SIMULATION-BASED OPTIMIZATION OF MAINTENANCE CREW CONFIGURATION IN MINING OPERATIONS

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ABSTRACT

SIMULATION-BASED OPTIMIZATION OF MAINTENANCE CREW CONFIGURATION IN MINING OPERATIONS

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A mining company is expected to have three essential assets which are human resources, ore reserve to be exploited, and an equipment fleet. On this basis, trucks, excavators, drilling machines, crushers, mills, classifiers, and concentrators are commonly covered in mining equipment fleets. On the other hand, human resource employed in operational activities is vital for labor-intensive production industries like mining. Here, the number and qualifications of people employed in a mining site should be decided according to the divisional capacity requirements allocated to different operational branches. Among these divisions, the maintenance facility is generally one of the most labor-intensive parts since a maintenance crew configuration requires a vast number of people with different qualifications to ensure the equipment fleet's performability. In this regard, the current research study aims to develop a continuous-event simulation model to optimize the maintenance crew's configuration, i.e. capacity and qualification, for an operable mining area where different clusters of failure modes are available for multiple equipment working coordinately for joint production. The developed model was implemented for a five-excavator fleet employed in a surface coal mine. The model input dataset covered three years records of maintenance works classified in mechanical and electrical failure types. The simulation outcomes showed that the total cost of indirect and direct financial consequences of maintenance crew could be minimized for a crew including six persons in the electrical division and four persons in the mechanical division. Moreover, the downtime profiles of the excavators for this optimized scenario were also evaluated. The analysis showed that Excavator ID-31 is expected to be down most among the five excavators for the observation period.

Keywords: Continuous Event Simulation, Optimization, Maintenance Crew, Mining, Workforce

ÖZ

MADEN İŞLETMELERİNDE BAKIM EKİP KONFIGURASYONUNUN SIMULASYON TABANLI OPTIMIZASYONU

Şahiner, Şahin Furkan
Yüksek Lisans, Maden Mühendisliği
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Şubat 2022, 92 Sayfa

Bir madencilik şirketinin üç temel varlığa sahip olması beklenir: İnsan kaynakları, işletilecek cevher rezervi ve ekipman filosu. Bu temelde, kamyonlar, ekskavatörler, sondaj makineleri, kırıcılar, değirmenler, sınıflandırıcılar ve konsantratörler, madencilik ekipmanı filolarında yaygın olarak yer almaktadır. Diğer yandan, operasyonel faaliyetlerde istihdam edilen insan kaynağı madencilik gibi emek-yoğun bir sektörde büyük önem taşımaktadır. Burada, bir maden sahasında görevlendirilen kişilerin sayıları ve nitelikleri, farklı iş türlerine atanmış departmanların kapasite gereksinimlerine göre şekil almaktadır. Bu departmanlar arasında bakım ve onarım atölyesi, ekipman filosunun faaliyet verimliliği sağlamak amacıyla farklı yetkinliklerde fazla sayıda elemana ihtiyaç duyduğundan, genellikle bir maden sahasındaki en insan-yoğun departmanlardan bir tanesidir. Bu bağlamda, mevcut araştırma çalışması, koordineli olarak ortak bir üretim faaliyet için çalışan çoklu sayıda ekipmanda görülen farklı tür arıza modlarının yaşandığı çalışır bir maden sahasında bakım-onarım ekip konfigürasyonunu (farklı yetkinliklerdeki kişi sayıları) optimize etmek maksatıyla bir sürekli olay simülasyonu geliştirmeyi amaçlamaktadır. Geliştirilen model, bir açık ocak kömür madeninde kullanılan beş ekskavatörlü filo için uygulanmıştır ve model girdi verileri mekanik ve elektrik arıza türleri olarak sınıflandırılabilecek üç senelik bakım-onarım kayıtlarını içermektedir.

Gerçekleştirilen simülasyon sonuçları, doğrudan ve dolaylı ilgili masrafların toplamının, ekibin elektrik bölümündeki kişi ayısı altı mekanik bölümündeki kişi sayısı dört olduğu durumlar için en aza indirgendiğini göstermiştir. Ayrıca, bu optimize edilmiş senaryo için ekskavatörlerin duruş davranışları da incelenmiştir. Analizler, 31 Nolu Ekskavatörün gözlem süresi boyunca diğer beş ekskavatör içerisinde en çok duruşa sahip ekskavatör olduğunu göstermiştir.

Anahtar Kelimeler: Sürekli Olay Simülasyonu, Optimizasyon, Bakım-Onarım Ekibi, Madencilik, İş Gücü

To My Family and Friends

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CHAPTER 1

INTRODUCTION

1.1 Background

With mass production and globalization, machines have started to play a vital role in manufacturing in many sectors. At this point, strong links between production operations and maintenance have become one of the most basic requirements for the overall success of companies. Machinery malfunctions may directly or indirectly interrupt production leading to significant financial losses for organizations. Therefore, it has become inevitable for production companies to have a competent and proper maintenance department with a sufficient skilled workforce with different competencies to ensure the continuity of production. In this context, since mining is a machine-intensive sector, mining companies need to establish a well-organized maintenance department in their operation areas. There are many different types of mining equipment with varying complexity employed in surface mines, underground mines, and mineral processing facilities. These equipment are exposed to multiple failure modes requiring different maintenance actions. The maintenance workshops consist of various units and employees with different qualifications in mining areas. Besides the diversity and complexity in the maintenance policies in mining, maintenance works also account for a high share in the operating cost. Some of the observation about the relationship between maintenance cost and operating cost have been listed in the literature as follow:

- Equipment maintenance cost in mining accounts for 20% to 35% of the total operating cost (Unger and Conway, 1994).

- Maintenance cost in Chile and Indonesia exceeds 60% of operating cost for the surface mines (Wonh *et al.*, 2000)
- Maintenance cost dominates from 40% to 50% of the equipment operating cost for the mining industry (Kumar and Forsman, 1992).
- A Finnish company announced that the maintenance costs in their mines correspond to 30% of the production cost (Harjunpaa, 1992).
- Unplanned maintenances result in a 10% production loss in Australian underground coal mines (Clark, 1990).

It is understood from the literature that maintenance works are inevitable for machinery-based production industries, may occupy a remarkable amount of operating cost, and may cause excessive direct and indirect (production loss) financial consequences. Therefore, the trade-off between the physical cost of maintenance works and the value of unit production loss should be considered jointly when determining the organization and content of the maintenance policies. One critical factor in maintenance-based decisions is the configuration of the maintenance crew, which refers to the number of people with different qualifications employed in a maintenance team. A similar trade-off exists when determining maintenance crew since over-employment and under-employment of crew members change the balance between direct and indirect cost flows.

In this sense, the current study aims to develop a continuous simulation algorithm capable of determining optimal maintenance crew in quantity and qualification which minimizes the total cost considering the stochastic failure behaviors experienced for an equipment fleet in a mining site.

1.2 Problem Statement

Maintenance is essential in production areas to improve and sustain the reliability and operability of systems. Maintenance activity alone may cause production loss due to the unavailability of the required workforce in the maintenance department. In some cases, however, maintenance actions can be costly and restricted by limited resources. For this reason, there is a balance between system breakdown costs and maintenance-related expenses. Underrated maintenance works may lead to excessive failure-resulting in downtime and system deterioration. Therefore, an optimal maintenance policy, minimizing the total indirect and direct cost items related to employee expenses, should be developed to sustain production and improve operational profitability. Especially in machine-intensive sectors like mining, where production is performed with multiple and well-coordinated heavy-duty machines, maintenance costs can be enormous and occupy a significant part of the total operating cost. Table 1.1 shows how maintenance cost may dominate operating cost in the mining sector compared to different industries.

Table 1.1 Percentile Weight of Maintenance in Operating Cost for Different Sectors (Ben-Daya *et al*., 2016)

Industry Sector	**Weigth of Maintenance Cost (%)**
Mining (Highly Mechanized)	20-50
Primary Metals	15-20
Electric Utilities	5-15
Manufacturing Processing	3-15
Fabrication/Assembly	3-5

In addition, allocating limited resources to a set of tasks is a common problem encountered in many industries. Therefore, labor resource allocation and configuration are crucial to maximizing systems' service levels and minimizing direct and indirect costs. In this context, determining optimal human resource configuration for maintenance activities is vital, especially for a highly machine-intensive industry mining.

1.3 Objectives and Scopes of the Study

The current study aims to develop a simulation algorithm capable of optimizing maintenance crew configuration for an operation where multiple types of equipment with random failure modes are available by considering the cost and the equipment availability. The developed model minimizes the cumulative maintenance crew-induced cost items classified as direct and indirect. On this basis, direct crew-induced cost items, which are constant per person, may include different cost items such as salary, insurance, food service, shuttle service, rent help, and family help. On the other hand, production losses of system downtime due to scheduled maintenance downtime and potential maintenance crew unavailability are considered indirect cost determinants. In addition to this primary objective, this study entails determining the following sub-objectives:

- An industrial research to reveal the factors determining maintenance crew configuration in the mining industry.
- Establishing the dependencies between production loss and maintenance workforce.
- Development of maintenance crew simulation algorithm in a continuous event simulation environment.
- Implementation of the model using an operational dataset after pre-processing data groups.

Moreover, as a main requirement, verification and validation of the developed simulation algorithm have been performed.

Under the scope of the current study, the model implementation uses the historical maintenance dataset of a five-excavator fleet operated in a surface coal mine. The failures are clustered under two common failure types as mechanical and electrical. Therefore, the required crew numbers for different qualifications are evaluated according to these two groups.

1.4 Research Methodology

The research methodology of this study is explained in five significant stages given below. Besides, the research methodology flowchart can be seen in Figure 1.1.

i. Identification of the system interactions
    - Machine component and failure mode identification
    - Evaluating and integrating model parameters and variables

ii. Development of the algorithm in the Reliasoft Blocksim environment
    - Creating submodules related to the interactions among the failure types for each equipment and interactions between different equipment in a fleet
    - Integration of resource allocation strategies
    - Debugging system variables and parameters for a hypothetical observation period to observe the convenience of dependencies and outcomes in each computation

iii. Pre-processing of a real dataset
    - Acquisition and clustering of data according to failure types and individual equipment
    - Data outlier detection, data trend analysis, and determination of parametric values for the lifetime and maintenance characterization of each failure type for each equipment

iv. Implementation of the model using the pre-processed input models and other required input parameters, and sensitivity analyses with different human resource configuration

v. Evaluating and optimizing maintenance crew particular to the stochastic machine failure profiles

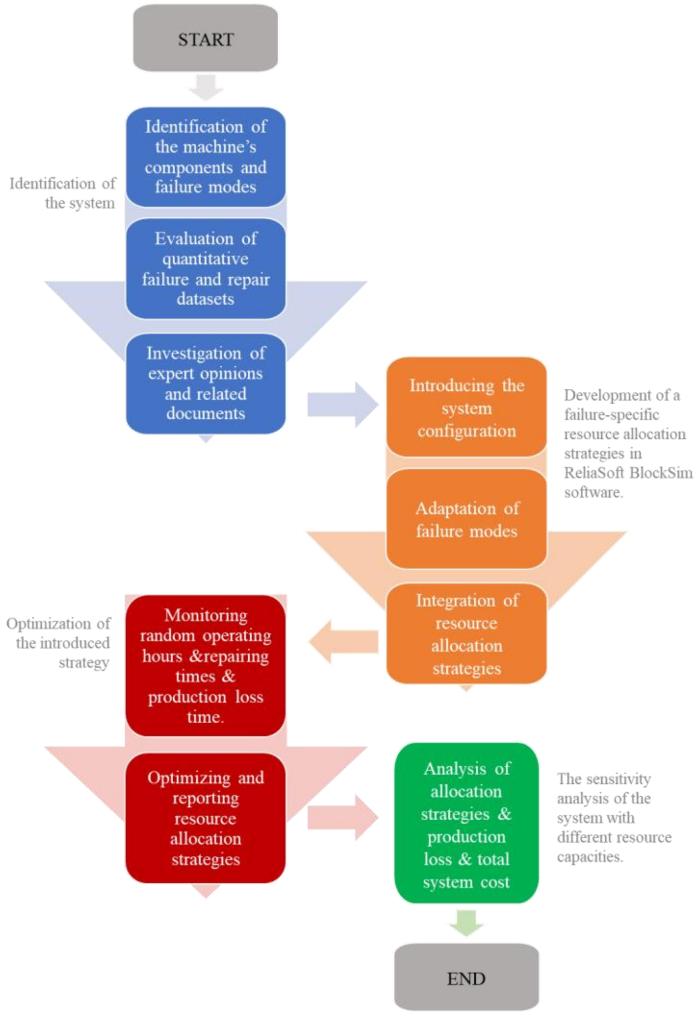


Figure 1.1 Research Methodology Flowchart

1.5 Significance and Expected Contributions of This Thesis

Even though some research on maintenance and workforce has been conducted in the literature, their joint application in the mining industry has not been observed. In this sense, the current study intends to develop a continuous simulation model including stochastic machine failure modes and different workforce combinations to optimize the maintenance crew configuration as a generic model. In this way, using the study outcomes, an optimal balance between production loss tolerance and maintenance crew-related physical costs can be detected to minimize the total of direct and indirect financial consequences.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Since the current study intends to develop a continuous-event simulation model to determine the optimal configuration, i.e. quantity and qualification, of the maintenance crew for an operable mining operation, this section tries to explain the terms and theories behind human resource allocation in production industries and maintenance models. In this sense, the survey topics cover human resource allocation problems, maintenance activities, maintenance optimization and modeling, and maintenance policies' applicability in mining. Besides, the event simulation concept is also extensively discussed, together with its recent applications in the mining industry.

2.2 Maintenance and Workforce Requirement

In this chapter, general maintenance concepts and types and their applications in the mining area will be discussed. In addition, studies on workforce management in both mining and other production sectors will be mentioned.

2.2.1 Maintenance Concept

The basic definition of maintenance is to keep a system with variable complexity and functionality in good condition by checking or repairing its components regularly. Therefore, a maintenance policy combines actions with different intentions that enable a part to operate throughout the system's service life where the component is included (BSI, 2010). This concept necessitates grouping of the actions, i.e. work packages, within a maintenance policy. Therefore, this section will discuss the classification of maintenance works and the previous maintenance studies related to the mining sector.

Maintenance activities can be divided into two main groups as preventive maintenance (PM) and corrective maintenance (CM) (Ben-Daya *et al*., 2016). Figure 2.1 illustrates a detailed branching of maintenance work packages that may be covered in a policy.

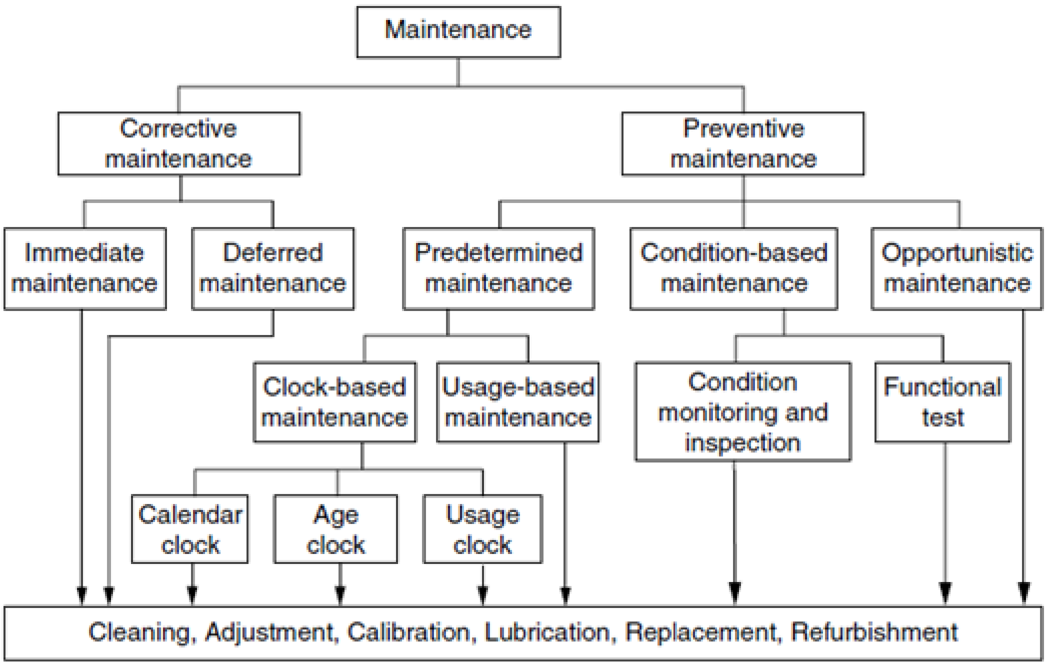


Figure 2.1 Classification of Maintenance activities (Ben-Daya *et al*., 2016)

Preventive maintenance is defined as activities carried out at pre-determined intervals or according to prescribed criteria. It intends to reduce the probability of failure or the functional degradation of the equipment. Preventive maintenance can be performed in two main groups as pre-determined or condition-based (Garg and Deshmukh, 2006):

- Pre-determined maintenance is carried out at pre-specified time intervals for single or multiple items (i.e. scheduled maintenance) without regarding item(s) deterioration levels.
- Condition-based maintenance is performed whenever the monitoring values of pre-specified indicators, such as vibration, pressure, temperature, and displacement, are above the pre-determined threshold values. These indicators should detect anomalies that can turn to failure soon. Performance and indicator monitoring may be carried out on request or continuously.

On the other hand, corrective maintenance is carried out after fault recognition and intends to turn a failed component back to its operable state with the desired functionality. Corrective maintenance can be immediate or deferred in terms of fault response type (Garg and Deshmukh, 2006):

i. Immediate maintenance is carried out without any delay after a fault to avoid individual or cumulative consequences of failure.
ii. Deferred maintenance is not carried out immediately after fault detection but is performed with a delay in a scheduled activity or the following system downtime.

There is also a third category of preventive maintenance called opportunistic maintenance. Opportunistic maintenance is generally an integral part of maintenance policies. It regulates which components will be maintained preventively if the system is already down due to another element's failure. Therefore, there exists an opportunistic time in the failure downtime for the preventive repair or replacement of a component not failed at that moment.

Achievement of each work package in a maintenance policy requires a different number of maintenance crew with varying qualifications. Improper composition of maintenance crew may cause interruptions in production due to unavailability of the required maintenance crew since another maintenance work occupies the majority of the crew simultaneously. On the other hand, over-employment of maintenance crew will increase human-resource-related direct cost values. Therefore, crew configuration should be determined so that the cumulative of direct and indirect cost items should be minimized.

2.2.2 Maintenance Studies in Mining Industry

Maintenance actions should serve to improve the operability and reliability of systems. However, improving reliability can be costly in some cases and is constrained by technical and financial limitations. Therefore, there is a trade-off between the economic consequences of maintenance activities and system deterioration. A maintenance policy should be developed so that the system's reliability should be kept above the intended level, according to the unit value of production and its role in production. Implementing over-rated preventive work packages may cause additional investment costs and higher system unavailability due to preventive downtimes.

In contrast, underrated preventive works may lead to a jump in the percentile weight of corrective actions in a policy that results in excessive failure downtimes and system deterioration. Therefore, a maintenance policy covering an optimal balance of both corrective and preventive measures should be developed to sustain production and improve operational profitability. Especially in machine-intensive sectors like mining, where the production is performed with multiple and well-coordinated heavy-duty machines, maintenance costs can be enormous and occupy a significant part of the total operating cost.

A mining company is expected to have three essential assets: human resources, ore reserve to be exploited, and an equipment fleet. Here, human resource employed in the operational areas is especially vital for mining companies. The number and qualifications of people should be decided according to the mining area's divisional capacity requirements. On this basis, the maintenance facility is generally observed to be the most labor-intensive part since a maintenance crew configuration requires a vast number of people with different qualifications to ensure the equipment fleet's performability. Some of the recent literature studies related to mining equipment maintenance are discussed in this chapter.

Barberá *et al*. (2012) presented a case applying the GAMM (Graphical Analysis for Maintenance Management) method that supports the overall maintenance management decision-making process through the graphical analysis of data. Two slurry pumps located in a mining plant in Chile were analyzed within this scope. Deficiencies of the pumps were evaluated using GAMM, and some improvements were suggested to improve the decisions on pump maintenance. Ali and Reza (2013) developed a new approach using two statistical models that are univariate exponential regression (UER) and multivariate linear regression (MLR). This approach aims to determine the overhaul and maintenance cost of loading equipment in surface mining. Various equipment parameters such as bucket capacity, machine weight, and engine power were considered in the model. The study outcomes were used as a practical tool for determining cost items related to overhauling and the other maintenance activities applicable to loading equipment. Morad *et al.* (2014) investigated ten operating trucks' maintenance policy performance in Sungun Copper Mine to inquiry opportunities to minimize the related failure downtimes. On this basis, truck components' failure and maintenance profiles were revealed, and system reliabilities were discussed by considering the functional importance of components, using the weighted importance measure method. Following a Monte Carlo Simulation, the study results showed that the trucks could operate for about 11,000 h throughout the scheduled operation period of 12,000 h.

In addition, Kovacevic *et al.* (2016) described a two-step method to analyze the factors and aspects influencing human errors during mining machines' maintenance activity. The developed method includes the cause-effect analysis and the group fuzzy analytic hierarchy process. The analysis results showed that the most crucial aspects are related to work instructions and organization, individual training and characteristics, work experience, and specifications of available equipment. Nikulin *et al.* (2016) presented a computer-aided application that can evaluate the operational and maintenance strategy in a complicated process with employed equipment. Different scenarios were constructed to correlate the reliability and maintainability profile of the systems and their operational behavior. Gölbaşı and Demirel (2017) developed a simulation algorithm, called the time-counter, to minimize direct and indirect maintenance cost items and optimize the mining machine's inspection intervals. The proposed model was applied to two different draglines working in a coal mine in Turkey. The algorithm included the maintenance activities applicable in the target mining area, stochastic uptime and downtime behaviors of machine components, and all the administrative system breaks, including lunch breaks, shift changes, holidays, and other planned production interruptions. The results showed that the total maintenance costs could be reduced for Dragline-1 and Dragline-2 by 5.9% and 6.2%, respectively.

