailed output variables were inserted to the model covering a 5-year period and simulated 500 times for each of these three scenarios. According to the statistical analysis conducted on the outputs, stock-out downtimes and maintenance downtimes of the system were fitted into best distributions. It was observed that stock-out and maintenance downtimes of these three scenarios can be identified using Johnson Transformation with bounded distribution type with the parameters represented in Table 4.12.

Table 4.12 *Johnson Transformation Parameters of the Output Dataset for the (s, S) Policies*

Scenario	Downtime	Parameters	P-value
s=9 S=29	Stock-out	γ=0.28; δ=0.69; ε=-11.57; λ=595	0.28
	Maintenance	γ=1.75; δ=1.51; ε=-3.30; λ=37.91	0.18
s=9 S=49	Stock-out	γ=1.07; δ=0.87; ε=-11.21; λ=451	0.16
	Maintenance	γ=0.48; δ=0.96; ε=-1.16; λ=20.11	0.52
s=9 S=449	Stock-out	-	-
	Maintenance	γ=0.92; δ=0.99; ε=-0.92; λ=23.12	0.23

Figure 4.16 illustrates the histograms and the box plots representing the annual statistics of the original output data of stock-out and maintenance downtimes of the best and two extreme scenarios for the continuous review policy. Fit-lines on the histograms point to the Johnson Transformation distribution lines where the red dots on the box plots represent the expected value of the back-transformed data for the corresponding scenario. Using the outcomes of these three scenarios, the operational characteristics of the system were summarized in an annual framework as given in Table 4.13.

