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DEVELOPMENT OF A SIMULATION-INTEGRATED DYNAMIC INTEGER PROGRAMMING MODEL FOR OPTIMIZING TRUCK REPLACEMENT DECISIONS IN MINING

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

İNANÇ TAHA SERBEST

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
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IN
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DEVELOPMENT OF A SIMULATION-INTEGRATED DYNAMIC INTEGER PROGRAMMING MODEL FOR OPTIMIZING TRUCK REPLACEMENT DECISIONS IN MINING

submitted by **İNANÇ TAHA SERBEST** in partial fulfillment of the requirements for the degree of **Doctor of Philosophy** in **Mining Engineering, Middle East Technical University** by,

Prof. Dr. Naci Emre Altun
Dean, Graduate School of **Natural and Applied Sciences** ________________

Prof. Dr. Nuray Demirel
Head of the Department, **Mining Engineering** ________________

Assoc. Prof. Dr. Onur Gölbaşı
Supervisor, **Mining Engineering, METU** ________________

Examining Committee Members:

Prof. Dr. Bahtiyar Ünver
Mining Engineering, Hacettepe University ________________

Assoc. Prof. Dr. Onur Gölbaşı
Mining Engineering, METU ________________

Prof. Dr. Ayşe Sevtap Selçuk Kestel
Institute of Applied Mathematics, METU ________________

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Mining Engineering, Hacettepe University ________________

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ABSTRACT

DEVELOPMENT OF A SIMULATION-INTEGRATED DYNAMIC INTEGER PROGRAMMING MODEL FOR OPTIMIZING TRUCK REPLACEMENT DECISIONS IN MINING

Serbest, İnanç Taha
Doctor of Philosophy, Mining Engineering
Supervisor: Assoc. Prof. Dr. Onur Gölbaşı

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Capital equipment replacement planning is a critical decision problem in cyclic continuous operations, especially in mining, where haulage fleets operate over long project lives under changing production and operating conditions. Equipment aging, expanding haul distances, and time-varying production targets jointly influence productivity, operating costs, and investment requirements. Conventional equipment replacement approaches often address operational performance and economic evaluation separately, which limits their ability to support long-term, system-level decision-making under realistic conditions.

This thesis study develops a simulation-integrated dynamic integer programming framework to support long-term replacement and investment planning for truck-based haulage systems. A discrete-event simulation model is first constructed to represent detailed haulage operations, including route-specific cycle times, age-dependent equipment availability, fuel consumption, and productivity under evolving road networks and operational conditions. These simulation outputs are then transferred into a mathematical optimization model as age-, period-, and location-dependent parameters of individual trucks.

The integer-programming optimization model determines acquisition, utilization, replacement, and retirement decisions for a heterogeneous truck fleet over a multi-period planning horizon. The objective is to minimize the Net Present Value of total fleet-related costs, including capital investments, operating costs, idle capacity production losses, and salvage and second-hand sale revenues, while satisfying location-specific production targets in each period. The model explicitly considers new and second-hand equipment alternatives, availability-based productivity degradation, and multi-location deployment constraints.

The proposed framework is applied to a real open-pit mining operation with 195 different routes over a 15-year planning horizon. The application results show that all production targets are met with a dynamically adjusted fleet size and replacement schedule. The optimized solution yields a minimum discounted total cost of €27.96 million and demonstrates that replacement and investment decisions evolve in response to equipment aging, mine expansion, and changing haulage conditions. Sensitivity analyses indicate that production targets strongly influence fleet size and investment timing, while financial parameters mainly affect overall cost levels. The results confirm that integrating discrete-event simulation with dynamic optimization provides a practical and reliable tool for long-term equipment replacement planning in mining and other cyclic continuous systems.

Keywords: Capital Equipment Replacement Planning, Dynamic Integer Programming Model, Discrete-Event Simulation, Cyclic Haulage Operations, Open-Pit Mining, Truck Fleet Optimization

ÖZ

MADENCİLİKTE KAMYON YENİLEME KARARLARININ OPTİMİZASYONU İÇİN SİMÜLASYON ENTEGRE DİNAMİK TAMSAYILI PROGRAMLAMA MODELİNİN GELİŞTİRİLMESİ

Serbest, İnanç Taha
Doktora, Maden Mühendisliği
Tez Yöneticisi: Doç. Dr. Onur Gölbaşı

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Sermaye ekipmanlarının yenilenme (ikame) planlaması, özellikle üretim ve işletme koşullarının zaman içinde değiştiği ve taşıma filolarının uzun proje ömürleri boyunca faaliyet gösterdiği madencilik gibi döngüsel ve sürekli operasyonlarda kritik bir karar problemidir. Ekipmanların yaşlanması, artan taşıma mesafeleri ve zamana bağlı olarak değişen üretim hedefleri; verimlilik, işletme maliyetleri ve yatırım gereksinimleri üzerinde birlikte etkili olmaktadır. Geleneksel ekipman yenileme yaklaşımları çoğu zaman operasyonel performans ile ekonomik değerlendirmeyi ayrı ayrı ele almakta, bu durum ise gerçekçi koşullar altında uzun dönemli ve sistem düzeyinde karar vermeyi sınırlamaktadır.