Besides, Jonsson *et al.* (2018) discussed analyzing digitalized condition-based maintenance data of machinery operable in an iron ore mine in Sweden. Digital representation and digital mediation figurations are two complementary ways in work practices. Angeles and Kumral (2020) proposed a maintenance management approach to be used in the mining industry. The study improved the availability and reliability measures of equipment, and potential failures were evaluated and prevented by using a mining truck fleet's failure data in an open-pit mine in Canada. Optimal inspection intervals have been proposed in the methodology to ensure the desired reliability level of a truck fleet.

2.2.3 Workforce Consideration in Production Industries

Organizations need teams, including multiple members with different qualifications, to fulfill specific target achievement tasks (Guzzo and Shea, 1992). Dynamic and competitive market conditions have motivated many companies to prioritize their human resource management systems as a core component of corporate strategy.

Since the quality and effectiveness of human resource in an organization is crucial for the success of strategic and tactical targets, managers should continuously seek the tools and methods for improving the use and allocation of available resources in such a way that business performance and productivity is optimized by minimizing or maximizing effective parameters (Bouajaja and Dridi, 2017). Allocating limited resources to tasks is a common problem encountered in many industries. Like equipment resources, allocation, configuration, and labor resource arrangement have become crucial to maximize service level and minimize direct and indirect costs, especially in labor-intensive production industries like mining. Various studies have been conducted in the literature to reveal how human resources can be allocated in production industries. These studies are generally grouped under project management, job shop scheduling, hospital scheduling, aircraft maintenance, air traffic management, and shipping scheduling (Angalakudati *et al*., 2014). Moreover, it is seen that the conducted studies in the literature optimizing workforce management generally include mathematical models or simulation models. Some of these studies, including math models, are discussed first.

Techawiboonwong and Yenradee (2003) evaluated an aggregate production planning for multiple product types and developed a mathematical model where the worker resource can be transferred among the production lines. The total cost was detected to be reduced at a remarkable level in case the workers are allocated effectively to different production lines when the need arises. Quan *et al.* (2007) presented a novel evolutionary algorithm to solve the preventive maintenance scheduling problem, formulated as multiple objective problems, and evolutionary algorithms are utilized to solve the problem. Liang *et al*. (2008) conducted empirical research based on an analytical framework and mathematics models using the aggregate production function and a generalized method to disintegrate total factor productivity components. Martorell *et al.* (2011) presented multi-objective optimization of the maintenance of a nuclear power plant safety equipment applying the Particle Swarm Optimization technique. Murakami *et al.* (2011) proposed a model capable of allocating the human resources to the tasks so that the cumulative daily human resource cost was minimized and the human resource usage was smoothed by considering operational precedence and skill constraints. The model was applied to solve a case study for a hotel. Filho *et al.* (2012) discussed the human resource allocation problem in the health sector. Various occupations such as physicians, nurses, administrative personnel, and technicians for equipment maintenance were defined as the components of human resources in the health sector. The allocation problem was solved by using the Constraint Satisfaction Problem approach.

Moreover, Ighavwe and Oke (2014) formulated a non-linear integer programming model to solve a maintenance workforce sizing problem. The problem was modeled in a bi-objective framework maximizing productivity levels while minimizing the number of maintenance personnel. Ighavwe and Oke (2015) developed nonlinear mixed-integer programming to propose a multi-objective model for optimization of maintenance workforce and production variables. The novelty of this study is the presentation of a distinctly new approach that takes care of workers' reliability, defective product issues, and the time-sharing between production and maintenance departments. Ighavwe and Oke (2016) proposed a fuzzy goal programming model to formulate a single objective function for maintenance workforce optimization considering stochastic constraints. The performance of the proposed model was verified using data obtained from a production system and simulated annealing as a solution method. The results of simulation annealing and differential evolution are compared based on computational time and the quality of the solution. It was observed that the simulation annealing results offered better outputs than the differential evolution algorithm. The proposed model can generate reliable information for preventive and breakdown workforce maintenance planning based on the results obtained. Sleptchenko *et al.* (2018) formulated mixed-integer linear programming by analyzing the joint optimization of spare parts inventories and workforce allocation in a single-site maintenance system. The objective is to minimize the total system cost consisting of the spare parts and service engineers' annual holding costs and incidental outsourcing costs.

In addition to mathematical models, various simulation-based studies have evaluated the workforce in production or service industries. At this point, McGrath *et al.* (2003) proposed an integrated simulation-optimization framework to estimate technician requirements on a sub-shift basis. They generated performance measures, like technician utilization and work overflow, maximizing the existing system's efficiency by spreading the workload more uniformly across shifts. Safaei *et al.* (2012) developed an integrated simulation-optimization approach is proposed for the annual planning of power restoration workforce related to an electricity distribution company in a province of Canada. Turan *et al.* (2020) developed a risk-based simulation-optimization approach. They applied a new joint optimization model that seeks the optimal values of the repairable spare parts stocks and workforce capacity in the repair facility together with the best repair priority assignment that minimizes total cost by taking into account the risk attitude of the decision-maker. Turan *et al.* (2021) developed a holistic framework for joint optimization of strategic facility location, capacity allocation, and workforce planning in the military context and solved using a simulation-based optimization approach. Moreover, Turan *et al.* (2022) developed a simulation-optimization method by combining a system dynamics simulation model and a genetic algorithm to solve a joint strategic workforce planning and fleet renewal problem in a military context. A trade-off was addressed among several costs (e.g., workforce, maintenance, operating, etc.) and operational availability of the fleet.

2.2.4 Workforce Allocation in Maintenance Works

Determining optimal human resource configuration for maintenance activities is highly crucial, especially for machine-intensive industries like mining. A maintenance department may embody multiple divisions where different crew configurations, i.e. number of people according to their qualifications, are available according to the company's production profile and complexity and types of machines included directly or indirectly in production phases. Operations are performed at the surface or underground in mining areas, depending on the mining method. Some particular types of machinery, which are generally heavy-duty assets with a high production rate, are required and may differ according to the mining type and mining production capacity. On this basis, a mining company is expected to have an extensive machine fleet where different loading, hauling, drilling, and auxiliary equipment are included. Each machine can experience different failure modes during an operation where those failure modes may have different occurrence frequencies and consequences with varying downtime profiles. Therefore, the maintenance crew, which is a limited resource holding a specific number of people in each division, should be determined to optimize the trade-off between the cumulative financial consequences of different crew configurations. Various studies in the literature have intended to improve human resource allocation in maintenance works.

Accordingly, Yang *et al*. (2003) developed a mixed-integer mathematical model that includes various flexible strategies so that an airline company can manage the allocation of its maintenance crew effectively. The model's objective function minimizes the total number of maintenance workforce while satisfying each time slot's requirements. Suryadi and Papageorgiou (2004) developed a mathematical model to optimize process plant performance where different failure modes are observed. First, a preventive maintenance planning and crew allocation problem was formulated as an optimal control problem by integrating an aggregate production planning model. The Markov process with continuous-time analysis was used to build up the maintenance model in this phase. Then, the constructed problem was transformed into a mixed-integer linear programming model. Cheung *et al.* (2005) proposed an approach to facilitate the allocation of labor resources, a complex and fuzzy problem existing in the aircraft maintenance services industry. A shortage of experienced and qualified engineers was detected to make the labor allocation process more difficult. Fondamentale *et al.* (2009) conducted a study related to task scheduling of a factual case to improve human resource allocation. An algorithm was developed to organize maintenance works requiring different technician configurations with varying levels of skill. Zhaodong *et al.* (2010) developed a model to optimize the human resource allocation on aircraft maintenance by considering the predefined sequence of maintenance works. The optimal solution was achieved with a genetic algorithm by minimizing the total maintenance period.

On the other hand, Nguyen and Bagajewicz (2010) constructed a maintenance model using a Monte Carlo simulation to organize and optimize different equipment preventive maintenance frequencies. Besides, spare parts inventory policy, including the number and type of spare parts in stock and labor allocation in plants, were included in this integrated model with a genetic algorithm. Puteri *et al.* (2017) proposed a mathematical model to optimize human resource allocation in aircraft line maintenance by classifying employees into two groups: qualified aircraft maintenance engineers and aircraft maintenance technicians. The model evaluates the number of people required for each service while minimizing the expenses related to employees. Liou and Tzeng (2009) developed a model capable of solving airline maintenance's human resource allocation problem through De Novo programming. Besides, the multiple objective programming (MOP) method was used and compared with De Novo programming.

Comprehensive literature research showed that human resource optimization in mining had not been studied even though the mining operations highly rely on the performance and efficiency of maintenance activities and crew. The current study aims to fill the related research gap in the literature.

2.3 Event Simulation Modeling and the Applications in Mining

Event simulation is the imitation of operations that can happen in a real-world process or system over time. A simulation involves generating an artificial history for a system and the observations related to that artificial history to draw inferences concerning the real system's operating characteristics (Banks *et al.*, 2014). A simulation generally aims to:

- Reveal the internal interactions in a complex system,
- Observe model behaviors and attitudes under informational, organizational, and environmental changes,
- Determine variable(s) having the significant role(s) in changing the system state,
- Reinforce analytic solution methodologies,
- Verify analytic solutions,
- Visualize a system in simulation using animations, and
- Characterize modern and quite complex systems.

On the other hand, in case a single or multiple of the following statements become valid for a system, they cannot be appropriate for a simulation study (Banks *et al.*, 2014):

- System behaviors holding a remarkable complexity that cannot be defined totally in a simulation environment.
- Human behaviors holding a high complexity.
- The situations where simulation ability is overestimated and the supervisor is asking unreasonable expectations that cannot be modeled in a simulation environment practically.
- Simulation time that is much higher than the decision-making period.

Although simulation has some disadvantages such as being time-consuming in some cases and expensive, difficulty in interpretation of simulation outputs, and requirement to have training and practice to build up a proper simulation model, it has multiple and undeniable advantages as listed below:

- New policies, new operating procedures, and the other conditions that can lead to system state variations can be applied in the simulation environment without disrupting the actual ongoing operations.
- Network problems or physical layouts can be tested without consuming any physical resources.
- Hypotheses can be tested to check the feasibility conditions.
- The importance of variables and their mutual interaction can be evaluated in detail.
- Bottleneck analysis can be performed to reveal the weakest chain in a system.
- The operating states of a system can be evaluated step by step
- Sensitivity analysis can be carried out to discuss the effectiveness levels of system variables and parameters.

Systems in event simulation can be categorized as discrete or continuous. In some cases, systems can combine discrete and continuous subsystems. A discrete system is one in which the state variable(s) change only at a discrete set of points in time. In discrete systems, event occurrences are ordered in time, and the period, where system state change is not observed, is neglected. Therefore, the system is evaluated considering the earliest of the upcoming events at each time. On the other hand, a continuous system is the one in which the state variable(s) change continuously over time. This study will use continuous event simulation to monitor system state changes and the interactions among system variables more sensitively. An example of discrete and continuous systems can be observed in Figure 2.2.

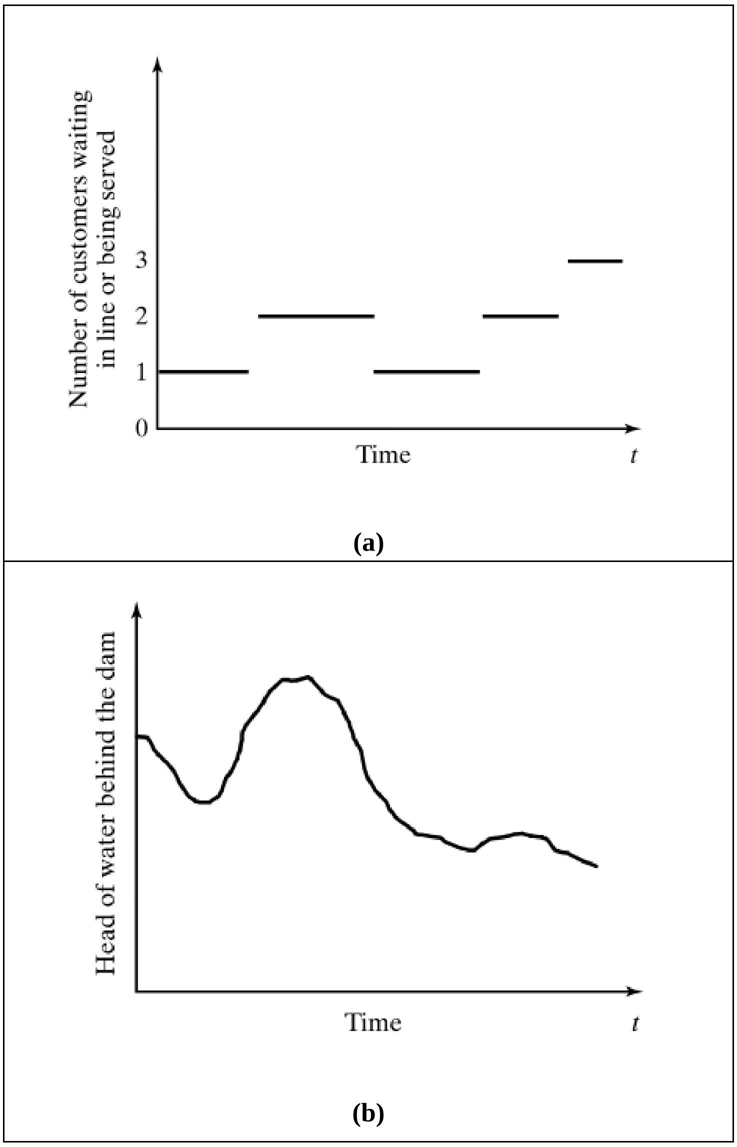


Figure 2.2 Discrete (a) and Continuous System Behavior (Banks *et al.*, 2014)

A simulation work's significant steps cover the determination of model objectives and problem formulation, data acquisition, model construction, verification and validation of model outcomes, sensitivity analysis, documentation and reporting, and implementation phases (Figure 2.3).

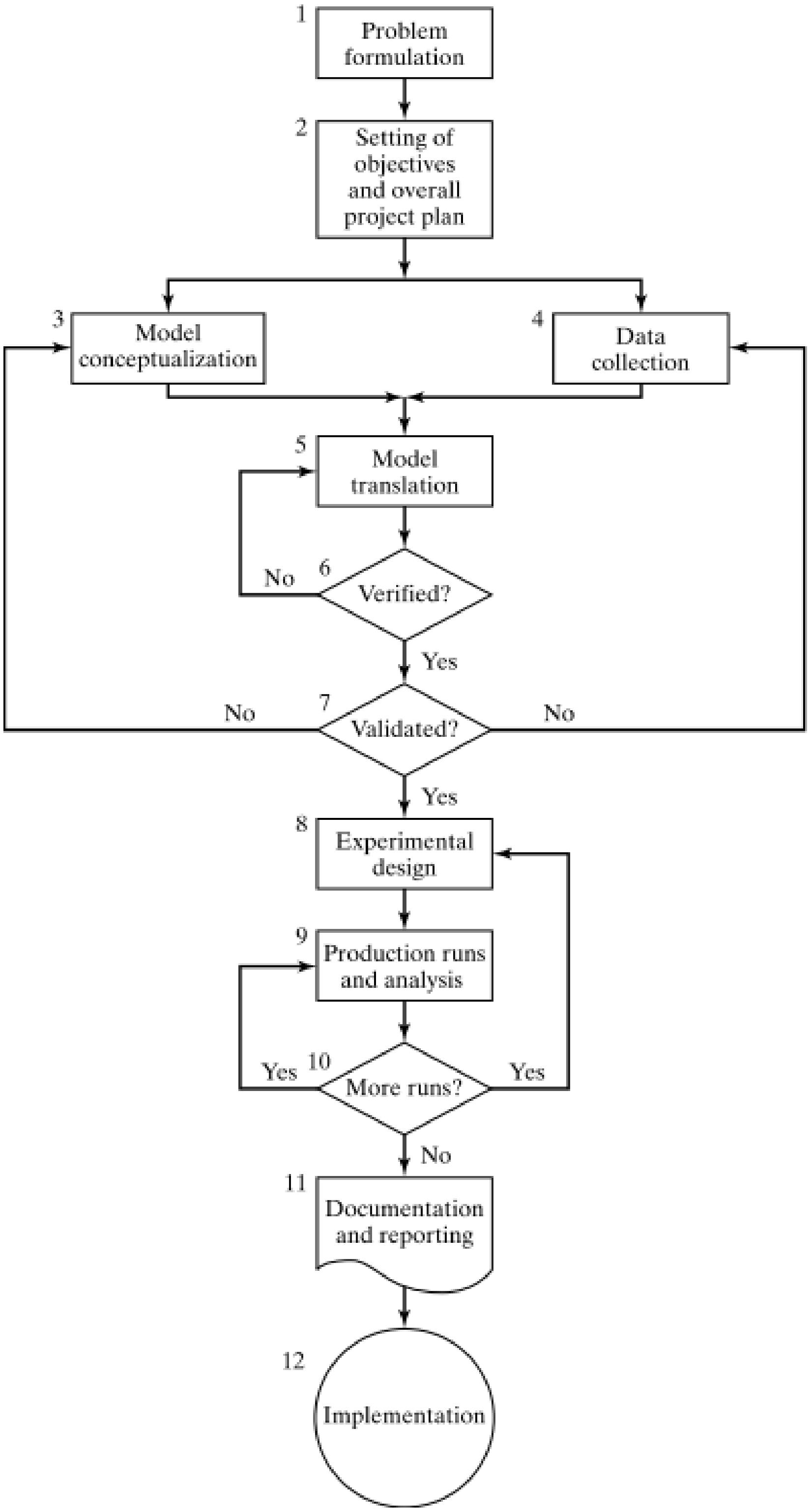


Figure 2.3 General Framework of a Simulation Algorithm

Simulation studies in mining have been generally performed to evaluate the operational level uncertainties, preexisting conditions, and/or optimization of processes applicable in mining. Rist performed the first simulation study in mining in 1961 to optimize the number of wagons in an underground mine's haulage system by using Monte Carlo simulation (Sturgul, 2015). On this basis, the current section summarizes some of the recent event simulation studies related to mining problems.

On this basis, Hashemi and Sattarvand (2014) developed a model in a discrete-event simulation environment capable of modeling the interactions between loading and hauling systems in mines. Productivity assessment scenarios were developed to improve the dispatching systems to minimize truck queueing time. The model was applied for a case, and a reduction in the total waiting time by 7.8% was obtained by converting the fixed loader-hauler allocation system to a flexible allocation system. Upadhyay and Nasab (2018) presented a discrete-event simulation and optimization framework to reveal uncertainties in mining operations for a robust short-term production planning and proactive decision-making process. The model also captures the dependencies between failure modes and truck performance, road conditions and tire cost, and dispatching algorithms and truck availability. A detailed cost analysis of production operations is presented in the study.

Besides, Golbasi and Demirel (2017) introduced an inspection interval optimizer called the time-counter algorithm to determine the best cost-wise decisions in maintenance policies specific to the equipment itself. The algorithm, constructed in a stochastic, continuous, and dynamic simulation structure, evaluates maintenance profiles and deteriorating conditions of equipment components when detecting the optimal regular inspection intervals having a constant implementation duration. The model was applied to two different draglines and optimized the inspection intervals as 232h and 184h. Upadhyay and Nasab (2019) presented an optimization tool using discrete-event simulation to facilitate the decision-making process for the proper allocation of shovels. The model objective aimed to allocate shovels to the production faces considering their production capacities to minimize shovel movements while maximizing the total production amount. Rahimdel *et al.* (2017) analyzed the vibration variation at the axles of dump trucks in a kaolin mine exposed to different operational conditions. The simulation results indicated that haul road quality, truck speed, and the distribution of the material in the truck damper are critical for the vibration amount. The analysis results were used in an optimization model to detect the optimal operating conditions for the truck. Sembakutti *et al.* (2017) evaluated the effects of production uncertainties associated with shovel loading, truck waiting times, truck cycle times, and fleet availability. The model used the Monte Carlo simulation and was implemented for a case study. Sembakutti *et al.* (2018) proposed an approach to determine the optimal replacement times for shovel teeth. This approach included a risk-quantification using Monte Carlo simulation to generate a confidence interval for the replacement times. Ozdemir and Kumral (2018) proposed an agent-based Petri net simulation model to check whether production targets are feasible and control feed grade in mineral processing by evaluating different realizations under uncertain operational conditions. Besides, the model outcomes captured the fuel consumption of the haul trucks. The proposed model was also implemented for a case study. Afrapoli *et al.* (2019) proposed an integrated simulation-optimization framework to determine a proper haul fleet configuration in surface mines. The framework did not consider the effects of downstream processes in operation and the effects of the fleet management system. It is shown in the study that the developed framework has the potential to decrease the number of trucks by 13%, compared to manual and deterministic calculations.

On the other hand, Afrapoli *et al*. (2019) developed a multi-objective transportation model for a real-time truck dispatching system. The proposed model intended to assign trucks to the shovels dynamically to minimize shovel idle times, truck wait times, and deviations from the production targets. The model was constructed in a discrete-event simulation environment and implemented for an iron mine. The results showed that the hauling system in the mine is over-capacity considering the loading capacity available, and the total hauling capacity can be reduced by 20 percent. Morad *et al.* (2019) analyzed the truck allocation problem with a simulation-based optimization method. Optimization of loader-truck allocation was achieved in the study so that the total number of trucks was minimized by considering the uncertainties that may exist in a dispatching operation. The model was implemented for a copper mine. After the application, some recommendations were given to remedy the haulage fleet problems that may reduce system productivity. Ozdemir and Kumral (2019) analyzed the effect of human factors on the reliability of the mining equipment. A case study for mining haul trucks was also conducted in the study. This case study showed that the truck reliabilities might drop in varying amounts between 0.84% and 2.45% in each shift. The results also concluded that 16.9% of these reliability drops were associated with operator skills. It was mentioned that the study outputs could be used in a simulation of a material handling system.