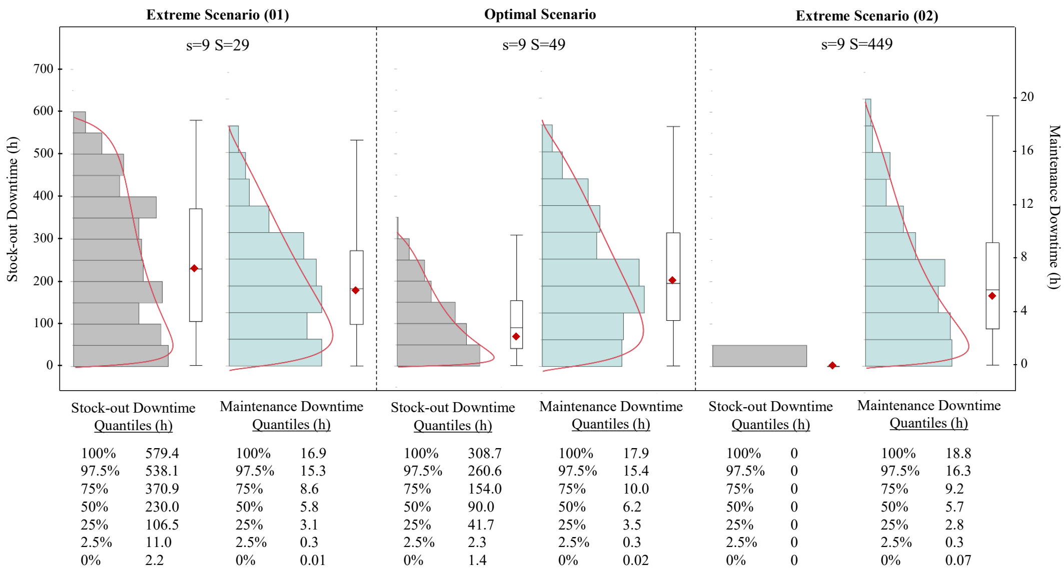


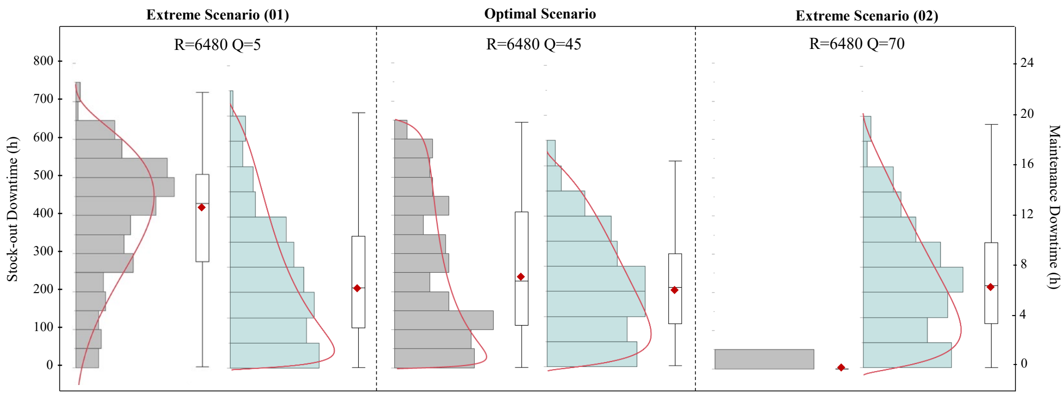
Figure 4.16 Statistics of the Annual Stock-out and Maintenance Downtimes for the Continuous Review Policy Scenarios

Table 4.13 *Annual Operational Characteristics of the Continuous Review Policy Scenarios*

System Characteristics	**(s=9 S=29)**	**(s=9 S=49)**	**(s=9 S=449)**
% Truck Availability	86.44	88.11	88.20
% Operational Truck Availability	96.49	98.34	98.44
% Stock-out Downtime	56.26	5.80	0.00
% Prob. of having Stock-out at least once	100	68.20	0
Maximum Number of Stock-out	9	3	0
Expected No. of Maintenance	121	122	123
Expected No. of Replacement	68	69	69
Expected No. of Stock-out	5	≤ 3	0
Expected No. of Order	4	2	1

First of all, it was observed that the truck availabilities increase as the order quantity increases, as expected. Likewise, the annual expected numbers of maintenance and replacement increase as the order quantity increases since operations are not interrupted by stock-out condition. In addition, it was observed that the percentile weight of stock-out downtime, the probability of having stock-out at least once, and the expected numbers of stock-out and order decrease as the order quantity increases. For the best-case scenario of the continuous review policy, an average of 122 maintenance activities are expected to take place in a year where 69 out of 122 activities require component replacement. In addition, it is observed that the system encounters with stock-out condition at most 3 times in a year, among 500 replications. Accordingly, the probability of having stock-out at least once a year was calculated as 68.20%, where the stock-out number is detected to be 3 at most. Herein, the most important parameter is not how many times the system is experiencing the stock-out condition, but the total downtime caused by stock-out conditions. Therefore, percentile weight of stock-out downtime in the total downtime was estimated to get a more accurate approach on this topic. At this point, the stock-out downtime weight was calculated as 5.80% for the best-case scenario. Thus, since the complete elimination of the stock-out condition by increasing the order quantity causes an observable jump in the direct cost, it was concluded that the system ensures the balance between the cost items by allowing stock-out in a certain extent in the best-case scenario.

Similarly, for the periodic review policy having the optimal scenario as (R=6,480, Q=45), two extreme scenarios were identified as (R=6,480, Q=5) and (R=6,480, Q=70). Thus, these three scenarios were simulated 500 times each for an observation period of 5-year. Stock-out and maintenance downtimes obtained from each simulation run were fitted into best distributions. It was observed that stock-out and maintenance downtimes of these three scenarios can also be identified using Johnson Transformation with bounded distribution type, and the parameter values are represented in Table 4.14. Figure 4.17 illustrates the histograms and the box plots representing the original output data. Fit-lines on histograms refer to the Johnson Transformation distribution lines. The red dots on the box plots are the expected values of the back-transformed data for the corresponding scenario. The annual operational characteristics of the system were also obtained as shown in Table 4.15.