In addition, Ozdemir and Kumral (2019) proposed a two-stage dispatching system to maximize the utilization of truck-shovel systems. They divided the truck and shovel fleets into sub-fleets to work on the specific pit by a simulation-based optimization in the first stage. And then, the trucks are simultaneously dispatched to the shovels in the pit by linear programming in the second stage. By testing the proposed approach in a mine, it is shown that the total quantity was increased by 9.4% in a shift that corresponds to 6.0 K tonnes of material. Golbasi and Turan (2020) introduced a production- and cost-integrated maintenance policy optimizer using a discrete-event simulation environment. The developed algorithm can determine the optimal maintenance policy among multiple combinations of corrective, preventive inspection, and opportunistic maintenance work packages, particular to the uptime and downtime characterization of equipment fleet in a production area. The model objective can be converted to minimizing total cost or maximizing availability. The algorithm was implemented for two different earthmoving cases for each model objective. Bernardi *et al.* (2020) compared the materials handling systems of a mine to assess the applicability and weaknesses of the techniques by developing a discrete event simulation. On this basis, various geometry configurations of a mine were introduced into the simulation to optimize handling systems in different scenarios by minimizing the operating cost. Golbasi and Kina (2022) developed a fuel consumption simulator in a discrete-event environment that can evaluate multi-road network and multi-vehicle scenarios for haul trucks operating under stochastic payload and precipitation conditions. The model was applied to a cement production operation using fifteen different routes between the clay mine, the limestone mine, the re-fueling station, two crushers, and the parking station to sustain daily production requirements. The simulation revealed that routes' precipitation conditions and downhill/uphill profiles can increase the fuel consumption rate up to 15-20 and 40 percent, respectively.

CHAPTER 3

DEVELOPMENT OF THE MAINTENANCE CREW CONFIGURATION OPTIMIZATION MODEL

3.1 Introduction

Since there is no factory-style indoor production in mining, and the environment and operation conditions affect production significantly, operating expenses and unplanned production losses in the mine sites should be constantly monitored. Maintenance expenses, which are among the operating cost items, are the most controllable expenses. Especially in machinery-intensive industries such as mining, the way to achieve high production targets is through a high level of required equipment availability. Maintenance activities aim to keep the machine's availability at the desired level and provide corrective and preventive actions for malfunctions. Maintenance and repair actions are the factors that have the most significant impact on machine availability. One of the most critical requirements to reach this desired availability is an adequately organized maintenance management and a maintenance workshop with a sufficient number and qualified workforce. An integrated and well-organized policy includes issues such as identifying the workforce with obligations and responsibilities in the fulfillment of these actions, decisions regarding coordination between departments, and the frequency of performing maintenance-repair activities. When the practices in the mines are examined, it is seen that the contents of these policies are generally determined according to subjective experiences, and they cannot be kept up-to-date according to the changing machinery and production conditions. A maintenance department that is not suitable for the maintenance crew and mining conditions leads to an increase in the frequency of failure of machine parts and indirectly to an increase in production losses. Therefore, it is essential to establish a maintenance and repair team of sufficient number and quality and to analyze the machine lifetimes of the equipment very well due to uncertainties.

In this context, a continuous event simulation algorithm that provides the optimal crew configuration scenario in a dynamic and stochastic structure is developed considering the best cost-wise outputs. The detailed explanations of the algorithm and the model will be given in chapter 3.2.

3.2 Algorithm Logic and Model Description

The algorithm intends to determine optimal maintenance crew configuration, i.e. optimal required number of competent people with a different qualification in a maintenance team in a mining area so as to sustain the operations most economically by developing a trade-off between the physical expenses and production losses due to over or under-employment of the skilled workers. At this point, there are multiple physical cost items of the maintenance crew, arising from wages, employment insurance, food service, transportation, and/or accommodation. In case of over-employment in different branches of maintenance department may cause a drastic increase in the direct cost. On the other hand, if an under-employment condition is experienced in a maintenance branch in a mine site, it may remarkably increase the production loss of machinery since maintenance requirement of the related failure types cannot be ensured for a while due to holding available crew members in the other maintenance works. Therefore, overlapping maintenance activities for similar failure modes, which require similar technical competency, have a high potential to interrupt machinery availability if failure mode characterization and occupancy rates of crew members are not evaluated jointly. Since mining areas employ hundreds of equipment with different numbers and operational intentions, any misevaluation of maintenance behavior can cause catastrophic situations and drop equipment utilization with additional unavailability periods capable of damaging short-term production plans. The section will discuss the development steps of the maintenance crew algorithm considering these uncertainties. The general considerations of the algorithm are given as follows:

i. The developed algorithm has a continuous, stochastic, and dynamic simulation structure. The continuous form of the algorithm means that the status of the defined system is continuously monitored with a pre-defined time interval. In case of any change in the system status, the algorithm captures and stores the value(s) of designated variable(s) and takes a decision before passing to the sequential step. Besides, the multiple critical variables in the algorithm, which can affect the decision in a specific simulation, are assigned randomly from the pre-determined distribution functions. Therefore, the algorithm is highly stochastic and requires detecting the required number of simulations to ensure that the derived cases are good representatives of the system outcomes. The dynamic structure of the algorithm points to that the simulation is a highly time-based model where the status changes of the system should be evaluated considering the active simulation time comparatively and jointly.

ii. Considering the algorithm structure in item (i), the model is started at $\mathrm{t_a} = 0$ where $\mathrm{t_a}$ is active simulation time and incremented by $\Delta\mathrm{t}$ until $\mathrm{t_a}$ is arrived at $\mathrm{t_t}$, which is target simulation time. $\Delta\mathrm{t}$ and $\mathrm{t_t}$ determine how many loops should be performed in a single simulation. The target time, $\mathrm{t_t}$, should be large enough to monitor and capture all possible scenarios that can exist in the system. For instance, if a failure mode occurrence is available in a range between 7 and 10 weeks after maintenance work, then the simulation should not be operated less than $\mathrm{t_t} = 7$ weeks. On the other hand, since the system parameters and variables will be evaluated for each $\mathrm{t_a}$ updated by $\Delta\mathrm{t}$, this time increment should not be so large as not to skip the system components' signification variations. However, it must be known that very small $\Delta\mathrm{t}$ will give close-exact results but increase the computational time remarkably.

iii. Once the simulation time is activated, occurrence times of the failure types, $\mathrm{TBF_{ij}}$, are assigned randomly from their probability density functions, $\mathrm{f(x)_{ij}}$ for equipment ID i and failure type j. Failure type accounts for all failure modes that trigger a specific maintenance crew branch. For instance, if a maintenance crew other than the maintenance management people in a mining area splits into two main branches as electrical mechanical, then the related failure modes experienced in the area need to be divided into two groups. In this way, whenever any equipment failure mode appears, this failure mode will request the required number of crew from the related maintenance branch.

iv. The algorithm evaluates $\mathrm{TBF_{ij}}$ values individually for each piece of equipment and jointly for the equipment fleet. These survival times are located on calendar time first. Failure modes connected in a series dependency extend each other's expected occurrence time in case of maintenance downtime. If equipment is exposed to three failure modes and the existence of any failure mode downs the equipment itself, then these failure modes are in a series connection. On the other hand, if this system keeps operating in failure of any failure mode, system elements are in a parallel configuration. There can be other complex dependencies such as parallel-series, k-of-of-n, and stand-by. Especially for series-dependency failure modes, a failure mode occurrence prevents other failure modes from aging. Therefore, failure mode occurrence points, which are called lifetime finish points in the algorithm $(\mathrm{LF_{ij}})$, are extended for the maintenance downtime of the active failure.

v. For $\mathrm{LF_{ij}} < \mathrm{t_a}$ for any updated simulation time, the algorithm assumes that $\mathrm{j^{th}}$ failure type of $\mathrm{i^{th}}$ equipment has not been experienced yet. The model uses four different signals $(\mathrm{S_{ij}})$ for each $\mathrm{LF_{ij}}$ that are 0, 1, 2, and 3 to specify the maintenance status of the failure mode. $\mathrm{S_{ij}} = 0$ refers $\mathrm{LF_{ij}} \leq \mathrm{t_a}$ condition.

vi. If $LF_{ij} \geq t_a$, then the maintenance module is activated for the related failure mode. When this module is activated for the first time, S_{ij} takes the value of 1 to indicate that a preliminary evaluation will take place for maintenance duration in man-hour (TTR_{ij}), number of crew (C_{ij}), and exact maintenance duration ($eTTR_{ij}$). The maintenance duration of the failure mode is determined randomly from the probability density functions of the maintenance downtime records, $g(x)_{ij}$. This duration is assumed to be decreased in proportion with the crew number assigned. The correlation between crew number and maintenance time according to this crew number can be determined by site observations. An example of how to determine such a correlation can be viewed in Figure 3.1. As seen in the figure, the site observations may point to that failure type 03 can be recovered by one to four people with a TTR correlation function of $-4.8x + 34.5$, and more than four people will have no effect on the maintenance duration. On this basis, $eTTR_{ij}$ value will be determined by random TTR_{ij} and crew number on duty (C_{ij}) and will be the actual downtime in the maintenance activity.

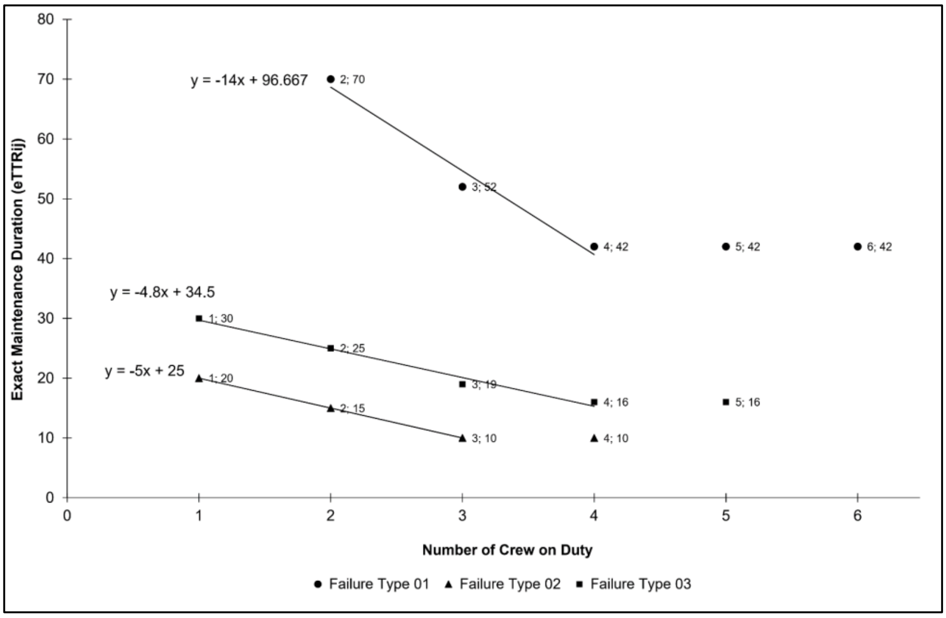


Figure 3.1 Sample Functions Correlating Maintenance Duration with Crew Number on Duty

vii. Number of crew (C_{ij}) for the activity is assigned depending on the up-to-date crew information in the area. At this point, each failure type j is assumed to have a minimum and maximum number, called ${C_j}^{min}$ and ${C_j}^{max}$. Here, ${C_j}^{min}$ points to the minimum number of crew to initiate a maintenance activity for failure type j. On the other hand, ${C_j}^{max}$ refers to maximum crew number for maintenance work of failure type j such that any crew number above this value will not affect maintenance duration and performance of the related failure type. Considering these aspects, active C_{ij} value can be determined in two ways. If the algorithm detects that the available total crew number for failure type j at t_a (${C_j}^{t_a}$) is higher than ${C_j}^{max}$, then the maximum number of crew is assigned to the active crew requirement, $C_{ij} = {C_j}^{max}$. If the total available crew number for failure type j is lower than ${C_j}^{max}$ value but higher than the minimum required number of crew (${C_j}^{min} \leq {C_j}^{t_a} \leq {C_j}^{max}$), then all the available crew is captured by the active maintenance work, $C_{ij} = {C_j}^{t_a}$.

viii. In these two cases where the assigned $C_{ij} \geq {C_j}^{min}$, the differences between the assigned and minimum required are stored as potential crew supply numbers (${C_{ij}}^{supply} = C_{ij} - {C_j}^{min}$). ${C_{ij}}^{supply}$ values are calculated for each equipment and each failure type simultaneously and refer to the crew number currently on duty for maintenance work but can be allocated to another equipment's maintenance if their maintenance activities cannot be started since the minimum crew number is not satisfied. Therefore, it can be understood that equipment j with ${C_{ij}}^{supply} = 0$ is either a) operating safely at t_a (no maintenance requirement), b) maintained at t_a with minimum crew number or c) cannot be maintained since there is no minimum number of crew available to start the maintenance.

ix. If maintenance cannot be started due to ${C_j}^{t_a} \leq {C_j}^{min}$, a different module called crew supply-demand is activated to inquire whether there is an available crew supplier that can meet the requirement of maintenance to be started. This module retrieves the all supply values of equipment $1 \text{ to } \mathrm{i}$ and failure mode $1 \text{ to } \mathrm{j}$ $(\mathrm{C_{ij}}^{\mathrm{supply}})$. Here, the failure type of equipment requiring maintenance crew is called demander, and demanded crew number is calculated as $\mathrm{C_{ij}}^{\mathrm{demand}} = \mathrm{C_{ij}} - \mathrm{C_j}^{\mathrm{t_a}}$. For instance, if three people is required at minimum to initiate a particular maintenance work and only two people are available at $\mathrm{t_a}$, then one person will be demanded from other potential suppliers. If crew demand is provided from potential suppliers, the maintenance status of the demander and supplier(s) will be re-evaluated. Depending on whether the supplier is providing its current crew supplier value wholly or partially to the demander, the modified crew capacity of the supplier can be changeable. On the other hand, the crew number of demanders is updated as $\mathrm{C_{ij}} = \mathrm{C_j}^{\mathrm{min}}$ since the main intention is to allocate people from suppliers to enable starting the maintenance. Signals of these equipment will take the value of 2. Any $\mathrm{S_{ij}} = 2$ condition activates maintenance modification module. In this module, exact maintenance durations regarding up-to-date $\mathrm{C_{ij}}$ values ($\mathrm{eTTR_{ij}}$) are re-calculated.

x. If $\sum_{\mathrm{i}} \mathrm{C_{ij}}^{\mathrm{supply}}$ for failure type j is smaller than $\mathrm{C_{ij}}^{\mathrm{demand}}$ when required, it means that the total demand of equipment i cannot be provided from suppliers $1 \text{ to } \mathrm{i}$. If this condition is experienced, maintenance will not be carried out for the period of $\Delta\mathrm{t}$. Therefore, it will create an additional production loss for the related equipment due to the unavailability of the maintenance crew. Since system variables are evaluated in each $\mathrm{t_a} = \mathrm{t_a} + \Delta\mathrm{t}$, whenever crew unavailability case is experienced, the cumulative production loss is re-evaluated including another time interval, $\Delta\mathrm{t}$. Whenever enough crew number is not satisfied for equipment i, signal $\mathrm{S_{ij}}$ turns to a value of 3 to indicate that equipment i is exposed to additional maintenance downtime of crew unavailability. The signals indicating and storing equipment conditions are summarized in Table 3.1.

Table 3.1 Dynamic Signals of Equipment i in the Algorithm

Signal	Inquiry Period	Condition(s)
0	$\mathrm{LF_{ij}} < \mathrm{t_a}$	The failure occurrence point has not arrived.
1(1)	$(\mathrm{LF_{ij}} \geq \mathrm{t_a} \geq \mathrm{MF_{ij}})$	Failure occurrence point has just arrived, and the first evaluation and allocation of maintenance downtime and crew requirement are achieved.
1(2)	$(\mathrm{LF_{ij}} \geq \mathrm{t_a} \geq \mathrm{MF_{ij}})$	Maintenance keeps going without any modification in the activity schedule. The signal is preserved.
2	$(\mathrm{LF_{ij}} \geq \mathrm{t_a} \geq \mathrm{MF_{ij}})$	Maintenance activity requires a modification in maintenance duration and crew number for both demander and supplier(s).
3	$(\mathrm{LF_{ij}} \geq \mathrm{t_a} \geq \mathrm{MF_{ij}})$	Maintenance has not been started due to crew unavailability.

xi. $\mathrm{MF_{ij}}$ variable in Table 3.1 refers to the maintenance finish point of failure type j in equipment i at the active simulation time $\mathrm{t_a}$. Whenever any lifetime finish point of failure type arrives, Signal 1(1) is assigned as discussed previously. Here, $\mathrm{MF_{ij}}$ is updated first as $\mathrm{LF_{ij}} + \mathrm{eTTR_{ij}}$. If the maintenance activity is started without any crew unavailability condition, and any modification in the maintenance activity schedule due to supplying some crew members to other maintenance activities is not experienced, then this first assigned $\mathrm{MF_{ij}}$ value is preserved. On the other hand, if Signal 2 is active for the equipment, $\mathrm{MF_{ij}}$ is updated dynamically according to new $\mathrm{eTTR_{ij}}$ value for both the related demander and supplier(s). $\mathrm{MF_{ij}}$ value is also updated in Signal 3 since there will be additional downtime due to the unavailability of the maintenance crew. This unavailability situation will postpone the expected finish time of the maintenance on the calendar time.

xii. Whenever $MF_{ij} \leq t_a$ is detected by the algorithm, a new lifetime is assigned to the failure type of the related equipment, and new LF_{ij} is updated as $MF_{ij} + rvm(TBF_{ij})$ where rvm() is a random number generator according to the introduced $f(x)_{ij}$. Once the new LF_{ij} is determined, the signal S_{ij} turns to the value of 0.

xiii. The inquiries in the time range $[t_a, t_a + \Delta t]$ are completed only if all the inquiries of each failure type in each equipment are completed. Then, the acquired information is re-evaluated before passing to the next time range. Here, array data of the available total crew numbers (${C_j}^{t_a}$) for all failure types, up-to-date info for crew supply potentials of all maintenance-busy equipment (${C_{ij}}^{supply}$), crew demanders and their demands in number (${C_{ij}}^{demand}$), and active maintenance (MF_{ij}) and lifetime (LF_{ij}) finish points are called just before ending the evaluation for the active time range. Equipment availabilities (A_i), total downtime (D_i), total downtime due to crew unavailability(DC_i), total direct cost values (CO_i^{direct}) and total indirect cost values ($CO_i^{indirect}$) are captured and stored cumulatively for each piece of equipment. At this section, direct cost values are evaluated as the physical expenditure of maintenance activity, where indirect cost values are determined as a function of unit downtime cost and total downtime until t_a. Unit downtime cost can be evaluated as the time-based value of unit production loss.

The parameters, variables, and probability density functions (PDF) required in the simulation model are summarized in Table 3.2, and the algorithm logic is illustrated in Figure 3.2 briefly.

Table 3.2 The Algorithm Variables and Input Values

Parameter/PDF	Description
$\mathbf{f(x)_{ij}}$	Lifetime probability density function of failure type j of equipment i
$\mathbf{g(x)_{ij}}$	Maintenance duration probability density function of failure type j of equipment i
$\mathbf{C_j}^{\mathbf{min}}$	Minimum number of crew to start maintenance for failure type j
$\mathbf{C_j}^{\mathbf{max}}$	Maximum number of crew that can be employed in a maintenance activity for failure type j
$\mathbf{UC_i^{indirect}}$	Unit production loss, i.e. downtime cost, of equipment i
$\mathbf{UC_{ij}^{direct}}$	Unit direct cost of maintenance for failure type j of equipment i
$\mathbf{\Delta t}$	Time increment
$\mathbf{t_t}$	Target simulation time
Variable	**Description**
$\mathbf{A_i}$	Availability of equipment i at t_a
$\mathbf{C_{ij}}$	Maintenance crew number on duty at t_a for failure type j of equipment i
$\mathbf{C_j}^{\mathbf{t_a}}$	Total number of crew available duty at t_a for failure type j of equipment i
$\mathbf{C_{ij}}^{\mathbf{demand}}$	Number of crew demanded additionally for failure type j of equipment i at t_a
$\mathbf{C_{ij}}^{\mathbf{supply}}$	Number of the crew on duty for failure type j of equipment i but that can be allocated to a maintenance activity of other equipment at t_a
$\mathbf{CO_i^{direct}}$	Cumulative direct maintenance cost of equipment i at t_a
$\mathbf{CO_i^{indirect}}$	Cumulative indirect maintenance cost of equipment i at t_a
$\mathbf{D_i}$	Cumulative downtime of equipment i at t_a
$\mathbf{DC_i}$	Cumulative downtime of equipment i due to crew unavailability at t_a
$\mathbf{LF_{ij}}$	The lifetime finish point of failure type j of equipment i
$\mathbf{MF_{ij}}$	The maintenance finish point of failure type j of equipment i
$\mathbf{S_{ij}}$	Signal for the status of equipment i at t_a
$\mathbf{t_a}$	Active simulation time
$\mathbf{TBF_{ij}}$	The time between occurrence points for failure type j of equipment i
$\mathbf{TTR_{ij}}$	Maintenance duration for failure type j of equipment i in terms of man-hour
$\mathbf{eTTR_{ij}}$	Exact maintenance duration for failure type j of equipment i considering

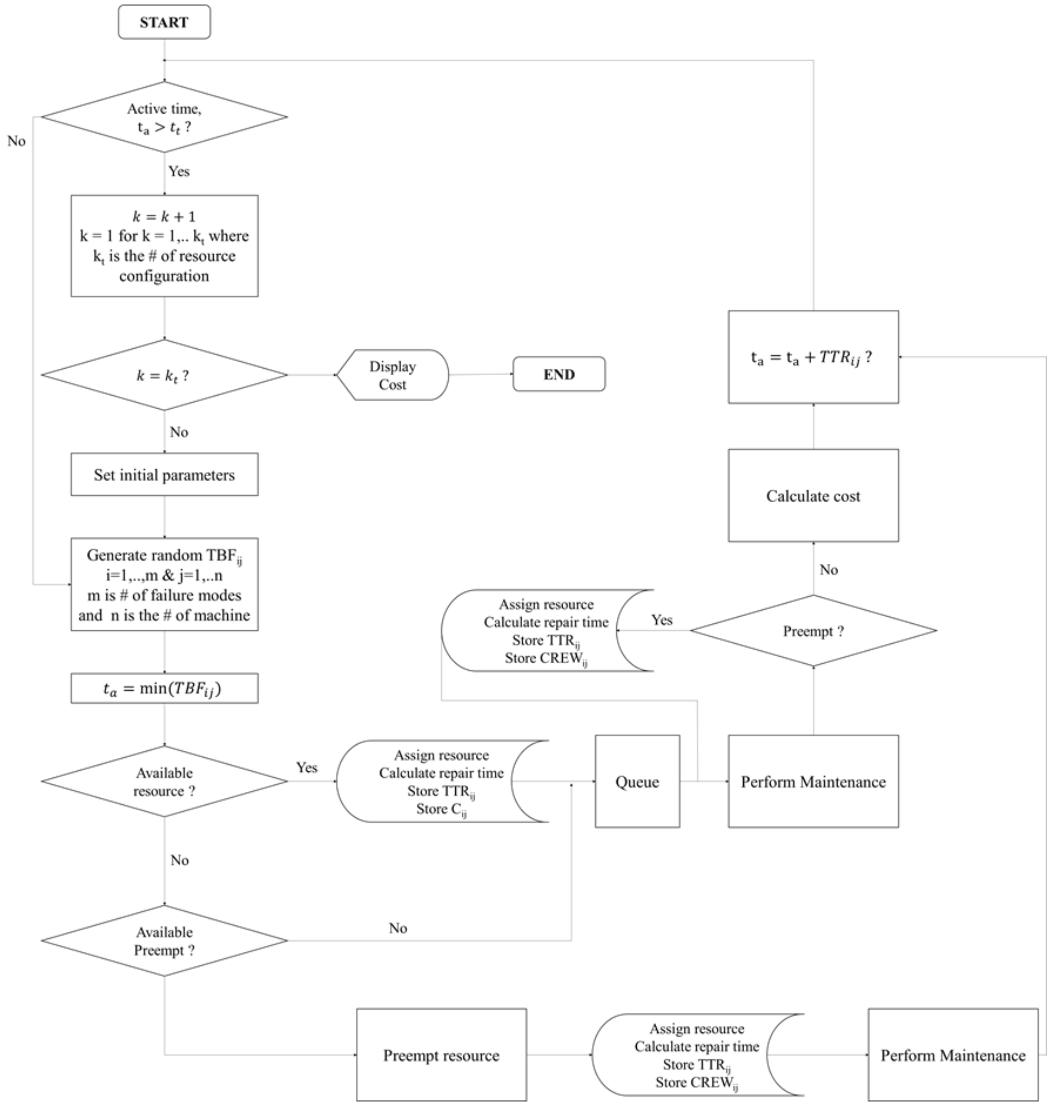
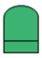


Figure 3.2 The Algorithm Logic used in the Simulation Model

3.3 Simulation Modelling in Reliasoft BlockSim

ReliaSoft BlockSim is a robust simulation environment for analyzing system reliability, availability, and maintainability. This software provides a wide range of assessments for repairable and non-repairable systems, which are valuable to product designers and asset managers, using exact computations or discrete event simulation. As well as providing reliability block diagrams, fault tree analysis and Markov analysis for system reliability assessment, Reliasoft Blocksim also employs event analysis to model and evaluate even the most complicated probabilistic or deterministic events. Hierarchy and decision-making process in the algorithm flow of event analysis is achieved by introducing inquiries into the flowchart modules embedded in the software (Table 3.3).

Table 3.3 Event Analysis Flowchart Modules and Descriptions in ReliaSoft Blocksim

Event Analysis Flowchart Module Name	**Symbol**	**Description**
Standad Block		It evaluates a mathematical expression and then delivers the outcome of the expression (output value) to the flowchart's next block(s).
Result Storage Block		It saves numerical values that are provided to it during simulations and then computes or stores the outcome.
Conditional Block		A conditional block works in the same way as a "if" statement does. It compares the entering value to a conditional statement, with true and false as potential outputs.
Binary Node		A binary node multiplies an incoming value by a predetermined value. The "true" path receives the resulting value. The primary purpose of binary nodes is to make developing decision trees easier.
Summing Gate		It performs a basic mathematical operation on all incoming values and delivers a single value to all outgoing routes.
Logic Gate		A logic gate compares several incoming values to a conditional expression, with true and false as potential outputs.
Branch Gate		It is acting as a switch button. It compares the input value to a set of scenarios and returns different results depending on whether case or branch evaluates to true.
Flag Marker		The flag marker indicates a place in the flowchart's route.
Go to Flag Blocks		The Go to flag sends the execution flow to the place.
Counter Block		The number of times the simulation has gone through a counter block is recorded, and the value is subsequently sent to the next block in the flowchart.
Reset Block		While the simulation is running, the software is forced to produce new values for all static functions by reset block.
UI block		Until the user offers some type of input, a UI block pauses flowchart simulation.
Subchart Block		Other flowcharts in the project are represented by subchart blocks. Subchart blocks are commonly used to simplify the whole flowchart.

This thesis study will intensively utilize the Event Analysis flowcharts (formerly known as RENO flowcharts) to construct the maintenance crew optimization model. In BlockSim, various distinct blocks provide the flexibility needed to design event analysis flowcharts that model circumstances as realistically as possible. The appearance and options of the blocks vary depending on the type of block. As illustrated in Table 3.3, the event analysis flow chart modules are described in different shapes and refer to different computational intentions. As discussed in Section 3.2, a simulation algorithm can be built up in different structures depending on its requirement for time-dependent monitoring, frequency of the monitoring, and the randomness that arises from the uncertainties in model factors. In this research study, the simulation model is characterized as dynamic, stochastic, and continuous. The system involves random input variables, and the system-state is monitored and evaluated continuously with a constant time increment.

The developed model is flexible for the number of failure modes and equipment that will be evaluated simultaneously to decide on the availability and unavailability of crew members qualified in different fields. Under this section, a system covering two equipment and two failure types each will be used to discuss the model's capability. The general view of the simulation model for this system is shown in Figure 3.3. There are four main submodules in the model that are ID01 - Simulation Start, ID02 - Maintenance Monitoring, ID04 - Crew Demander & Supplier, and ID04 - Fleet Condition Monitoring. In brief, the first submodule intends to initiate the simulation, generating the very first random values of the failure mode occurrence times and monitoring and updating simulation time, while the second module evaluates all possible scenarios between crew decisions and maintenance profile. On the other hand, the third submodule is a stand-by submodule that is triggered if any maintenance in any equipment is not started due to a deficit or unavailability of the required crew number. Last, the fourth submodule accumulates all the resultant data for each active time point and also decides on finalizing or sustaining the simulation. These submodules will be discussed in detail.

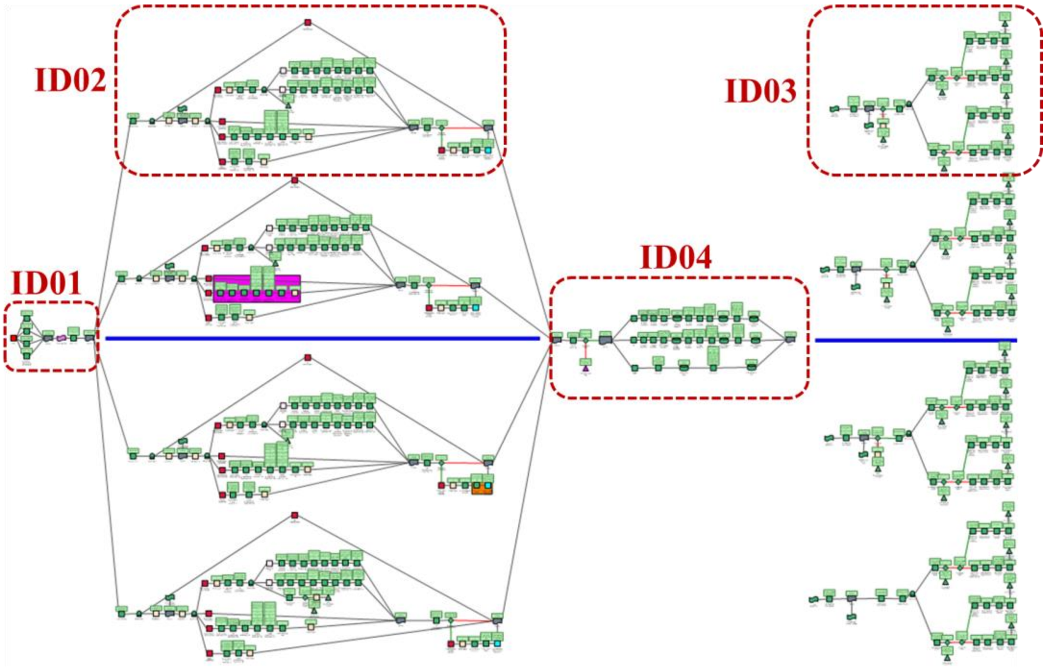


Figure 3.3 General View of the Simulation Model in ReliaSoft BlockSim

Probability distribution functions and parameters are the main simulation inputs that should be introduced before computing the model. On the other hand, any model resource having a value that can change during a simulation run should be defined as a variable. On this basis, parameters are in fact the variables with an initial value but not overwritten by any other value anytime in the inquiry calls. Accordingly, the model items discussed in Table 3.2 previously needs to be introduced to Reliasoft Blocksim Resource Manager by user-defined descriptions. These descriptions can be viewed in Table 3.4 for a two-equipment and two-failure type sample system. At this point, two common failure types that are mechanical and electrical, were introduced using notation ‘M’ and ‘E’ at the beginning of model resource names, if necessary. In addition, equipment01 and equipment02 were referred as ‘E1’ and ‘E2’, respectively, at the end of some resource names to be used for equipment-specific decisions that can be on a crew, maintenance duration, and similar inquiries.

Table 3.4 Description of Model Inputs and Variables in the Computational Environment

Parameter/PDF	Computational Desciption	Parameter/PDF	Computational Desciption
$\mathbf{f(x)_{ij}}$	M_TBF1.Distribution(t) M_TBF2.Distribution(t) E_TBF1.Distribution(t) E_TBF2.Distribution(t)	$UC_i^{indirect}$	M_cost_indirect E_cost_indirect
$\mathbf{g(x)_{ij}}$	M_TTR1.Distribution(t) M_TTR2.Distribution(t) E_TTR1.Distribution(t) E_TTR2.Distribution(t)	UC_{ij}^{direct}	M_cost_direct E_cost_direct
$\mathbf{C_j^{min}}$	E_crew_min_TTR M_crew_min_TTR	Δt	Active_time_increment
$\mathbf{C_j^{max}}$	M_crew_max_TTR E_crew_max_TTR	t_t	Simulation_target

Variable	Computational Description	Variable	Computational Description
$\mathbf{A_i}$	Availability_E1 Availability_E2	LF_{ij}	M_Lifetime_Finish_Point_E1 M_Lifetime_Finish_Point_E2 E_Lifetime_Finish_Point_E1 E_Lifetime_Finish_Point_E2
$\mathbf{C_{ij}}$	M_crew_busy_E1 M_crew_busy_E2 E_crew_busy_E1 E_crew_busy_E2	MF_{ij}	M_Maintenance_Finish_Point_E1 M_Maintenance_Finish_Point_E2 E_Maintenance_Finish_Point_E1 E_Maintenance_Finish_Point_E2
$\mathbf{C_j^{t_a}}$	M_crew_available E_crew_available	S_{ij}	M_Signal_E1 M_Signal_E2 E_Signal_E1 E_Signal_E2
$\mathbf{C_{ij}^{demand}}$	M_Crew_Additional_Demand E_Crew_Additional_Demand	t_a	Active_time
$\mathbf{C_{ij}^{supply}}$	M_crew_available_supply_E1 M_crew_available_supply_E2 E_crew_available_supply_E1 E_crew_available_supply_E2	TBF_{ij}	M_TBF1 M_TBF2 E_TBF1 E_TBF2
$\mathbf{CO_i^{direct}}$	M_total_cost_direct_E1 M_total_cost_direct_E2 E_total_cost_direct_E1 E_total_cost_direct_E2	TTR_{ij}	M_active_TTR1 M_active_TTR2 E_active_TTR1 E_active_TTR2
$\mathbf{CO_i^{indirect}}$	M_total_cost_indirect_E1 M_total_cost_indirect_E2 E_total_cost_indirect_E1 E_total_cost_indirect_E2	$eTTR_{ij}$	M_active_TTR1 / M_crew_busy_E1 M_active_TTR2 / M_crew_busy_E2 E_active_TTR1 / E_crew_busy_E1 E_active_TTR1 / E_crew_busy_E2
$\mathbf{D_i}$	M_total_downtime_E1 M_total_downtime_E2 E_total_downtime_E1 E_total_downtime_E2	DC_i	M_Cumulative_Crew_Downtime_E1 M_Cumulative_Crew_Downtime_E2 E_Cumulative_Crew_Downtime_E1 E_Cumulative_Crew_Downtime_E2

The model is first initiated with the Simulation Start Module illustrated in Figure 3.4. Once the simulation is initiated, the very first assignments of the failure type occurrence points ($\mathrm{LF_{ij}}$) of each equipment is achieved by generating random values ($\mathrm{TBF_{ij}}$) from the related lifetime probability distributions ($\mathrm{(f(x)_{ij})}$), and $\mathrm{LF_{ij}} = \mathrm{TBF_{ij}}$ is overwritten for the first time for both equipment's electrical and mechanical failure types. This assignment part will not be used up to the simulation end since these occurrence points will be updated dynamically later on whenever any related change in system status are triggered. When the evaluations in the current simulation time are completed in all modules within the algorithm (it will be discussed later), then the simulation flow will be directed to the Time to Loop Flag. The active simulation time is updated by increasing its value with a user-defined time increment for sequential analysis of the target system. Each time it passes here, the simulation time is steadily increased until the target simulation time is reached. Also, dummy blocks are used as control connectors without any mathematical operation. For instance, the first dummy block in the figure will allow the algorithm flow after ensuring all four random variables are generated.

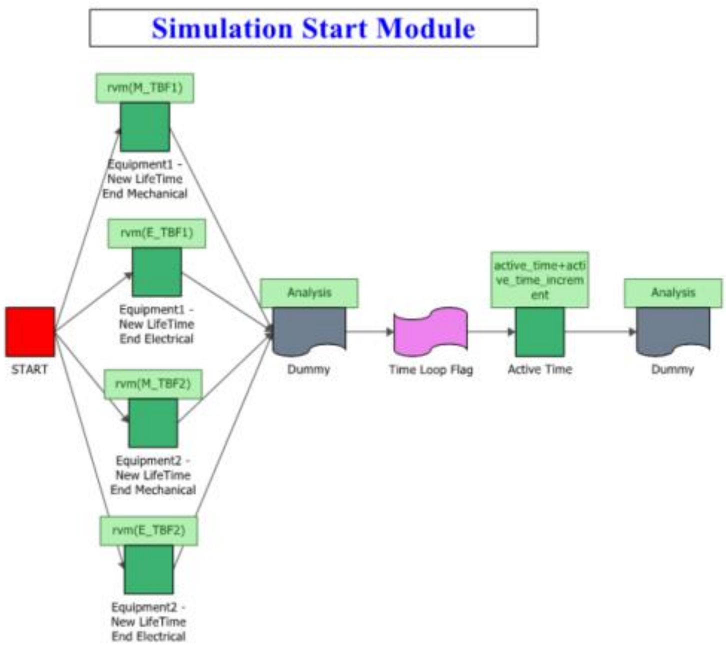


Figure 3.4 Simulation Start Module

The simulation flow is followed by the maintenance monitoring module (Figure 3.5). In this module, the model checks the conditions of failure types by jointly evaluating active simulation time and dynamically-updated LF_{ij} values to decide on maintenance requirements. In case active simulation time overcomes the related LF_{ij} value, then the model decides that maintenance time does not arrive yet, sustains $S_{ij} = 0$ and guides the flow to Path01 after the branch gate, as shown in Figure 3.5. No action is taken place for this failure type, and the latest variable values are preserved. If the active time is greater than the latest value of a lifetime finish point (LF_{ij}) for the equipment, the flow is directed to Path02, the maintenance action section. At this point, the maintenance action inquiry is performed according to the dynamic signals (S_{ij}) mentioned in Section 3.2. The potential four different actions defined in the model are as follows:

- Path02-1: Condition: $(LF_{ij} \geq t_a)$ & $(S_{ij} = 0)$ → Decision: Maintenance downtime values $(TTR_{ij}, eTTR_{ij}, MF_{ij})$ and crew values $(C_{ij}, C_{ij}{}^{supply}, C_{ij}{}^{demand})$ are evaluated for the first time.
- Path02-2: Condition: $(LF_{ij} \geq t_a \geq MF_{ij})$ & $(S_{ij} = 1)$ → Decision: Maintenance keeps going with its latest up-to-date values without any change in time and crew.
- Path02-3: Condition: $(LF_{ij} \geq t_a \geq MF_{ij})$ & $(S_{ij} = 2)$ → Decision: A modification is required in the time-based and crew information of the active maintenance activity for the related equipment.
- Path02-4: Condition: $(LF_{ij} \geq t_a \geq MF_{ij})$ & $(S_{ij} = 3)$ → Decision: Maintenance downtime is activated, but maintenance activity cannot be started since the required minimum number for the maintenance activity has not been satisfied. Therefore, additional maintenance downtime will be recorded for each Δt.

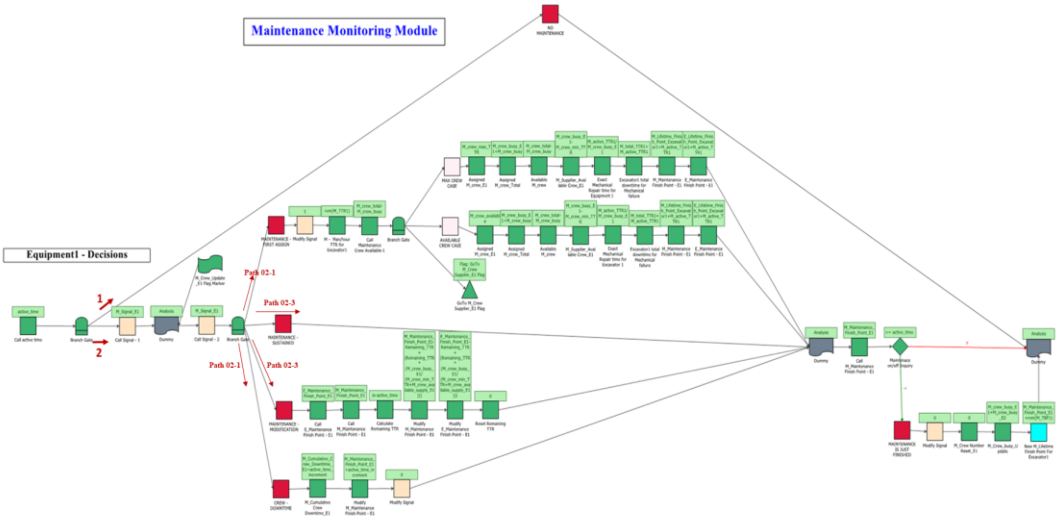


Figure 3.5 Maintenance Monitoring Module

The Path02-1, which is called MAINTENANCE - FIRST ASSIGN, can be viewed in Figure 3.6. If this path is activated, one of three following decisions can be taken:

- Path02-1-1: Condition: M_crew_available ≥ M_crew_max _TTR → Decision: 'MAX CREW CASE' is activated. Here, the available crew authorized for mechanical-type maintenance is allocated to the related maintenance activity at the practically highest number to reduce the exact maintenance duration ($eTTR_{ij}$). In this condition, M_crew_busy_E1 and M_crew_busy_total are updated. Exact time to repair (M_active_TTR1) is calculated and M_crew_available is updated. In addition, total downtime (M_total_TTR1) for both failure type and the equipment are captured. And finally, maintenance (M_Maintenance_Finish_Point) and lifetime (M_Lifetime_Finish_Point) finish points are updated.
- Path02-1-2: Condition:M_crew_min _TTR ≤ M_crew_available ≤ M_crew_max _TTR → Decision: 'AVAILABLE CREW CASE' is activated. that is, maintenance is performed with the available number of crew. Similar to max crew case, M_crew_busy_E1 and M_crew_busy_total are updated. M_active_TTR1 is calculated, M_crew_available is updated, and

also M_total_TTR1 is captured. Lastly, maintenance and lifetime finish points are updated.

- <u>Path02-1-3</u>: Condition: M_crew_available ≤ M_crew_min_TTR → Decision: The module is directed to Crew Demander & Supplier Module (it will be discussed later on) to inquire the busy crew on duty for maintenance of other equipment but can be re-appointed (supplied) to the maintenance of current equipment.

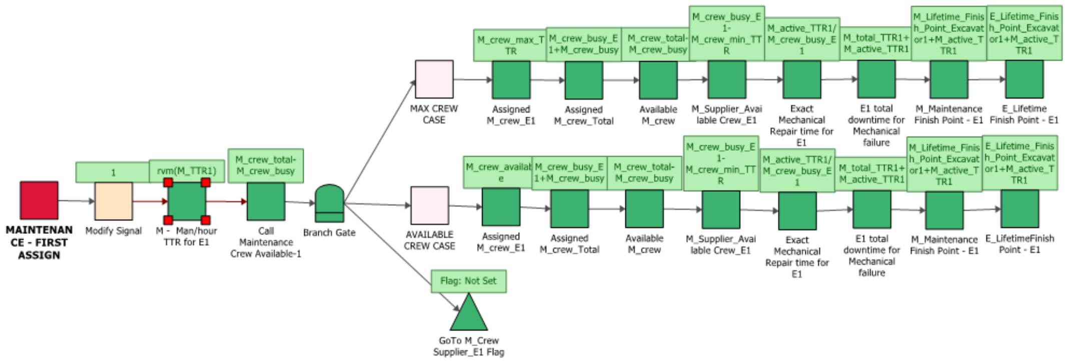


Figure 3.6 Maintenance Monitoring Module–Maintenance First Assign (Path02-1)

On the other hand, Path02-2, which is called MAINTENANCE - SUSTAINED, can be viewed in Figure 3.7. As discussed earlier, usage of this path requires the related failure type to have signal $S_{ij} = 1$ without any modification in the maintenance schedule. In this case, simulation preserves the latest values of variables for the failure type of related equipment until the assigned maintenance finish point time arrives.