Quantile	Extreme Scenario (01) Stock-out Downtime Quantiles (h)	Extreme Scenario (01) Maintenance Downtime Quantiles (h)	Optimal Scenario Stock-out Downtime Quantiles (h)	Optimal Scenario Maintenance Downtime Quantiles (h)	Extreme Scenario (02) Stock-out Downtime Quantiles (h)	Extreme Scenario (02) Maintenance Downtime Quantiles (h)
100%	723.6	20.3	644.0	16.4	0	19.4
97.5%	640.2	18.6	598.0	15.1	0	15.6
75%	507.5	10.5	409.1	9.0	0	10.0
50%	432.0	6.4	227.7	6.3	0	6.5
25%	279.2	3.2	110.9	3.4	0	3.5
2.5%	40.9	0.3	8.9	0.2	0	0.3
0%	2.6	0.03	0.6	0.06	0	0.001

Figure 4.17 Statistics of the Annual Stock-out and Maintenance Downtimes for the Periodic Review Policy Scenarios

Table 4.14 *Johnson Transformation Parameters of the Output Dataset for the (R, Q) Policies*

Scenario	**Downtime**	**Parameters**	**P-value**
R=6,480 Q=5	Stock-out	γ=-2.29; δ=1.73; ε=-960; λ=1732	0.12
	Maintenance	γ=0.84; δ=1.10; ε=-1.81; λ=25.91	0.20
R=6,480 Q=45	Stock-out	γ=0.40; δ=0.66; ε=-3.93; λ=663	0.68
	Maintenance	γ=0.74; δ=1.24; ε=-2.26; λ=23.76	0.33
R=6,480 Q=70	Stock-out	-	-
	Maintenance	γ=0.67; δ=1.29; ε=-2.92; λ=25.35	0.14

Table 4.15 *Annual Operational Characteristics of the Periodic Review Policy Scenarios*

System Characteristics	**(R=6,480 Q=5)**	**(R=6,480 Q=45)**	**(R=6,480 Q=70)**
% Truck Availability	62.93	88.16	88.19
% Operational Truck Availability	70.24	98.40	98.44
% Stock-out Downtime	96.35	2.41	0.00
% Prob. of having Stock-out at least once	100	19.40	0
Maximum Number of Stock-out	40	2	0
Expected No. of Maintenance	86	123	123
Expected No. of Replacement	48	69	69
Expected No. of Stock-out	36	≤ 2	0
Expected No. of Order	10	2	2

For the optimal scenario of the periodic review policy, an average of 123 maintenance activities are expected to take place in a year, where 69 of them are performed as component replacement. It was also observed that the system goes into stock-out state due to component replacement requirement could not met at most 2 times in a year, among 500 replications. Accordingly, the probability of having stock-out at least once a year was calculated as 19.40%. The maximum number of stock-out expected for a year is determined as 2. Percentile weight of the stock-out downtime in the total downtime is calculated as 2.41% for the best-case scenario. It was again observed that the system provides a balance between direct and indirect financial consequences of the inventory policy and allows stock-out in a certain extent even for the optimal scenario.

The company is expected to specify an inventory policy, among the optimal scenarios of continuous or periodic review policy types. However, this decision depends on a number of factors related to dynamics of the current inventory management system and the corporate structure, where the inventory activities are established considering productivity, availability, supplier structure, and the financial risk appetite of the company. Inventory management applications of many companies do not align with the scheduled inventory policies at strategical level since the policies are generally incapable of predicting the uncertainties in inventory supply-chain, deteriorations in operating equipment, variations in system availability requirements, and robustness of the available inventory policies. Moreover, the inventory records on the indirect cost items are not kept adequately detailed. Therefore, the overall assessment of the total cost of an inventory management system cannot be achieved. Hence, since a valid comparison in terms of total system cost between the company's policy and the optimal policy cannot be performed in many industrial cases, the companies are prone to keep their inventory policies without evaluating their cost-wise and operational effectiveness. In this regard, a mining company may determine the most suitable review policy using the developed algorithm in the current study so that a clear comparison between the available and the optimal policies can be achieved.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Spare parts inventory is one of the major challenges, especially for production industries, since such inventory policies need continuous improvement specific to the production system and the working environment. Particularly, in machine-intensive sectors where the operational uncertainties are quite high, many other difficulties in predicting uptime and downtime behaviors of machinery components and the resultant spare part requirements can be experienced. For companies utilizing sophisticated technologies, the overstocking or understocking of spare parts can be vital to satisfy the requirement of mass and continuous production at relatively low capital investment. This condition is based on the company's financial and operational risk appetite that is highly changeable depending on the sector dynamics. In this regard, this study intends to develop a multi-scenario discrete-event simulation algorithm to optimize spare parts inventory problems with a dynamic and stochastic structure with a preventative of many different inventory systems. The multi-scenario structure of the algorithm is provided by utilizing parametric combinations of two continuous review policies defined as (s, Q) and (s, S) and two periodic review policies defined as (R, Q) and (R, S). The study methodology covers (i) identification of the system dynamics and characterization of uptime/downtime behaviors of the components, (ii) development of system configuration, and integration of inventory policies and maintenance actions into Arena® Software, (iii) implementation of the case study and optimization of the introduced inventory policies, and (iv) analyzing the inventory policies and their parameters, and evaluating the sensitivity of the total system cost to changing system decisions.