Figure 3.7 Maintenance Monitoring Module–Maintenance Sustained (Path02-2)

If the Path02-3, requiring the condition of $(\mathrm{LF_{ij}} \geq \mathrm{t_a} \geq \mathrm{MF_{ij}})$ & $(\mathrm{S_{ij}} = 2)$, is activated, then the MAINTENANCE - MODIFICATION process is applied. This path is the return path of Crew Demander & Supplier Module since signal value is modified as '2' only in Crew Demander & Supplier Module due to re-allocating some of the busy crew to other jobs. As will be explained, both the crew-demander equipment and crew-supplier equipment are allocated $\mathrm{S_{ij}} = 2$ since they will have a modification in their current crew number and exact maintenance durations. Once the relevant time and crew-based updates are completed, the signals of these equipment turn to '1'. Path02-3 can be viewed in Figure 3.8.

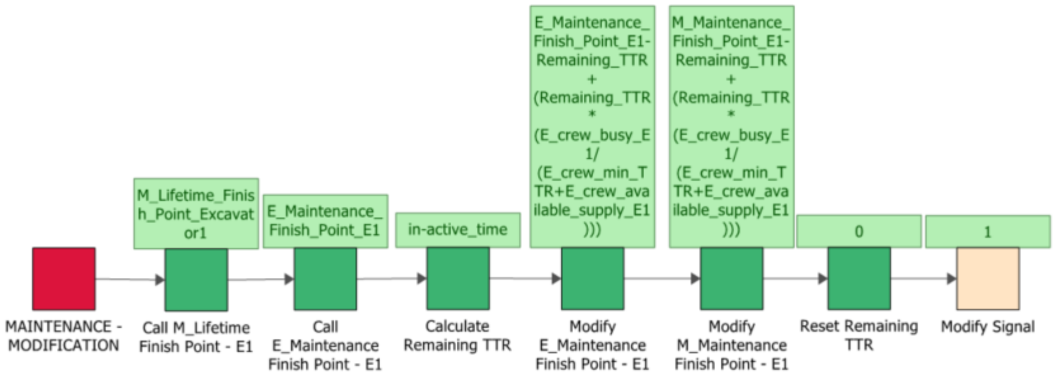


Figure 3.8 Maintenance Monitoring Module–Maintenance Modification (Path02-3)

If the Crew Demander & Supplier Module assigns the signal value of 3 to the equipment, then the Path02-4 entitled CREW - DOWNTIME is activated. This condition exists only if the Crew Demander & Supplier Module decides that there is not enough number of crew that can be re-allocated from the other maintenance activities to satisfy the required minimum number of crew to initiate the current work. Therefore, this path will update the crew unavailability-based downtime of the equipment cumulatively, increasing the downtime by the time increment $(\Delta\mathrm{t})$. The expected maintenance finish point will also be postponed by $\Delta\mathrm{t}$. After completing the required updates, the signal turns to '0'. By this way, the equipment will try to get over the crew unavailability condition in the new active time by moving to MAINTENANCE - FIRST ASSIGN part since it meets the condition

$(\mathrm{LF}_{ij} \geq \mathrm{t_a})$ & $(\mathrm{S}_{ij} = 0)$. If there is not still enough number of crew for the maintenance work, then this path (Path02-4) will be used again. The path can be investigated in Figure 3.9.

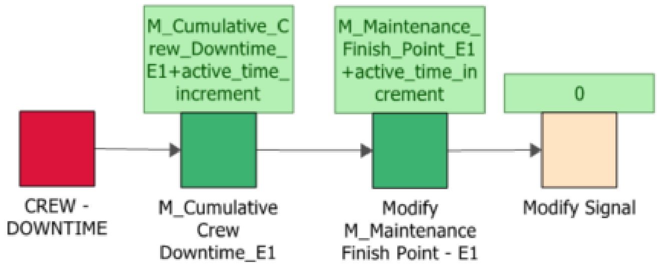


Figure 3.9 Maintenance Monitoring Module – Crew Downtime (Path02-4)

After evaluating one of the four decisions in the Maintenance Monitoring Module in each simulation loop, they are combined with a dummy black dictating completion of 1 out of 4 paths (Figure 3.10). Then, the recent maintenance finish point of the failure type is re-called. If the algorithm decides that the related maintenance is just finished, comparing with the active simulation time $(\mathrm{M\_maintenance\_Finish\_Point\_E1} \leq \mathrm{active\_time})$, the crew on duty $(\mathrm{M\_crew\_busy\_E1})$ is released, and the total crew on duty $(\mathrm{M\_crew\_busy})$ is updated accordingly. A new random lifetime (TBF_{ij}) is generated, and the related expected lifetime finish point on the calendar time (LF_{ij}) is updated. The signal turns to '0'. Having this new LF_{ij} and $\mathrm{S}_{ij} = 0$, the failure type starts to follow the Path01 called NO MAINTENANCE.

If the inquiry in Figure 3.10 shows that the maintenance is not over yet, Maintenance Monitoring Module will keep active in the sequential updated simulation time. Suppose the active simulation time arrives at the target simulation. In that case, the simulation time will not be updated, and all the stored information will be called in Fleet Condition Monitoring Module. This module will be explained in detail.

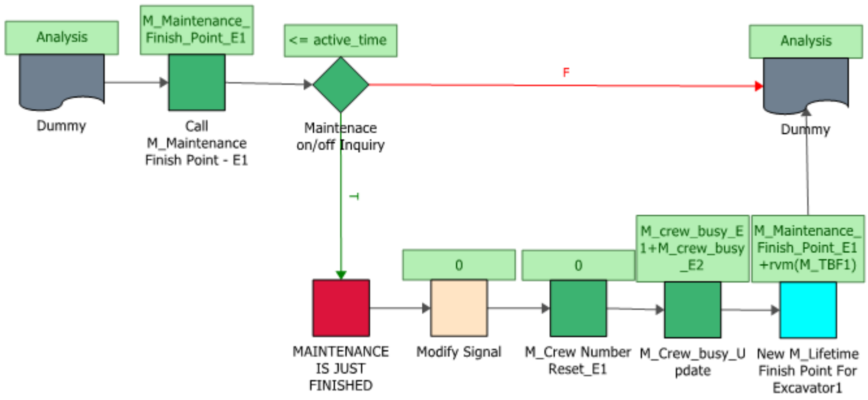


Figure 3.10 Maintenance Monitoring Module – Maintenance Just Finished

As mentioned previously in Path02-1-3, Path02-3, and Path02-4, Crew Demander & Supplier Module is frequently used in cases where the required minimum crew number for the given maintenance job is not ensured from the available crew. The flowchart diagram of this module is represented in Figure 3.11.

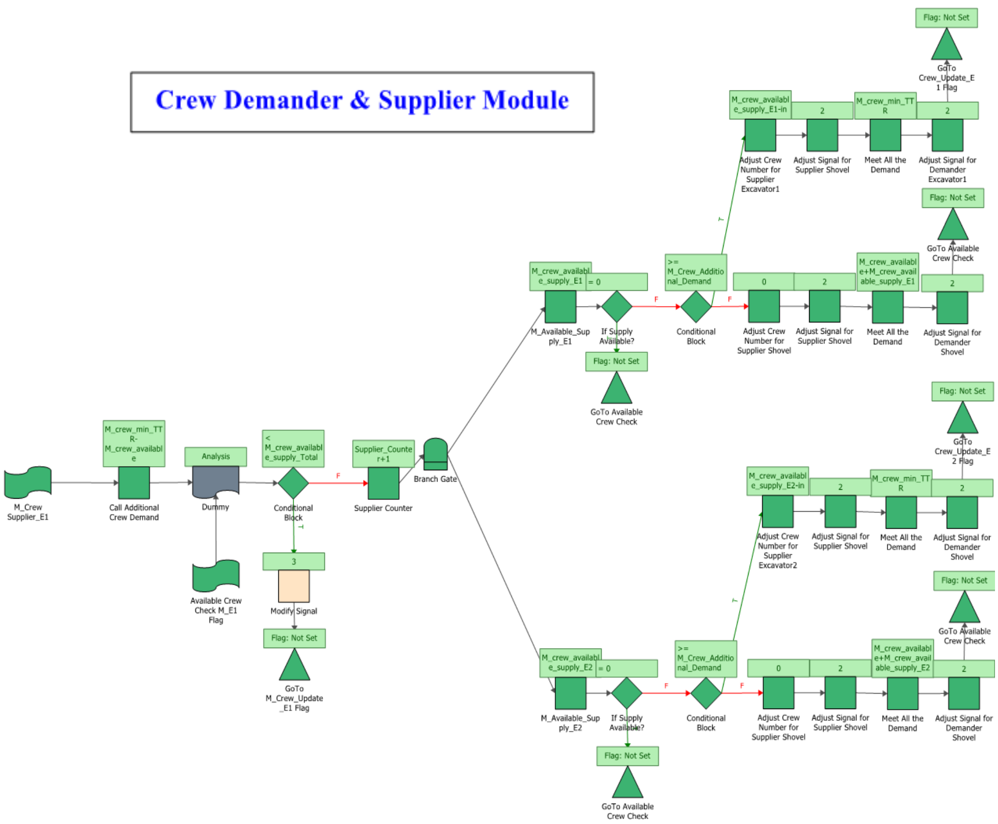


Figure 3.11 Crew Demander & Supplier Module

This module is activated when M_crew_available ≤ M_crew_min _TTR condition is observed in the maintenance monitoring module. First, how many crew members are available for the time being and what is the additional requirement are responded to reveal the actual demand number of the equipment (M_Crew_Additional_Demand_E1). This value is compared with the total number of the maintenance crew that can be allocated from maintenance activities in other equipment. The supply capacity of each equipment is determined in the Maintenance Monitoring Module by M_crew_busy_E1 − M_crew_min_TTR. The supply capacity of each equipment in the fleet for the active time is accumulated in a joint data pool and determines M_crew_available_supply_total. Therefore, if M_Crew_Additional_Demand_E1 > M_crew_available_supply_total at t_a, then the algorithm modifies the signal as '3' and moves to CREW – DOWNTIME path (Path02-4) since the minimum crew number is not satisfied (Figure 3.12).

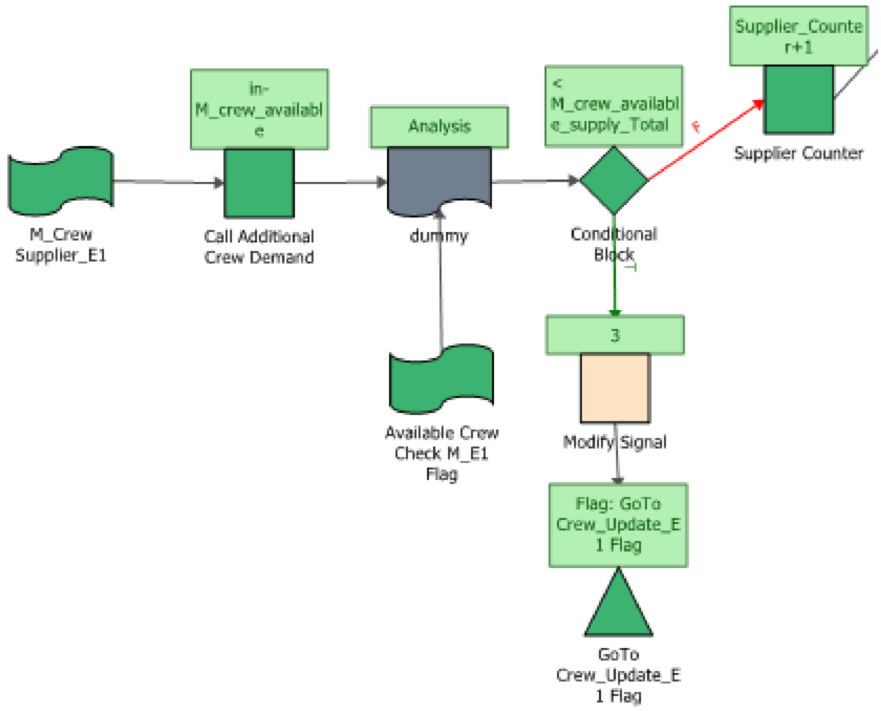


Figure 3.12 Crew Demander & Supplier Module – First Part

On the other hand, if the condition is false, there is a crew on duty which can be allocated to another maintenance works, then the simulation checks which equipment can supply how much workforce, as shown in Figure 3.13.

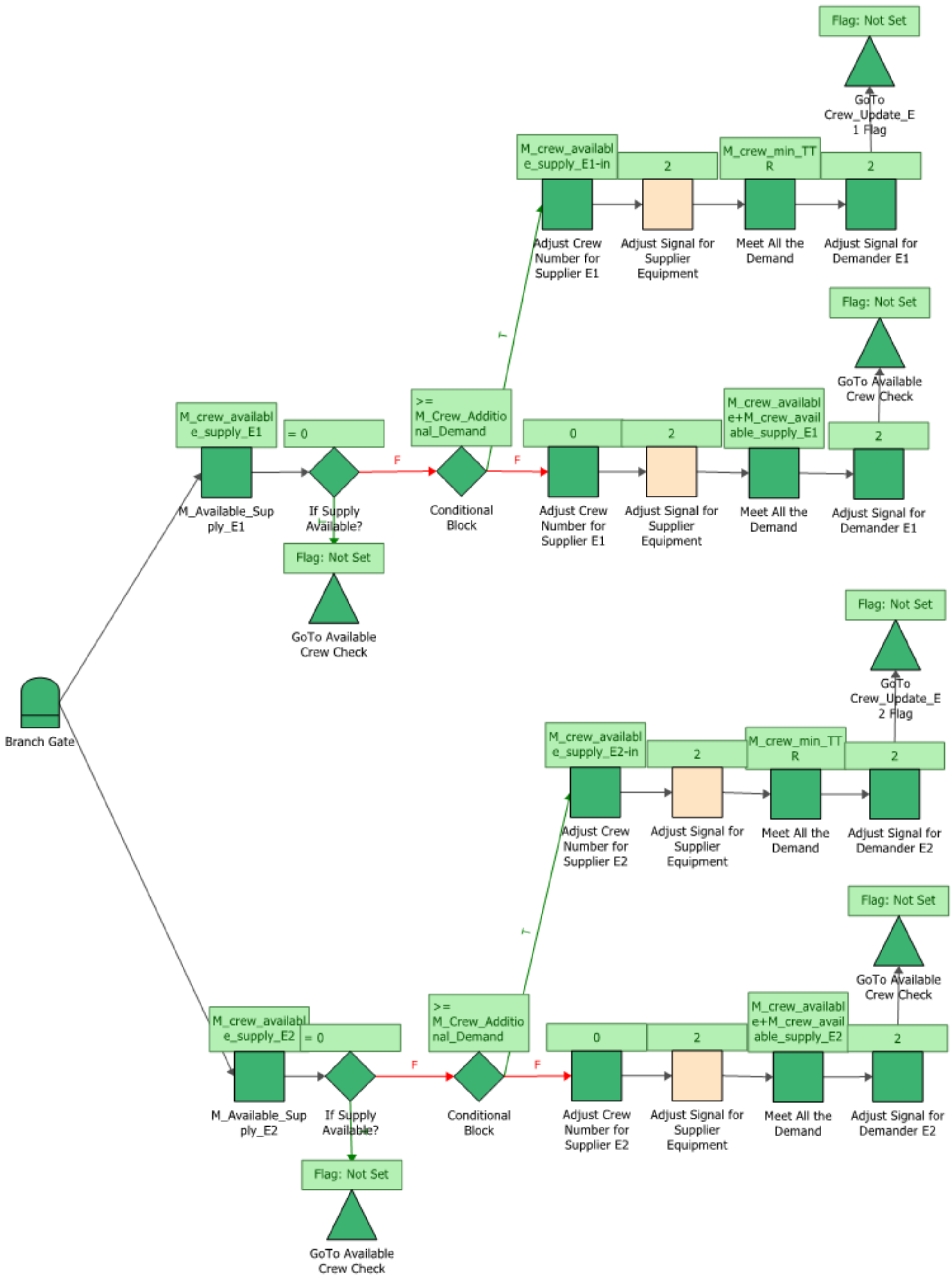


Figure 3.13 Crew Demander & Supplier Module – Second Part

This part determines how many crews can be supplied from which equipment. At this point, re-allocations from a single equipment may satisfy the crew demand fully or partially. Here, it was assumed that if the supply capacity of single equipment is higher than the demand, then all the demand will be supplied from this equipment. For instance, if Equipment02 has a crew supply capacity of three people ($\mathrm{M\_Crew\_Available\_Supply\_E2} = 3$) and Equipment01 has an additional demand of two people ($\mathrm{M\_Crew\_Additional\_Demand\_E1} = 2$), then all the demand will be met by Equipment02. If $\mathrm{M\_Crew\_Available\_Supply\_E2} = 1$, then this one person will be provided from Equipment02, and other supply capacities of the remaining equipment in maintenance will be inquired. Following all the inquiries, signals of all the equipment marked as active supplier(s) and demander will turn to ‘2’. The algorithm will immediately activate the MAINTENANCE - MODIFICATION path for demander, update its crew number and exact maintenance duration, and modify its signal as ‘1’. On the other hand, the supplier(s) with the signal of ‘2’ will be re-evaluated at the sequential time loop $(\mathrm{t_a} + \Delta\mathrm{t})$ in terms of their revised crew numbers, exact maintenance durations, and maintenance finish points since any drop in the crew number will increase the remaining maintenance completion time.

Finally, fleet condition monitoring module illustrated in Figure 3.14 captures the information gathered for the observation period at the end of each simulation as an array data. In this module, crew and repair downtime values for each of failure type are given seperately and in total foe each equipment introduced into the model. This module is activated when the latest incremented active time arrives at the target simulation time $(\mathrm{t_a} \geq \mathrm{t_t})$. Otherwise, the flow is directed to the time loop.

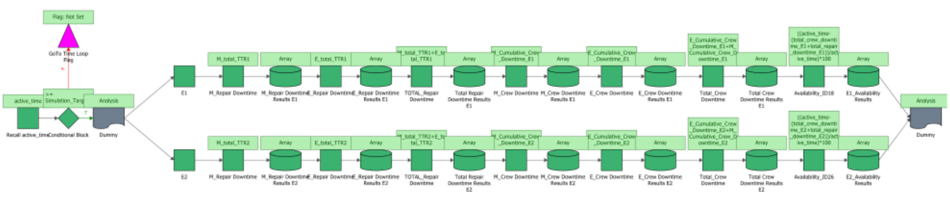


Figure 3.14 Fleet Condition Monitoring Module

CHAPTER 4

IMPLEMENTATION OF THE DEVELOPED MODEL FOR AN EXCAVATOR FLEET

4.1 Introduction

This chapter implements the developed algorithm for an excavator fleet operated in a surface coal mine. Accordingly, failure and maintenance datasets of individual excavators in the fleet are preprocessed first to determine the related probability distribution functions (PDF) to be used in the implementation. This part will be explained in Section 4.2 by highlighting the data processing stages in detail. Then, the remaining input parameters and the simulation application results will be discussed in Section 4.3 to reveal the model capabilities.

4.2 Pre-Processing of Data for the PDF Models

The simulation algorithm developed in the current thesis study is structured as continuous, dynamic, and stochastic simulation. It will be implemented for five excavators operated in ore and waste production of a surface coal mine in Turkey. At this point, different clustered failure and maintenance datasets of five excavators valid for an observation period between 2007 and 2009 need to be preprocessed first to determine the parametric values of the lifetime probability density functions of failure types for each piece of equipment ($f(x)_{ij}$) and maintenance duration probability density functions of failure types for each equipment ($g(x)_{ij}$) to enable generating random values for the related time between occurrence points (TBF_{ij}) and maintenance durations (TTR_{ij}) in the computational environment. The raw dataset covers the time elapsed between failures of the excavators, the repair time, the excavator ID, and a brief description of the failure. Following a preliminary evaluation of the raw data, the failure types were divided into two main groups: mechanical and electrical failure. It should be noted that since two main groups of crews need to be employed according to their technical skills, then different failure modes included in either of these groups were evaluated together. In brief, the maintenance crew qualified to perform maintenance activities in the mining site will be clustered in two groups accordingly.

The start and end dates of the failures were recorded in terms of date and hour. First, the time between two failures (TBF) and the time to repair (TTR) values were clustered according to the failure types for each excavator. Figure 4.1 represents an overview of the maintenance number and duration statistics for the five excavators according to their failure occurrence types at a period between 2007 and 2009.

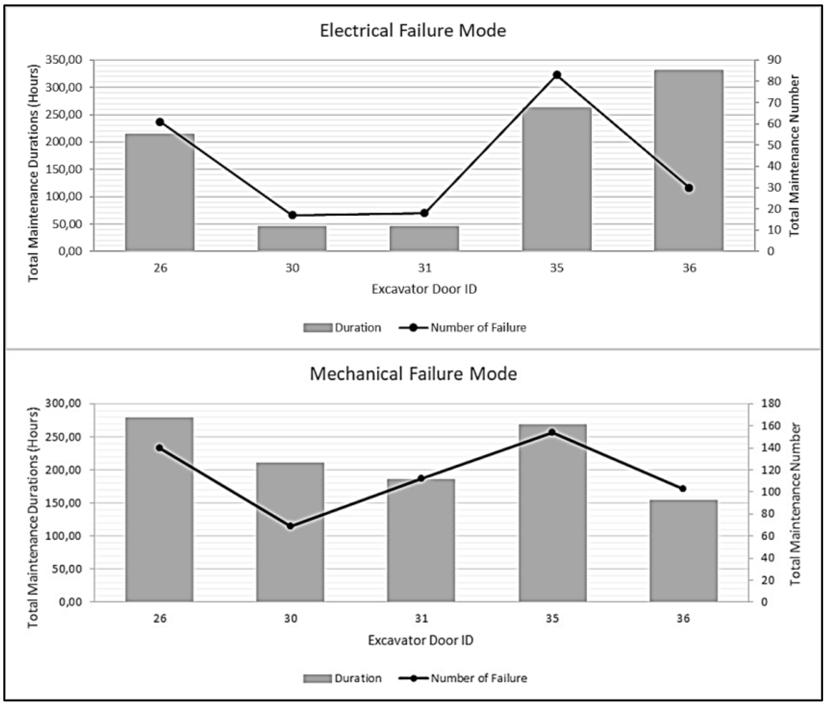


Figure 4.1 Maintenance Duration and Number Statistics of the Excavators for the Observation Period

In a three-year observation period, a total of 578 mechanical failure events were recorded for the excavator fleet, and these failures were recovered with maintenance activities resulting in a total downtime of 1098.67 hours. On the other hand, there is a total of 209 records for electrical failure type, and the related maintenance activities are observed to be completed in a total of 896.75 hours for the whole excavator fleet.