The proposed discrete-event simulation model was applied to the tires of a truck fleet operated in a surface coal mine in Turkey. This fleet covers seven homogeneous trucks with six tires each. A preliminary analysis using the tire failure dataset and the expert opinions reveals that four types of tire failures, deflation, cuts and punctures, impact damage, and irregular wear, are observed as tire failure modes. Then, the model is implemented using failure mode characteristics and four well-known inventory policies, (s, Q), (s, S), (R, Q), and (R, S) to comparatively evaluate both continuous and periodic inventory reviewing approaches. Hence, a total of 637 scenarios were generated from different reviewing and triggering mechanisms, and each scenario is simulated for a 5-year observation period. According to the results, the optimal scenarios for continuous and periodic review inventory policies were determined as (s=9, S=49) and (R=6,480, Q=45), respectively. An annual system cost of $2,604,032 was observed for the most optimal continuous review policy where the spare parts are ordered up to an inventory level of 49 whenever the component number in the inventory drops to 9. On the other hand, an annual system cost of $2,608,617 was reached for the most optimal periodic review policy where the fixed batch size of 45 is ordered every 6,480h. Besides, it was observed in both approaches that the system ensures the balance between direct and indirect cost items by allowing stock-out conditions to a certain extent even in the optimal scenarios.

The current model can be applied to different spare parts inventory problems of different sectors to determine the cost-wise best policies regarding the up-to-date machine and operational dynamics valid in the production area. Accordingly, the implementation part compares 637 scenarios by interacting tire failure behaviors with the parametric variations of four different types of inventory policies. Even though the model gives the most optimal options for continuous and periodic reviewing approaches, its comparison with the current total inventory cost in the mine could not be achieved since the policy parameters applied for a regular tire inventory are still missing due to potential shortages in the tire procurement. Consequently, the company may use the developed algorithm to determine the most optimal inventory policy and integrate it into their current inventory management structure.

5.2 Recommendations

A comprehensive multi-scenario discrete-event simulation model was established for the optimization of spare parts inventory problems available in production industries. This research study can be improved considering the following recommendations in future studies:

i. Joint inventory optimization of different spare parts, which may have a mutual interaction at operational level, can be considered to develop a more holistic inventory management system.

ii. In addition, component deterioration rate in the inventory and the limitations in inventory capacity according to the component types can be included into the model so that the long-term effectiveness of inventory decisions can be analyzed.

iii. Maintenance policy can be extended by considering imperfect maintenance, component rotation, and crew capacity and competency to reveal the impact of maintenance effectiveness on inventory decisions.

iv. Besides, supplier-based constraints such as multi-supplier structure, quantity discount, and minimum order quantity can be considered in the future studies so that the impact of supplier structure on inventory decisions can be examined.

v. Fluctuations and shortages in the global and domestic market for the corresponding spare parts can be integrated into the future model so that the effect of the market movement on the inventory decisions can be inspected.

vi. Additional constraints/variables regarding operational and environmental conditions can be introduced into the future model, such as tire condition monitoring system, driver competency, seasonality effect on operations, and spare machines used in a stand-by operation configuration to extend the available knowledge on inventory management.