Since the data convenience directly affect the validity and precision of the $g(x)_{ij}$ and $f(x)_{ij}$ distribution functions, the dataset of each failure type of each excavator should be pre-processed first before determining the parametric values of the distributions. On this basis, the data values not representing the general statistical behavior of the datasets should be detected. Outliers and inconvenient data due to human error lead to anomalies within the dataset resulting in unexpected outcomes. In addition, randomness and time-dependent trend of the related TBF and TTR data should also be checked since these records are on a time basis and can be categorized as a time series. It means that any ascending or descending trend of ordered TBF/ TTR values indicates that this type of data cannot be fitted into distribution since data behavior changes in time. Therefore, a time series dataset with a trend is better to be presented with a regression equation instead of distribution.

Extremely high or low values in a dataset may point to outliers, and the availability of outliers can interrupt the general data behavior remarkably. Outlier identification can be achieved using parametric tests particular to distribution type or nonparametric tests that do not consider the distribution type. Box and Whisker plots are one of the common nonparametric outlier detection tools that can be used for any data histogram. These plots require the determination of five measures: first quartile (Q_1), median (Q_2), third quartile (Q_3), minimum data limit, and maximum data limit (Figure 4.2).

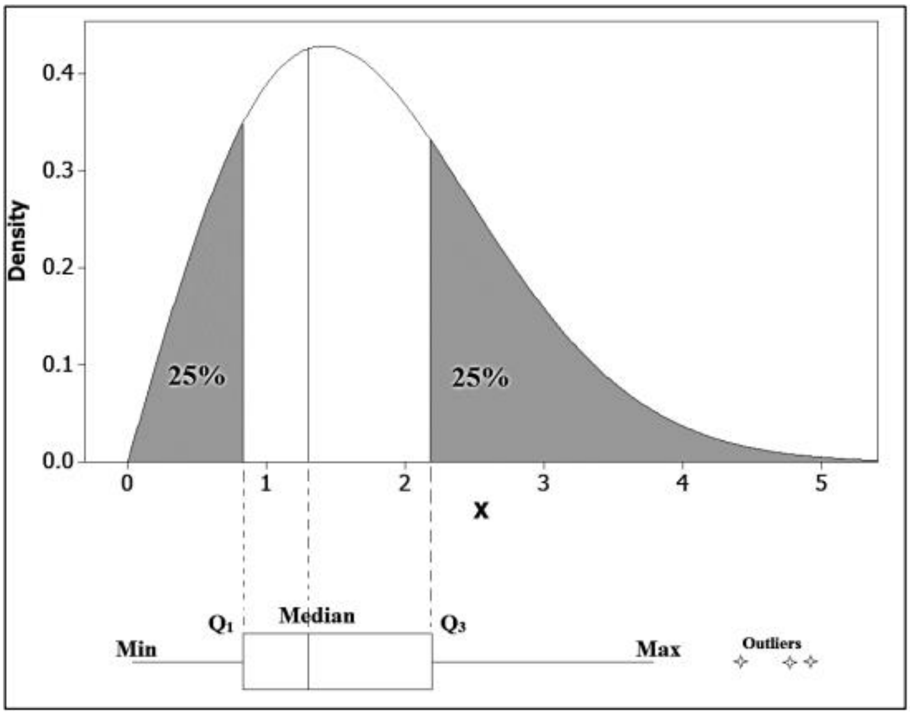


Figure 4.2 Box Plots used in Outlier Detection (Gölbaşı, 2015)

The median value in a probability function is an exact value that divides the area beneath the function curve into half and refers to $\int_{-\infty}^{median} f(x)\,dx = 0.5$. On the other hand, Q_1 and Q_3 values refer to $\int_{-\infty}^{Q1} f(x)\,dx = 0.25$ and $\int_{-\infty}^{Q3} f(x)\,dx = 0.75$, respectively. The difference between the Q_1 and Q_3 values is known as the interquartile range (IQR). On this basis, minimum and maximum limits of the allowable data range are determined as $[(Q_1 - 1.5 \times \mathrm{IQR}), (Q_3 + 1.5\mathrm{IQR})]$. Therefore, any value out of this range is a candidate for the outlier.

Due to its practical and nonparametric utilization, Box and Whisker plots were utilized in the current study to detect potential outliers for individual TBF and TTR datasets of two failure types for five excavators. Figures 4.3 and 4.4 show a representative example of the plot application for the TBF and TTR datasets of electrical and mechanical failure types for Excavator ID-18. The circles out of the maximum limits are evaluated as outliers. These plots were generated for all excavators separately, and the outliers in each TBF and TTR dataset were eliminated. The existence of outliers can be due to human error such as missing records or typos and/or correctly-recorded but non-presentative data. In some conditions, machines may exhibit occasional variations in TTR or TBF values with a significant deviation from expected values.

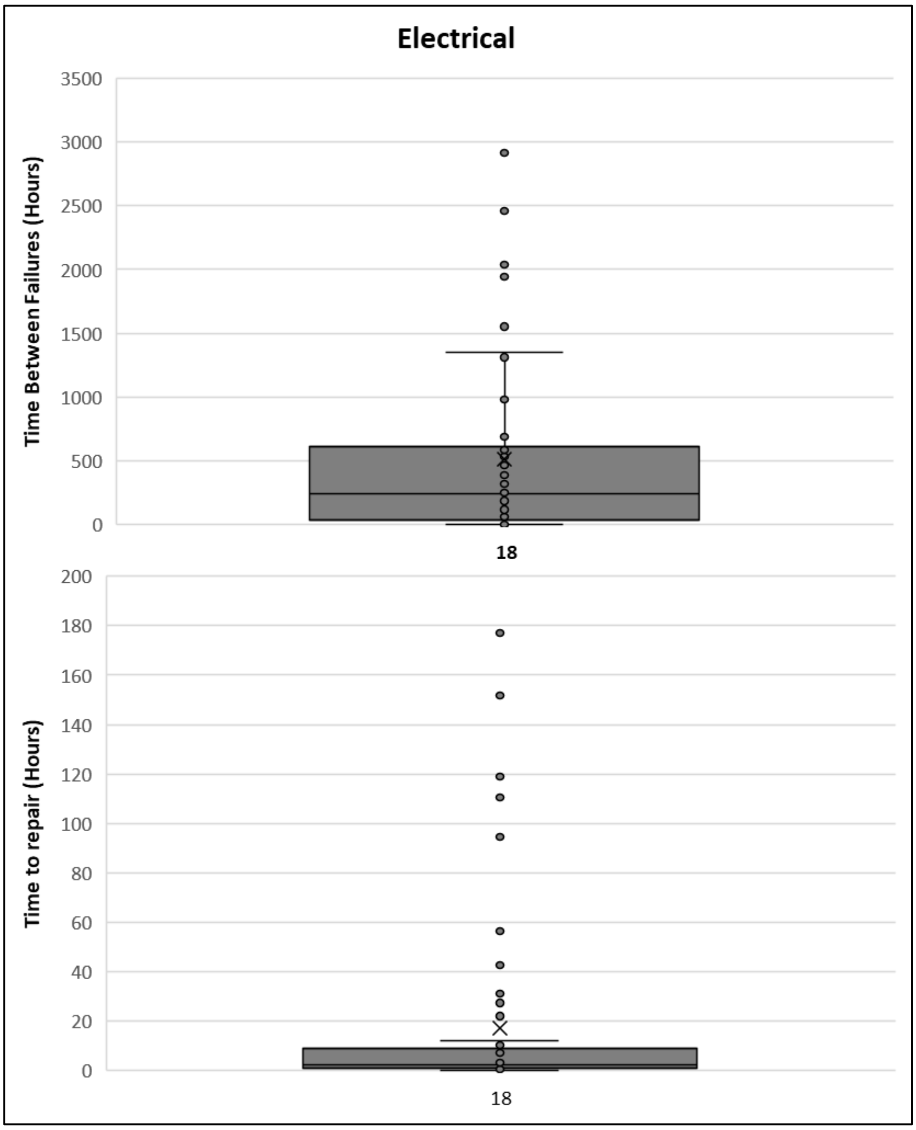


Figure 4.3 Outlier Detection with Box Plot for Excavator 18

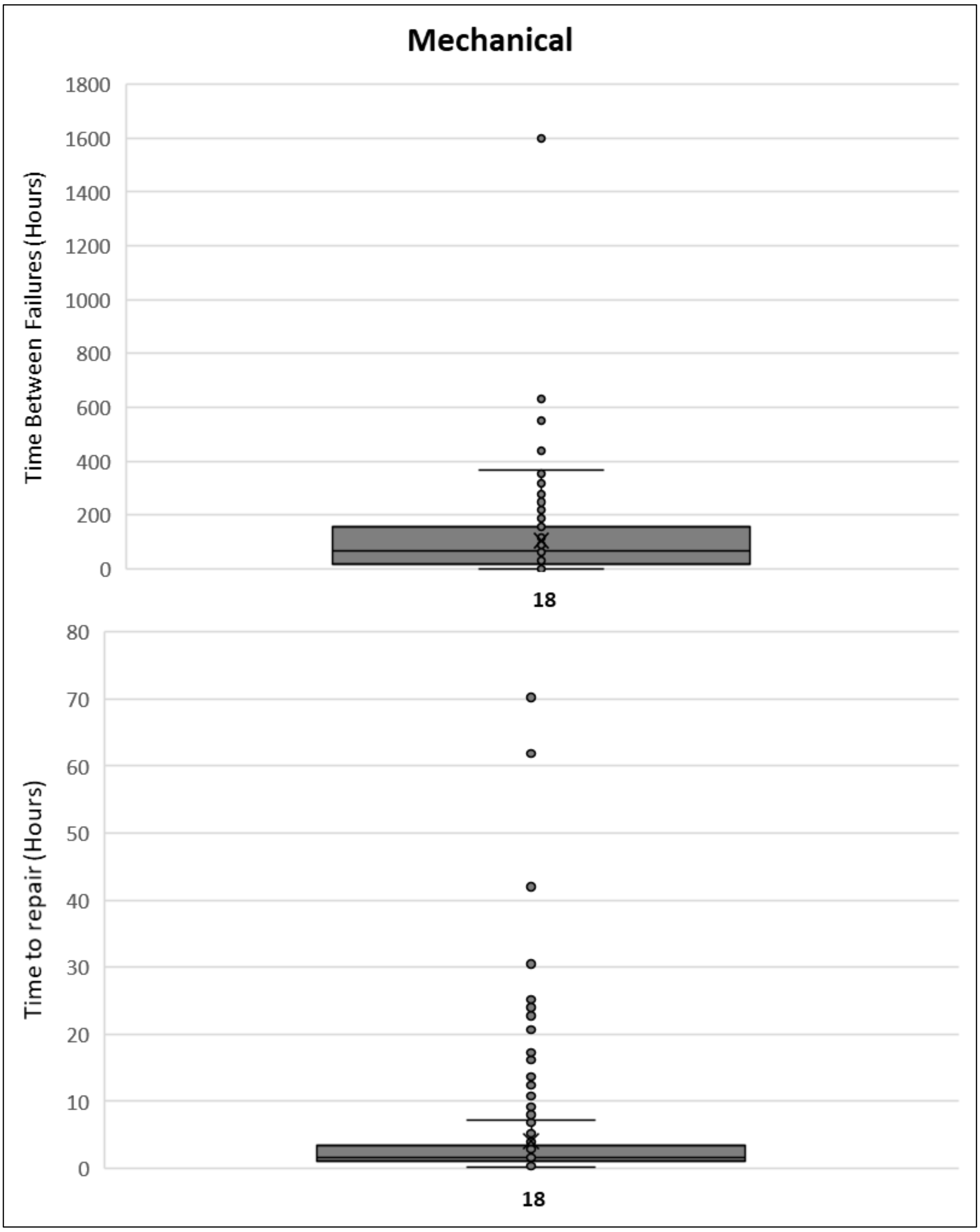


Figure 4.4 Outlier Detection with Box Plot for Excavator 18

After eliminating outliers from the datasets, the datasets were discussed for their time-dependent trends using qualitative and quantitative methods. Cumulative failure numbers (CFN) versus cumulative time between failure (CTBF) plot is one of the qualitative tests of analyzing the trend in a time series. Qualitative tests generally offer a fast and practical way of detecting data trends as a tentative preliminary analysis. However, the resultant deductions may require validation with the quantitative methods. If the plotted CTFB vs. CFN graph shows a near-straight line, it can be a good indicator of non-trend behavior. Figure 4.5 shows the electrical CTFB vs. CFN graphs of Excavator ID-26 and the mechanical CTFB vs. CFN graphs of Excavator ID-30.

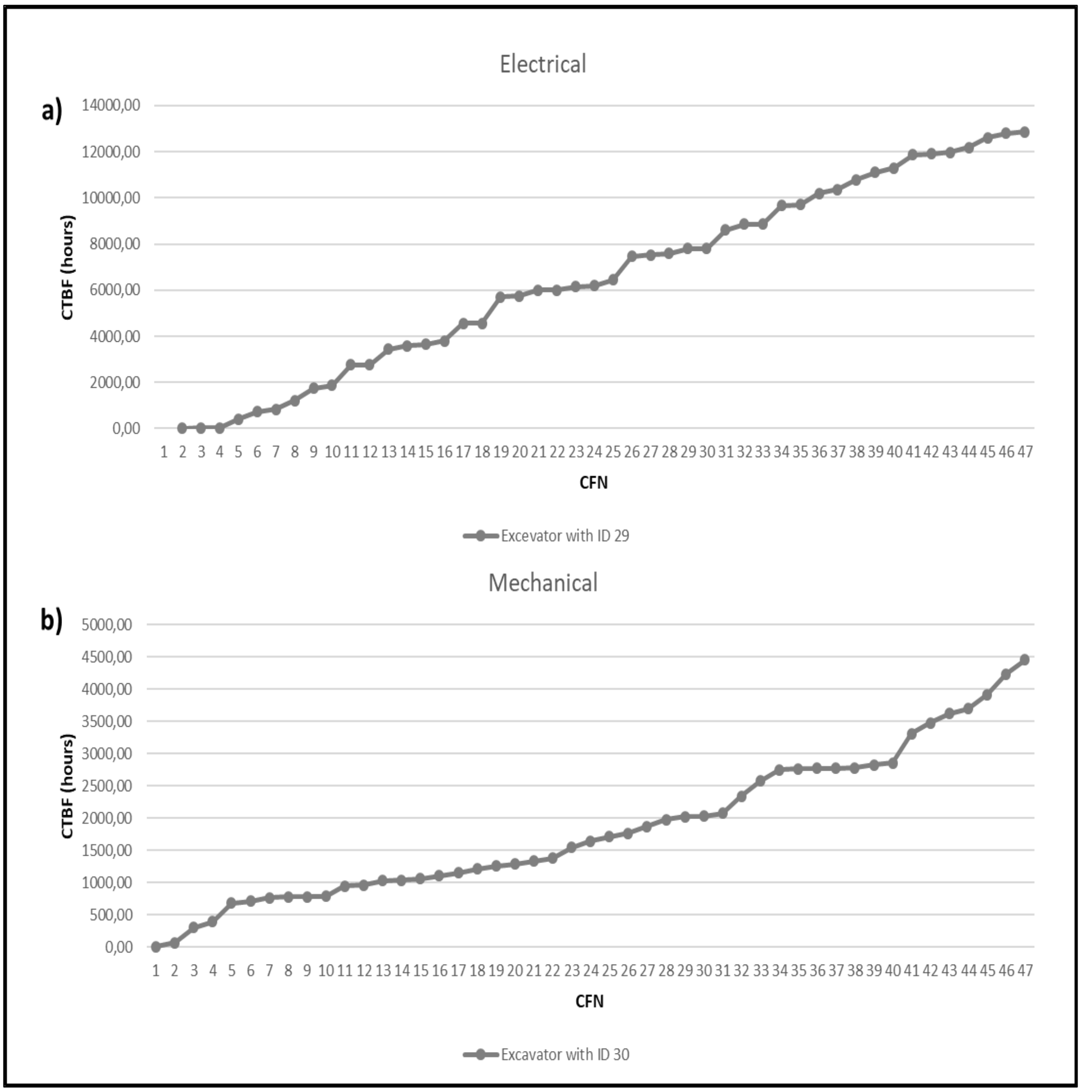


Figure 4.5 CTFB vs CFN Plot (a) Excavator with ID 29 (b) Excavator with ID 30

As observed from Figure 4.5, both lines show a near-straight behavior that may refer to non-trend behavior in the datasets. Since graphical methods are generally interpreted subjectively, they may need additional validations using quantitative tests to improve objectivity. Accordingly, this study uses four common statistical hypothesis testing methods: Crow/AMSAA, Laplace test, Lewis-Robinson test, and pairwise comparison nonparametric test (PCNT). Laplace and Crow/AMSAA tests investigate whether the ordered TBF/TTR data can be fitted a distribution or not while Lewis-Robinson and PCNT methods check whether the data is suitable for ordinary renewal process or not (Gölbaşı, 2015). It should be noted that the homogenous Poisson process (HPP) is the subset of the ordinary renewal process (ORP) in which it is accepted that when the failed component is repaired and returns to its original state as good as new. Therefore, the presence of HPP or ORP in these tests is generally strong evidence that there is no statistically-critical trend in the TBF/TTR dataset.

The Crow-AMSAA relies on validating whether the dataset is following a non-homogeneous Poisson process (NHPP) or homogenous Poisson process (HPP), and the acceptance of NHPP in the hypothesis becomes strong evidence of data trend. The critical parameter used in this model is β, and the failure intensity function is equal to $\lambda\beta t^{\beta-1}$. In the null hypothesis of the test, if $\beta = 1$ and then HPP is confirmed. On the other hand, if $\beta \neq 1$ is assumed in the alternative hypothesis test (β>1 growth or β<1 degradation), NHPP is validated. Equation 4.1 gives the best estimate of β with the use of maximum likelihood estimation. N and βT_i are the number of failures and the arrival time of the i^{th} failure, respectively (Gölbaşı, 2015; Wang and Coit, 2005).

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

$2N/_{\hat{\beta}} < \chi^2_{2N,1-\alpha/2}$ or $2N/_{\hat{\beta}} > \chi^2_{2N,\alpha/2}$ (χ^2: chi-squared distribution, α: confidence interval) means the null hypothesis ($\beta = 1$) is rejected.

In addition, PCNT determines if the data is suitable for renewal process modeling or not. $U_p > z\alpha/_2$ or $U_p < -z\alpha/_2$ means the null hypothesis (renewal process) is rejected. Calculation of testing parameter U_p is given in Equation 4.2. N and U are the numbers of failures and cases, respectively (Gölbaşı, 2015; Wang and Coit, 2005).

$$U_p = \frac{U - N(N-1)/4}{\sqrt{\frac{(2N+5)(N-1)N}{72}}} \tag{4.2}$$

The other trend test, the Laplace test, determines if the data fits in HPP or NHPP similar to the Crow/AMSAA test. $U_L > z\alpha/_2$ or $U_L < -z\alpha/_2$ means the null hypothesis (renewal process) is rejected, and U_L is calculated in Equation 4.3. Number of failures and the arrival time of i^{th} failure are shown by N and T_i, respectively (Gölbaşı, 2015; Wang and Coit, 2005).

$$U_L = \frac{\sum_1^{N-1} T_i - (N-1)\frac{T_N}{2}}{T_N\sqrt{\frac{N-1}{12}}} \tag{4.3}$$

The last trend test, the Lewis-Robinson test, determines the suitability of the data for renewal processing. If $U_{LR} > z\alpha/_2$ or $U_{LR} < -z\alpha/_2$, it means that there can be a trending behavior, and U_L is calculated in Equation 4.4. CV[X], coefficient of variance, is equal to $\sqrt{\mathrm{Var[X]}}/\overline{\mathrm{X}}$ where X is the TBF values in the dataset (Gölbaşı, 2015; Wang and Coit, 2005).

$$\mathrm{U_{LR}} = \frac{\mathrm{U_L}}{\mathrm{CV[X]}} \tag{4.4}$$

Even though Crow/AMSAA is a statistically robust test, data trend decisions may be made by evaluating the hypotheses testing outcomes and graphical illustrations. In this sense, quantitative hypothesis tests were performed on all the excavators' electrical and mechanical TBF and TTR data. Figure 4.6 summarizes the steps in data processing used in the study. In this context, the decisions of the quantitative hypothesis trend tests and the test statistics are given in Tables 4.1 to 4.4 for some of the excavators. It can be observed from the tables that the majority of the given TBF and TTR datasets follow non-trend behavior. It demonstrates that the excavators were not exposed to drastic and recognizable changes in their failure and maintenance profiles through a three-year period. Since these types of data are validated for time independence, they can be fitted into distributions. On the other hand, Excavators ID-31 shows a slight indicator of data trend in Tables 4.2 for electrical failure type. However, the acceptance of data trends for these excavators was observed to be captured by some of the tests. Having a detailed analysis of this potential data trend shows that the tests accepting data trend give the decision in a narrow limit. For instance, the test statistics of Crow/AMSAA for Excavators ID-31 in Table, which is valued at 53.3, is barely over the upper limit value, 95.0. Besides, two other tests also validate non-trend behavior. Therefore, non-trend behavior was assumed for this dataset. GRP (general renewal process) is applied for imperfect maintenance and deterioration for the datasets with a strong trend indicator. GRP parameters can be presented as Weibull distribution parameters.