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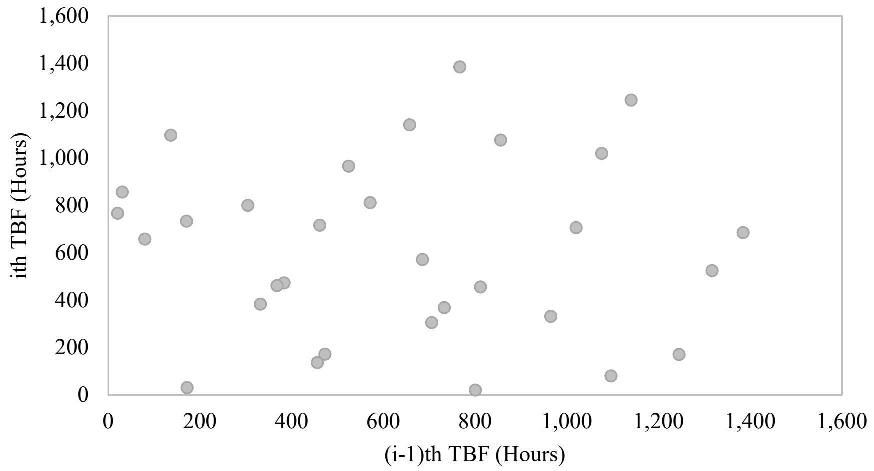
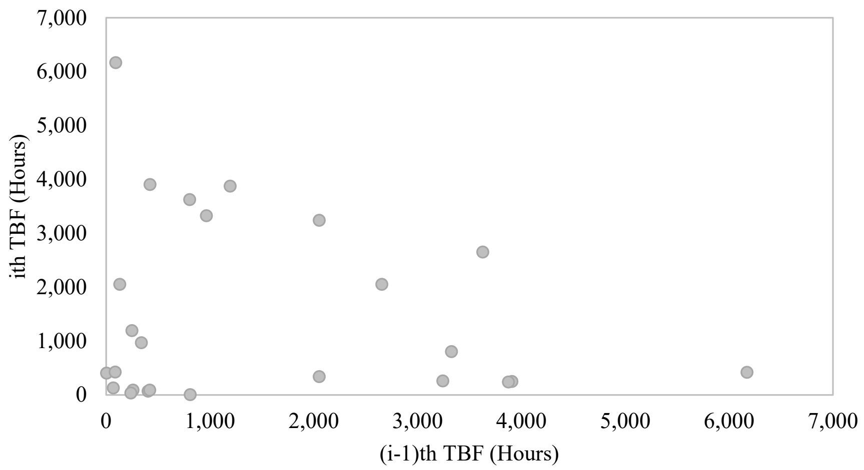
APPENDICES

A. Scatter Plots for Lifetime Datasets of F02 and F03



	Pearson Correlation Coefficient	P-value
Lag-1:	-0.037	0.845

Figure 5.1 Data Independency Test for the Lifetime Data of F02



	Pearson Correlation Coefficient	P-value
Lag-1:	-0.152	0.467

Figure 5.2 Data Independency Test for the Lifetime Data of F03

B. Confidence Intervals of TBF and TTR Values

Table 5.1 *Upper and Lower Bounds of TBF and TTR Values*

Code	TBF - Min. (h)	TBF - Max. (h)	TTR - Min. (h)	TTR - Max. (h)
F01	18	6,798	0.07	17.49
F02	360	30,175	1.75	20.65
F03	283	35,600	3.20	22.87
F04 - Left Front	4,948	6,001		
F04 - Right Front	4,945	7,979		
F04 - Left Rear Outer	4,859	8,391	3.20	22.87
F04 - Left Rear Inner	4,845	7,632		
F04 - Right Rear Inner	4,837	8,047		
F04 - Right Rear Outer	4,865	7,532		