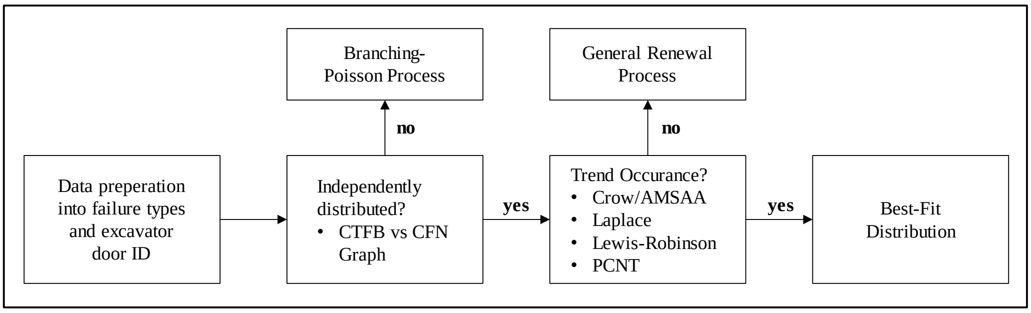


Figure 4.6 Steps in Data Processing

Table 4.1 Results of Trend Analysis for Electrical TBF of Truck-ID

Test Name	**Test Statistics**	**18**	**26**	**29**	**30**	**31**
Crow/AMSAA	${2N}/{\hat{\beta}}$	126.3	45.9	35.9	61.4	166.8
	$\chi^2_{2N.1-\alpha/2}$	93.3	19.8	21.3	40.5	143.0
	$\chi^2_{2N.\alpha/2}$	154.5	52.0	54.4	83.3	216.8
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
Laplace	U_L	-0.06	-0.86	0.03	-1.71	-0.13
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	Possible
Lewis-Robinson	U_{LR}	-0.06	-1.09	0.03	-1.41	-0.11
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
PCNT	U_p	1.41	1.73	-0.27	3.04	1.02
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend

Table 4.2 Results of Trend Analysis for Electrical TTR of Truck-ID

Test Name	**Test Statistics**	**18**	**26**	**29**	**30**	**31**
Crow/AMSAA	${2N}/{\hat{\beta}}$	97.8	46.1	32.1	160.3	53.3
	$\chi^2_{2N.1-\alpha/2}$	91.6	19.8	24.4	139.4	48.8
	$\chi^2_{2N.\alpha/2}$	152.2	52.0	59.3	212.4	95.0
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
Laplace	U_L	1.08	-0.35	0.84	0.98	2.17
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	Possible
Lewis-Robinson	U_{LR}	1.06	-0.26	0.87	0.98	1.47
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
PCNT	U_p	-0.06	0.58	-0.52	-0.33	-0.61
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend

Table 4.3 Results of Trend Analysis for Mechanical TBF of Truck-ID

Test Name	**Test Statistics**	**18**	**26**	**29**	**30**	**31**
Crow/AMSAA	$^{2N}/_{\hat{\beta}}$	289.9	155.5	239.1	311.3	199.3
	$\chi^2_{2N.1-\alpha/2}$	235.5	107.4	184.4	261.3	168.1
	$\chi^2_{2N.\alpha/2}$	328.2	172.4	267.3	358.5	247.6
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
Laplace	U_L	-0.10	-0.83	0.43	-1.06	1.05
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
Lewis-Robinson	U_{LR}	-0.04	-0.77	0.43	-1.11	1.15
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
PCNT	U_p	-0.70	0.90	0.84	1.40	-1.09
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend

Table 4.4 Results of Trend Analysis for Mechanical TTR of Truck-ID

Test Name	**Test Statistics**	**18**	**26**	**29**	**30**	**31**
Crow/AMSAA	$^{2N}/_{\hat{\beta}}$	270.0	138.8	206.5	311.3	181.1
	$\chi^2_{2N.1-\alpha/2}$	211.7	116.2	168.1	253.9	159.1
	$\chi^2_{2N.\alpha/2}$	300.0	183.6	247.6	349.9	236.6
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
Laplace	U_L	0.51	0.30	0.01	-0.50	1.18
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
Lewis-Robinson	U_{LR}	0.59	0.32	0.015	-0.71	1.62
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend
PCNT	U_p	-1.31	0.18	0.28	0.37	-1.08
	$z\alpha/_2$	1.95	1.95	1.95	1.95	1.95
	Decision	No Trend	No Trend	No Trend	No Trend	No Trend

After the outlier and data trend test, the datasets were evaluated to determine the parametric values of the best-fit distributions with a p-value higher than 0.05 for a 95% confidence interval (Tables 4.5 and 4.6).

Table 4.5 Lifetime Parameters for Electrical Failure Mode of Truck-ID

	Electrical - TBF			Electrical - TTR		
ID	**Best Fit Distribution**	**Parameter**	**p-value**	**Best Fit Distribution**	**Parameter**	**p-value**
18	Weibull 3p	β=0.63 η=164.38 γ=–0.71	0.056	Weibull 3p	β=0.76 η=2.82 γ=0.41	>0.05
26	Weibull 3p	β=0.96 η=572.27 γ=–13.59	> 0.5	Lognormal	μ=0.291 σ=1.28	> 0.5
29	Lognormal	μ=5.32 σ=0.97	0.879	Weibull 3p	β=0.82 η=2.12 γ=0.13	0.25
30	Weibull 2p	β=0.71 η=100.76	0.185	Lognormal	μ=0.66 σ=0.98	0.73
31	Weibull 3p	β=0.73 η=75.23 γ=0.06	0.277	Lognormal	μ=1.04 σ=1.62	> 0.5

Table 4.6 Lifetime Parameters for Mechanical Failure Mode of Truck-ID

	Mechanical - TBF			Mechanical - TTR		
ID	**Best Fit Distribution**	**Parameter**	**p-value**	**Best Fit Distribution**	**Parameter**	**p-value**
18	Weibull 3p	β=0.77 η=107.61 γ=–0.27	> 0.25	Lognormal	μ=0.473 σ=0.802	0.04
26	Weibull 2p	β=0.83 η=90.68	> 0.25	Lognormal	μ=0.65 σ=0.93	0.17
29	Weibull 2p	β=0.83 η=87	> 0.25	Lognormal	μ=0.29 σ=0.77	0.02
30	Weibull 3p	β=0.98 η=68.82 γ=–0.74	> 0.50	Weibull 3p	β=1.2 η=1.6 γ=0.24	0.09
31	Weibull 3p	β=1.02 η=107.11 γ=–3.79	0.04	Expo. 2p	λ=0.8187 γ=0.33	> 0.25

4.3 Input Parameters and Implementation Results

In this research study, the developed simulation model requires both probability density function (PDF) models and the parameters as input data. Analysis of the PDF models and how to integrate them into the developed model were discussed in section 4.2. Different from the PDF models, the input parameters are fixed values such as unit production cost or salary of the workers. All input parameters utilized in the model are represented in Table 4.7.

Table 4.7 Input Parameters of the Model

Parameter Name in ReliaSoft BlockSim Environment	**Description**	**Value**	**Unit**
active_time_increment	It is the value that increases the active time in each loop of the continuous simulation.	1	hour
M_crew_total	Total number of workers in the maintenance crew dealing with mechanical failure in maintenance department	Changeable in Each Run	Person
M_crew_max_TTR	Maximum number of workers that can be assigned to maintenance for mechanical failure	4	Person
M_crew_min_TTR	The minimum number of workers required to start maintenance for mechanical failure	2	Person
E_crew_total	Total number of workers in the mainteance crew dealing with electrical failure in maintenance department	Changeable in Each Run	Person
E_crew_max_TTR	Maximum number of workers that can be assigned to maintenance for electrical failure	4	Person
E_crew_min_TTR	The minimum number of workers required to start maintenance for electrical failure	2	Person
Simulation_Target	It is the value that specifies how long the simulation will monitor the system	4,383	Hour
Crew_Downtime_Cost	It is the unit value of production loss when the system is down due to maintenance or unavailability of minimum crew	163.8	$/Hour
SALARY	It is the monthly expense of each worker in the maintenance crew	607.3	$/month

The optimal crew configuration will be determined by detecting the optimal M_crew_total and E_crew_total values that minimize the total cost and/or maximize equipment availability. Therefore, in each computational run covering a specific number of simulations, these numbers will be changed automatically. In this way, the system interactions, resultant downtime values, and resultant cost values were obtained and re-evaluated for the same failure type and equipment fleet characterization.

Unit production loss value ($\$/h$) is determined by Equation 4.5 to determine the unit financial production loss of an earthmoving operation (Gölbaşı & Demirel, 2017). The values of Equation 4.5 parameters specific to the mining area are represented in Table 4.8.

$$Cu = \left(\frac{V_{bucket} \times F}{S} \div \frac{T_{cycle}}{\eta_{operation}}\right) \times C_{per\ bank\ m^3} \tag{4.5}$$

Table 4.8 The factors in Equation 4.5 & Cu Estimation

Factors	Description	Value
V_{bucket}, m^3	Bucket Capacity	8
F	Fill Factor	0.85
S	Swell Factor	1.45
T_{cycle}, min	Expected Cycle Time	0.75
$\eta_{operation}$, %	Operation Efficiency	73
$C_{per\ bank\ m^3}$, $\$/_{bank\ m^3}$	Unit Production Loss	0.60
Cu, $\$/_{min}$	Production Loss	2.73
Cu, $\$/_{h}$	Production Loss	163.8

In addition, the unit direct cost of the maintenance crew is determined from the Electronic Public Procurement Platform (EPPP) in Turkey (EKAP, 2022) regarding the value in February 2022. Table 4.9 presents information on cost items such as salary, food, and travel expenses (inputs), and the resultant cost of each crew member, including insurance charges and other considerations.

Table 4.9 The factors in Equation 4.5 & Cu Estimation

Cost Items (Inputs)		Amount
Monthly Minimum Wage		5004.00 ₺
Number of Days with a Road Charge		26
Daily/Monthly Travel Expenses		20.0 T₺ / 520.00 ₺
Number of Days with Meal Fee		26
Daily/Monthly Meal Expense		30.0 T₺ / 780.00 ₺
Unit Costs (Outputs)	**Minimum Labor Cost**	**Unit Prices (Contract and Cost Including General Expenses)**
Monthly Labor	7,663.83 ₺	7,970.48 ₺
National Holidays and General Holidays	204.34 ₺	212.51 ₺
Extra Work	40.87 ₺	42.50 ₺
Part Time Work	27.24 ₺	28.33 ₺
	TOTAL	*8,253.82 ₺*
		606 $ (13.6 ₺/$ rate on January 2022)

It should be noted that the minimum wage in Table 4.9 is the minimum amount of monthly payment for a mine worker, and it can be recalculated for different levels of salary policies. Following the determination of all input values covering probability distribution functions and other fixed parameter values, the algorithm was computed for a six-month observation period (4,383h) for one single simulation, and the system state was monitored continuously by the time increment of 1h. This six-month observation period was repeated for 200 simulations for each scenario where specific M_crew_total and E_crew_total values were taken. These values are changed comparatively between 2 persons and 10 persons with an increment of 2 persons. Then, 25 different scenarios with different numbers of crews in mechanical and electrical branches are repeated for 200 simulations each. The system was monitored. Simulation model screen can be viewed detailed in Figure 4.7. The simulation outputs, including crew-based downtime and total downtime based on the changed crew policy, are shown in Table 4.10 and Figure 4.8. Here, ten different maintenance monitoring modules, having ten related crew suppliers and demander modules, with a joint simulation start and fleet condition monitoring modules are shown in the figure. Details of each module with its working principles can be examined in Section 3.2.

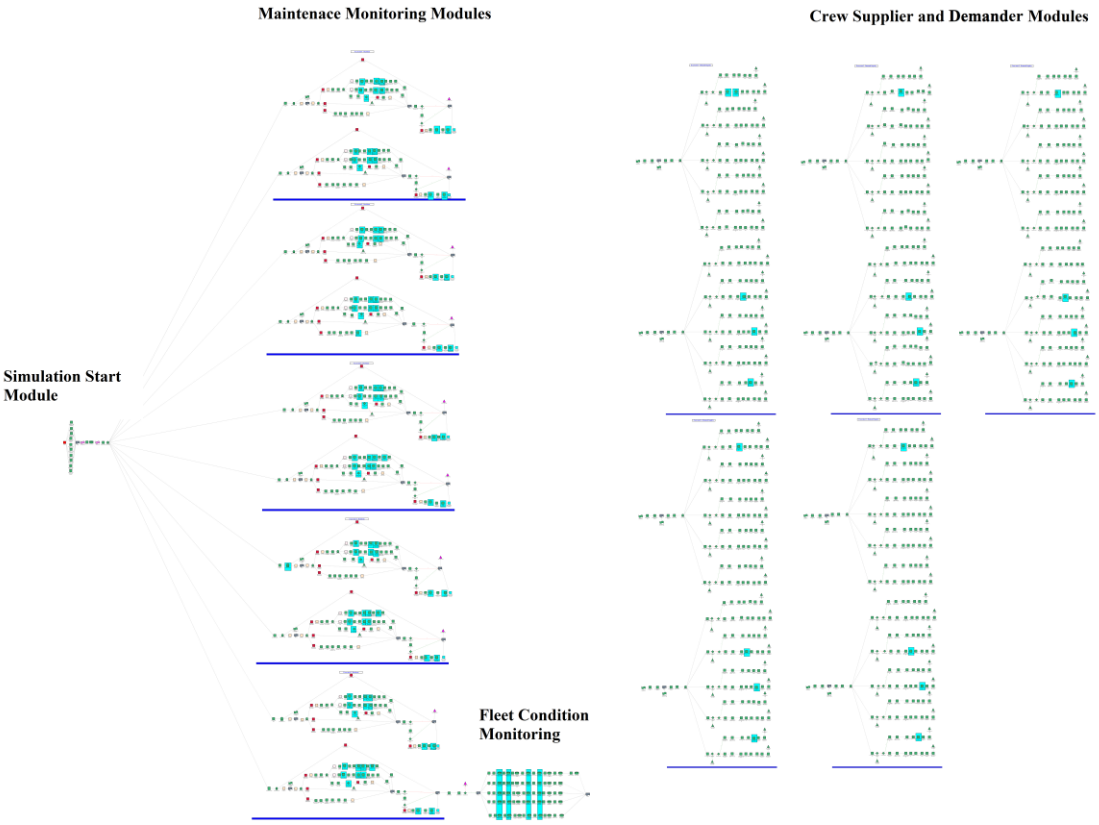


Figure 4.7 General View of Five-Excavator Simulation Screen

Table 4.10 Simulation Outputs in Terms of Downtimes Based on the Crew Configurations

# of simulation	Crew Policy		Excavator ID - 18		Excavator ID - 26		Excavator ID - 29		Excavator ID - 30		Excavator ID - 31		Fleet
	E	**M**	**Crew Based Downtime**	**Total Downtime**	**Crew Based Downtime**	**Total Downtime**	**Crew Based Downtime**	**Total Downtime**	**Crew Based Downtime**	**Total Downtime**	**Crew Based Downtime**	**Total Downtime**	**Total Downtime**
200	2	2	116.1	264.0	71.5	215.7	103.6	214.7	159.2	374.8	20.5	604.6	1673.7
200	2	4	66.2	170.2	22.0	107.0	55.6	128.6	91.8	261.8	10.7	479.2	1146.7
200	2	6	67.7	179.8	32.5	119.3	53.7	127.5	96.1	258.5	12.0	489.1	1174.2
200	2	8	77.5	188.0	44.4	130.5	70.0	142.4	103.7	267.2	11.5	538.1	1266.2
200	2	10	91.9	205.5	65.2	149.0	94.2	168.8	128.3	288.3	9.8	555.0	1366.6
200	4	2	9.2	126.6	8.5	149.7	10.3	109.7	12.0	227.6	8.8	282.7	896.4
200	4	4	0.3	75.8	0.3	73.5	0.7	62.1	0.2	170.2	0.0	260.7	642.3
200	4	6	0.2	81.1	0.1	78.1	0.0	60.4	0.3	162.7	0.0	308.7	691.0
200	4	8	0.2	75.6	0.1	75.5	0.2	59.6	0.1	163.7	0.0	292.9	667.2
200	4	10	0.0	77.0	0.1	76.4	0.1	60.1	0.1	160.1	0.0	267.3	640.9
200	6	2	7.6	120.5	6.6	148.2	9.6	109.5	13.8	229.4	9.4	284.9	892.5
200	6	4	0.1	71.9	0.0	70.3	0.0	58.7	0.0	170.0	0.0	262.7	633.6
200	6	6	0.0	76.7	0.0	74.9	0.0	60.5	0.0	162.4	0.0	253.6	628.2
200	6	8	0.0	72.5	0.0	74.9	0.0	58.5	0.0	163.6	0.0	264.3	633.8
200	6	10	0.0	76.1	0.0	77.3	0.0	57.9	0.0	160.1	0.0	276.9	648.3
200	8	2	7.3	120.1	5.9	147.5	8.9	105.8	13.6	229.2	9.4	300.6	903.2
200	8	4	0.1	72.0	0.0	70.3	0.3	59.6	0.1	170.2	0.0	288.5	660.6
200	8	6	0.0	76.7	0.0	74.9	0.0	58.2	0.0	162.4	0.0	258.0	630.3
200	8	8	0.0	72.5	0.0	74.9	0.0	56.9	0.0	163.6	0.0	252.2	620.0
200	8	10	0.0	76.1	0.0	77.3	0.0	57.4	0.0	160.1	0.0	254.0	624.9
200	10	2	7.3	120.1	7.1	151.3	9.6	107.7	13.2	228.8	8.3	304.1	912.0
200	10	4	0.1	72.0	0.2	70.9	0.1	59.2	0.0	170.0	0.0	251.2	623.3
200	10	6	0.0	76.7	0.0	75.5	0.0	59.6	0.0	162.4	0.0	261.6	635.8
200	10	8	0.0	72.5	0.0	75.6	0.0	57.7	0.0	163.6	0.0	254.5	623.8
200	10	10	0.0	76.1	0.0	76.3	0.0	53.9	0.0	160.1	0.0	239.0	605.4

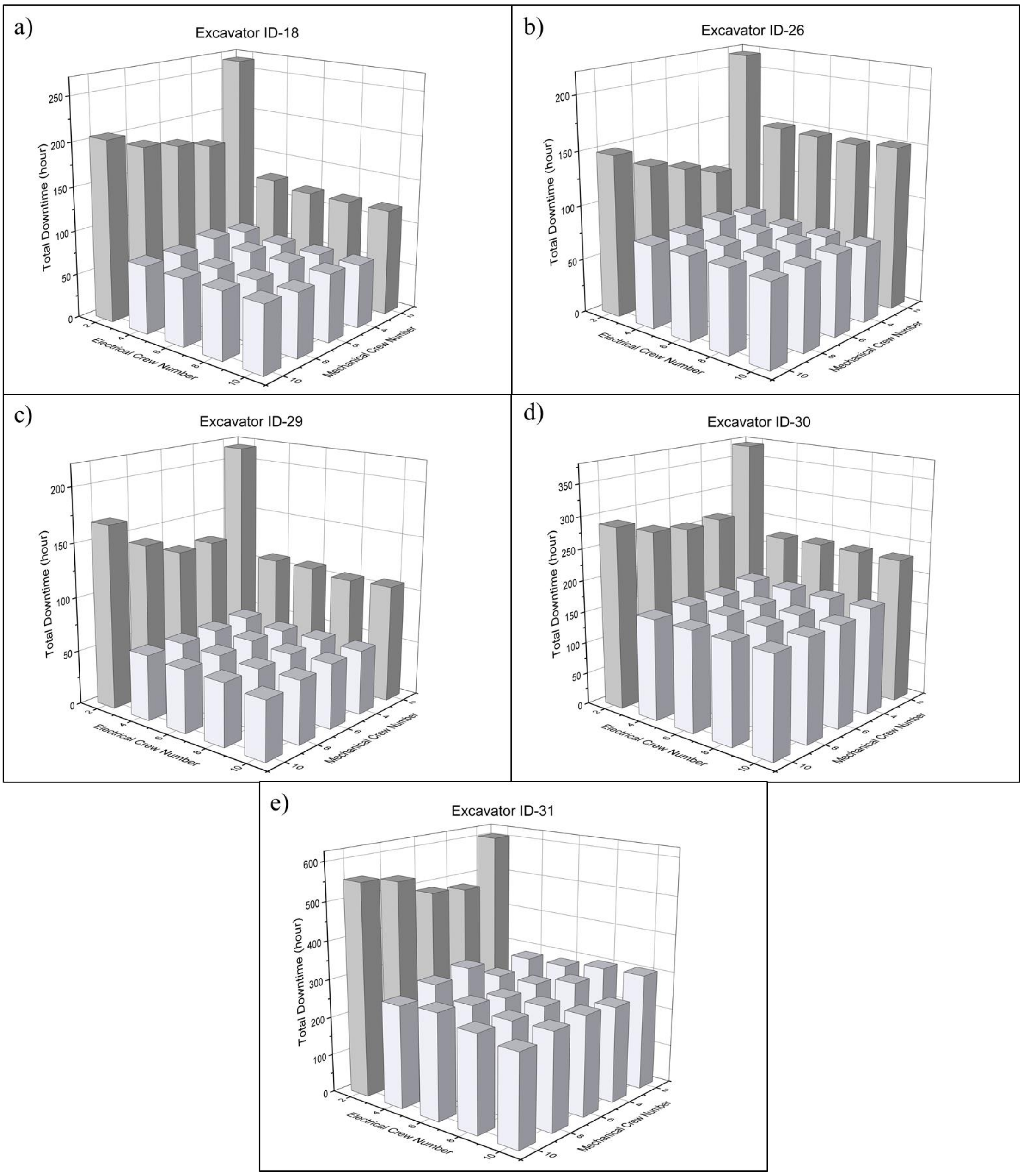


Figure 4.8 Total Downtime for Each Excavator for Each Crew Policy

200 simulations were made for each different crew configuration scenario. After 200 simulations, the total cost and efficiency values came to a balance, so the number of simulations was determined as 200, taking into account computational time consideration.

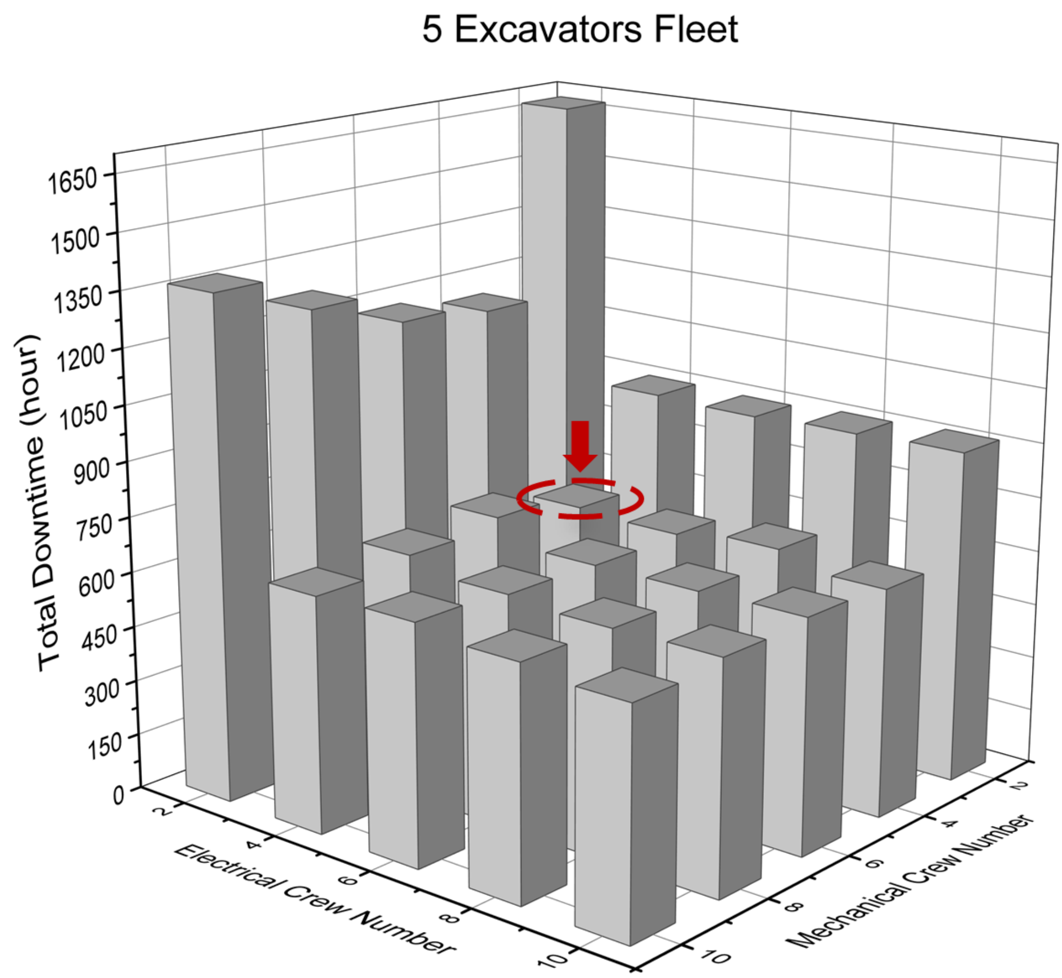


Figure 4.9 Total Downtime for 5 Excavators Fleet for Each Crew Policy

The simulation outputs showed that maximum downtime and minimum equipment availability were observed for the scenario where two persons for each mechanical and electrical maintenance division were employed as shown in Figure 4.8 and Figure 4.9. The scenario results also showed that the downtime values are balanced after threshold values, highlighted by green in Table 4.10, there the crew number is no longer effective in equipment availability. Therefore, since there is no visible effect of increased crew number after the threshold values, any added number will just increase the total cost by jumping the direct cost of crew members. The fleet's general evaluation, including five excavators, can also be seen in Table 4.11 and Figure 4.10. It can be concluded that the crew configuration having 4 persons in the electrical division and 4 persons in the mechanical division dropped the total cost of the maintenance crew, including direct and indirect expenses, to the minimum level.

Table 4.11 Excavator Fleet Cost Items for the Different Crew Configurations

Crew Policy		**Direct Cost ($)**	**Indirect Cost ($)**	**Total Cost ($)**
E (persons)	**M (persons)**			
2	2	14,575	274,153	288,729
2	4	21,863	187,828	209,691
2	6	29,150	192,339	221,489
2	8	36,438	207,400	243,838
2	10	43,726	223,844	267,570
4	2	21,863	146,828	168,690
4	4	29,150	105,207	134,358
4	6	36,438	113,186	149,624
4	8	43,726	109,288	153,013
4	10	51,013	104,981	155,994
6	2	29,150	146,186	175,337
6	4	36,438	103,782	140,220
6	6	43,726	102,903	146,629
6	8	51,013	103,815	154,828
6	10	58,301	106,185	164,485
8	2	36,438	147,949	184,387
8	4	43,726	108,212	151,938
8	6	51,013	103,238	154,251
8	8	58,301	101,561	159,862
8	10	65,588	102,364	167,952
10	2	43,726	149,379	193,105
10	4	51,013	102,091	153,104
10	6	58,301	104,144	162,445
10	8	65,588	102,175	167,764
10	10	72,876	99,165	172,041

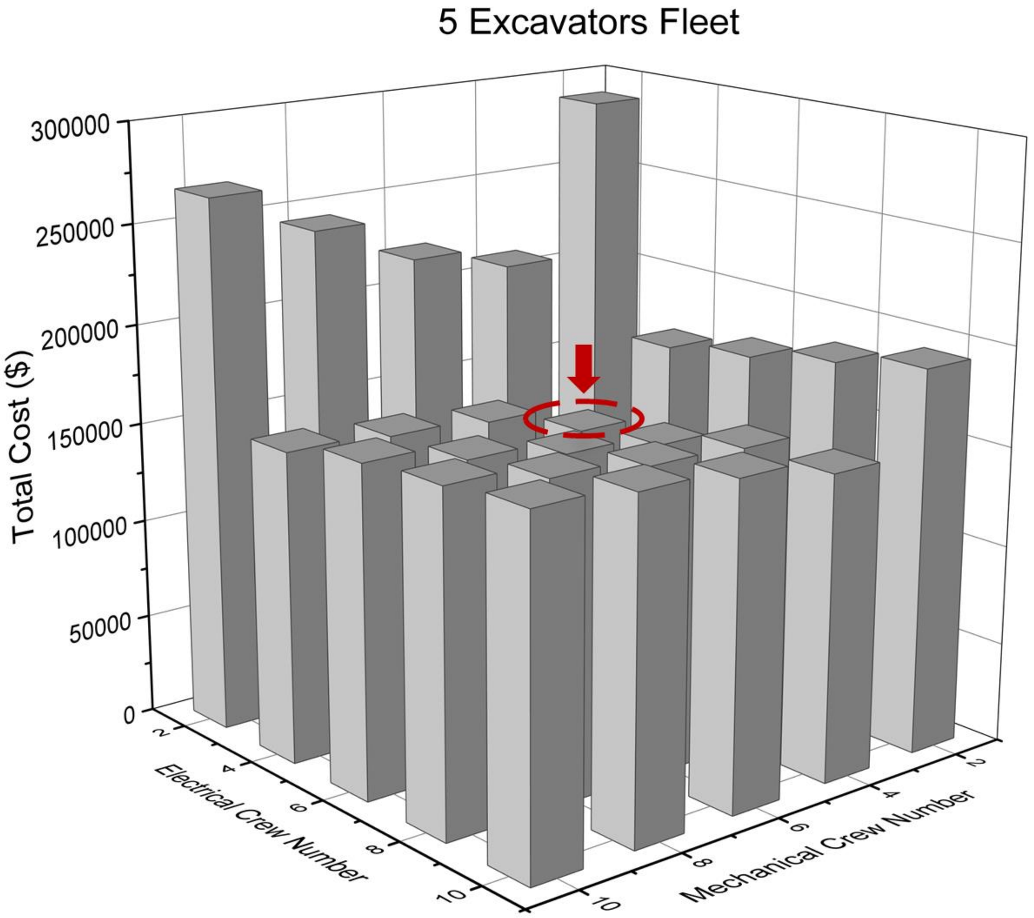


Figure 4.10 Total Cost for 5 Excavators Fleet for Each Crew Policy

After acquiring the computational results, an additional evaluation was performed for the optimized crew configuration ($E = 4;\ M = 4$) to reveal the total downtime characteristics of each excavator. Figures 4.8 to 4.12 represent the maintenance downtime histograms for Excavator IDs 18, 26, 29, 30, and 31, respectively.

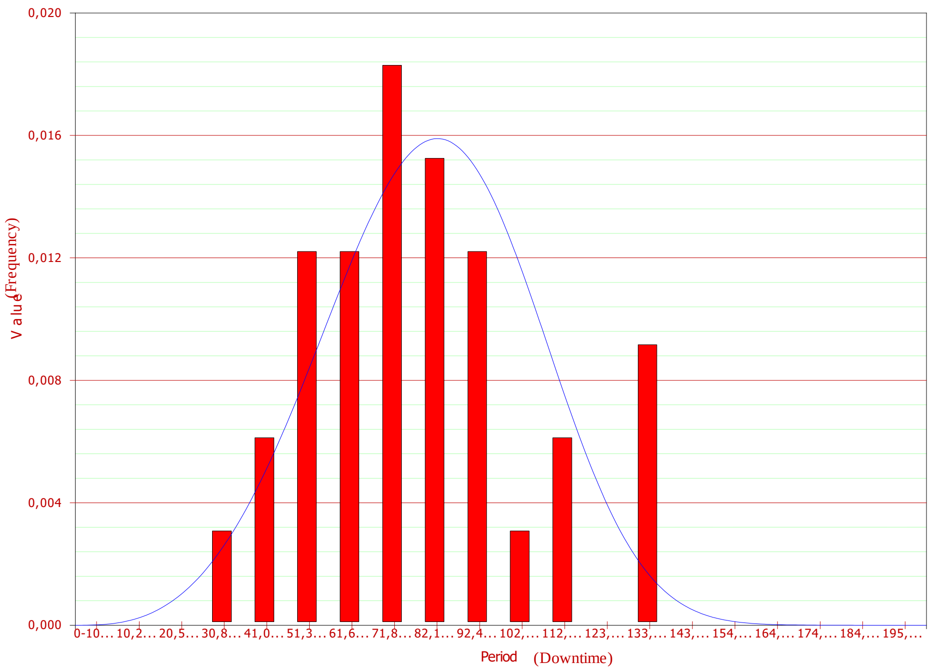


Figure 4.11 Total-Downtime Characteristics of ID18 After Optimized Crew

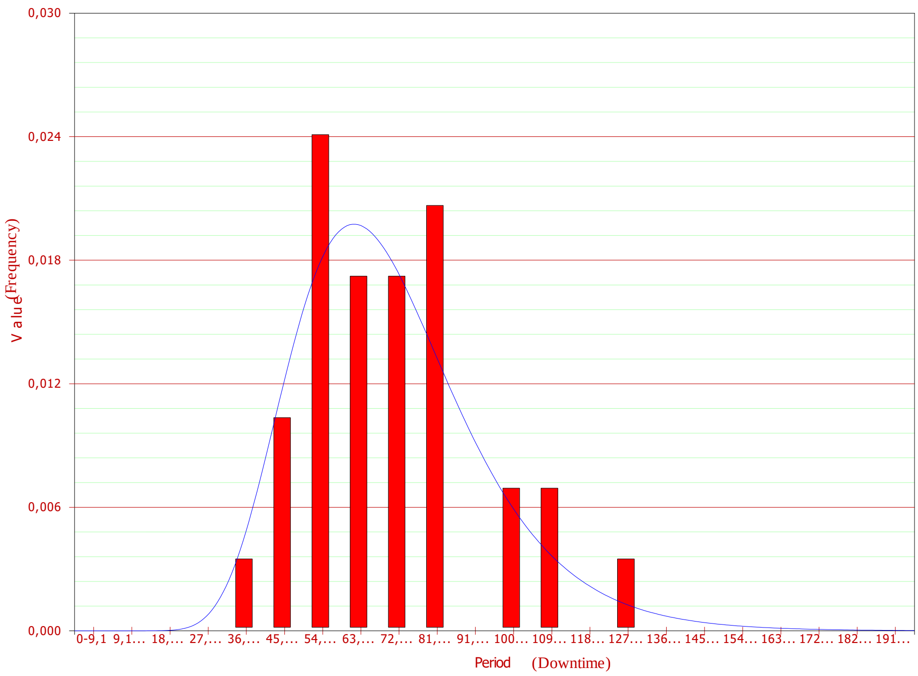


Figure 4.12 Total-Downtime Characteristics of ID26 After Optimized Crew

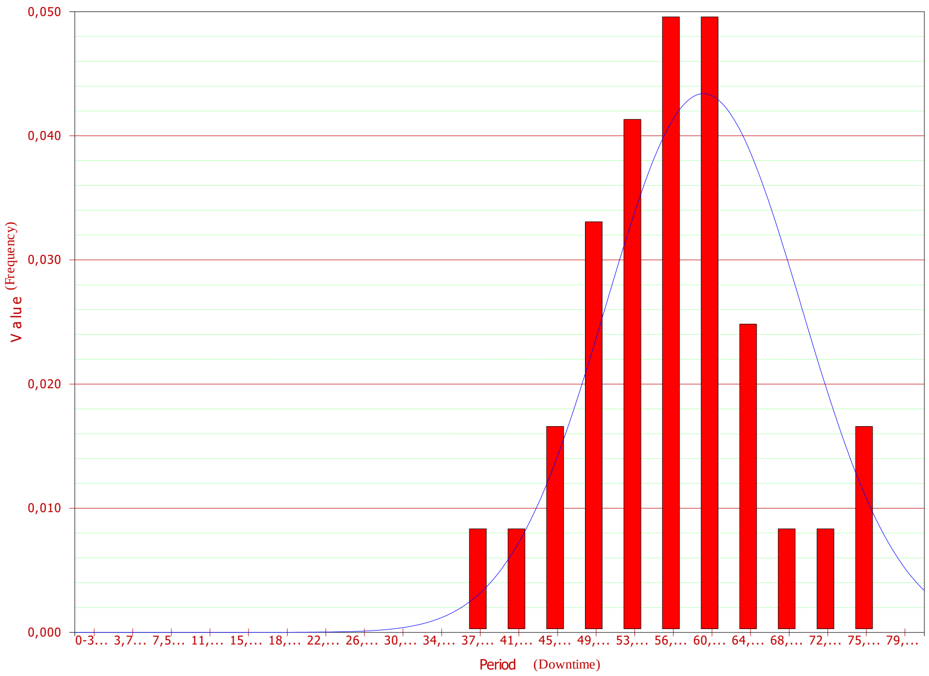


Figure 4.13 Total-Downtime Characteristics of ID 29 After Optimized Crew

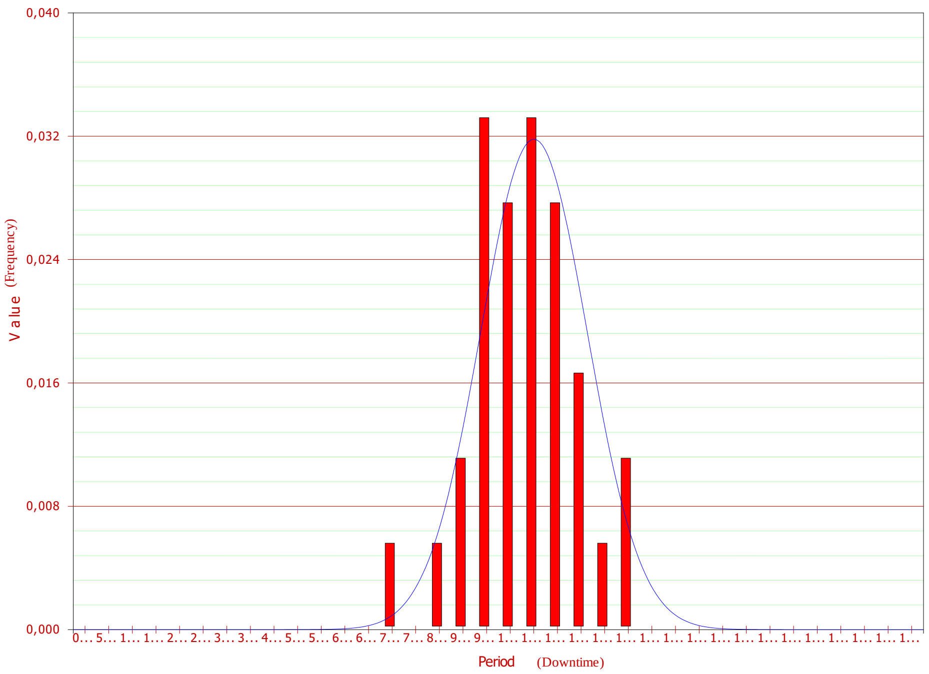


Figure 4.14 Total-Downtime Characteristics of ID 30 After Optimized Crew

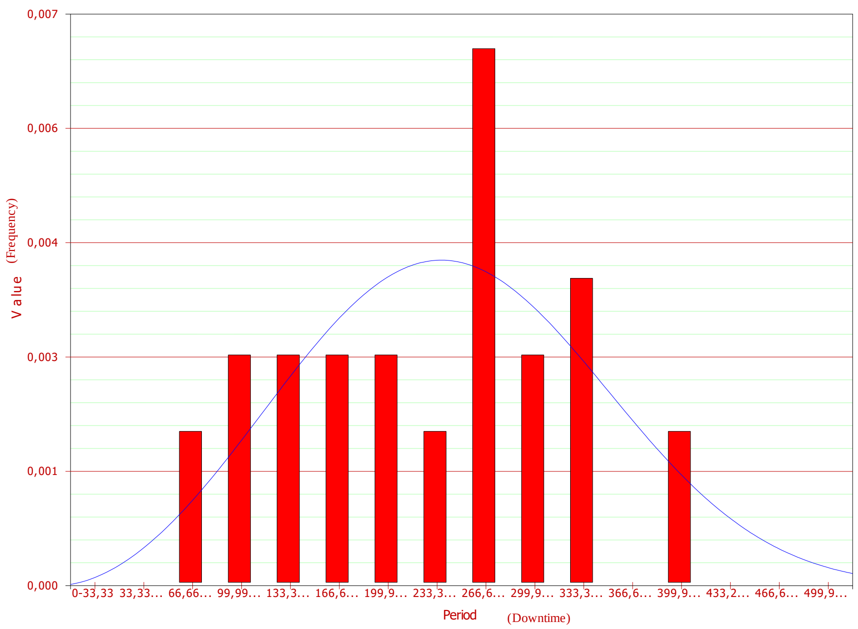


Figure 4.15 Total-Downtime Characteristics of ID 18 After Optimized Crew

The parametric values of the downtime distributions given in Figures 4.8 to 4.12 are summarized in Table 4.12. The downtime duration ranges given in 95% confidence interval show that downtime duration is expected to be the highest for Excavator ID-31 and the lowest for Excavator ID-18.

Table 4.12 Distribution Parameters of the Excavator Downtime Profiles

ID	**Best Fit Distribution**	**Parameters**	**Downtime Range (h)**		
			Upper	**Mean Life**	**Lower**
18	Weibull 2p	β=3.84 η=92.12	91.60	83.31	75.76
26	Lognormal	μ=4.28 σ=0.29	82.23	75.56	69.43
29	Normal	μ=59.21 σ=12.54	61.88	59.21	56.53
30	Normal	μ=108.38 σ=12.54	112.03	108.38	104.73
31	Weibull 3p	β=2.88 η=285.17 γ=−8.93	276.34	245.3	217.63

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Different crew configurations, i.e. number of workers according to their qualifications, are available depending on the company's production profile, complexity, and types of equipment incorporated directly or indirectly in production phases in a machine-based manufacturing company's maintenance department. Depending on the mining process, activities are carried out on the surface or underground in the operation area. Some specific machinery types, typically heavy-duty with a high output rate, are required and can show a variation according to the mining type and production capacity. On this basis, a typical mining company requires a large machine fleet, which embodies equipment for material loading, material hauling, ground drilling, and ground supporting. Each machine can be exposed to multiple failure modes with varying occurrence frequencies and severity levels during an operation. Therefore, the configuration of a maintenance crew, where the number of crew members with different competencies and technical skills need to be decided, is remarkably vital for sustaining maintenance works efficiently. At this point, there is a financial and availability induced trade-off since any over-employment may increase the direct crew cost, while any under-employment can lead to additional production loss due to the unavailability of the -crew members required in maintenance activities. Therefore, a maintenance crew should be determined so that repairing works for different failure types are not delayed for a long time due to crew unavailability, and also the direct cost of the whole crew should not increase to non-tolerable values.

On this basis, the current thesis study intends to develop a continuous event simulation algorithm for optimization of crew configuration particular to the mining area and equipment fleet themselves. The developed algorithm is capable of including the stochastic nature of failure occurrences, resultant downtimes, and interactions between the failure types in the same equipment and other equipment. The model offers to evaluate both downtime and cost-vise decisions for individual equipment and equipment fleet by branching the downtime profile into maintenance downtime and crew downtimes of different failure types. The developed model was applied to an excavator fleet embodying five different excavators holding different failure occurrence and maintenance characterizations. The failure modes were divided into two common failure types: mechanical and electrical, which will also determine the crew groups. The interactions in the system were evaluated by chaning the total mechanical and electrical crew members for each run, having 200 simulations each for an observation period of 4,383h per simulation. The simulation outputs showed that the optimized crew having 6 persons in the electrical division and 4 persons in the mechanical division minimizes the cumulative direct and indirect costs.

5.2 Recommendations

In this thesis study, a generic multi-scenario continuous simulation model was developed to optimize the maintenance crew configuration of maintenance department in the mining industry. In future studies, the research outcomes can be expanded to include the following recommendations:

- In addition to corrective maintenance, preventive maintenance and other potential maintenance activity types can be integrated into the model to build a more comprehensive model.
- Spare part inventory is another essential resource along with workforce capacity in maintenance. The lack of spare parts causes a delay in maintenance. The

developed model can be improved by including spart parts inventory policy in future studies to observe the impact of spare parts on maintenance downtimes.

- Additional constraints/variables regarding operational and environmental conditions can be introduced into further studies. For instance, long-term production plans and targets changing based on climate and fluctuations in market demand can be covered in future models to evaluate production and maintenance interactions jointly.
- Failure modes can be further detailed, and a more comprehensive analysis of equipment life and repair time can be analyzed to increase the competency groups even in the same maintenance division.

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