Bu tez çalışması, kamyon tabanlı taşıma sistemleri için uzun vadeli yenileme ve yatırım planlamasını desteklemek amacıyla simülasyon ile bütünleştirilmiş dinamik bir tamsayılı programlama modeli geliştirmektedir. Öncelikle, gelişen yol ağları ve değişen operasyonel koşullar altında güzergâha özgü döngü süreleri, ekipman yaşına bağlı kullanılabilirlik, yakıt tüketimi ve verimlilik gibi ayrıntılı taşıma faaliyetlerini temsil eden bir ayrık olay simülasyon modeli kurulmuştur. Elde edilen bu simülasyon çıktıları daha sonra, her bir kamyon için yaşa, üretim periyoduna ve

üretim konumuna bağlı parametreler olarak matematiksel optimizasyon modeline aktarılmıştır.

Tamsayılı programlama tabanlı optimizasyon modeli, çok periyotlu bir planlama süreci boyunca heterojen bir kamyon filosu için satın alma, kullanım, yenileme ve faaliyetten çekilme kararlarını belirlemektedir. Modelin amacı; her dönemde konuma özgü üretim hedeflerini sağlarken, sermaye yatırımları, işletme maliyetleri, atıl kapasite üretim kayıplarını ve de hurda ve ikinci el ekipman satışı gelirlerini içeren toplam filo maliyetlerinin Net Bugünkü Değerini en aza indirmektir. Model, yeni ve ikinci el ekipman alternatiflerini, kullanılabilirliğe dayalı verimlilik düşüşünü ve çoklu konumlarda konuşlandırma kısıtlarını açık biçimde dikkate almaktadır.

Önerilen modelleme çerçevesi, 15 yıllık bir planlama süreci için 195 farklı güzergâha sahip gerçek bir açık ocak işletmesine uygulanmıştır. Uygulama sonuçları, tüm üretim hedeflerinin dinamik olarak ayarlanan filo büyüklüğü ve kamyon yenileme planlamasıyla ile karşılandığını göstermektedir. Minimize edilmiş amaç fonksiyonu, €27,96 milyon tutarında asgari toplam maliyet üretmiş ve kamyon yenilemeleri ile yatırım kararlarının ekipman yaşlanması, madenin genişlemesi ve değişen taşıma koşullarına bağlı olarak zaman içinde değiştiğini ortaya koymuştur. Duyarlılık analizleri, üretim hedeflerinin, filo büyüklüğü ve yatırım zamanlaması üzerinde belirleyici olduğunu, finansal parametrelerin ise ağırlıklı olarak toplam maliyet seviyelerini etkilediğini göstermektedir. Sonuçlar, ayrık olay simülasyonu ile dinamik optimizasyonun birlikte kullanılmasının, madencilik ve diğer döngüsel üretim sistemlerde uzun vadeli ekipman yenileme planlaması için uygulanabilir ve güvenilir bir araç sunduğunu doğrulamaktadır.

Anahtar Kelimeler: Sermaye Ekipmanı Yenileme Planlaması, Dinamik Tamsayılı Programlama Modeli, Ayrık Olay Simülasyonu, Döngüsel Taşıma Operasyonları, Açık Ocak Madenciliği, Kamyon Filosu Optimizasyonu

To the Champ, my mother, my sister, and Elif.

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INTRODUCTION

1.1 Background

Cyclic continuous operations are production and service systems in which activities are repeated in regular cycles over long periods and rely on high-value capital equipment. Such systems exist in many industries, including mining, transportation, and logistics. In these operations, capital equipment is essential for maintaining continuous production and long-term system stability. Because equipment investments are large, the overall economic performance of these systems is strongly influenced by decisions related to equipment purchase, operation, and replacement.

The operating performance of capital equipment depends on factors such as age, capacity, and operational conditions. Operating costs in cyclic systems mainly arise from energy consumption, maintenance activities, spare parts usage, and labor. As equipment ages, physical wear increases. This leads to higher energy consumption, more frequent maintenance, longer downtime, and lower availability. Over time, these effects reduce productivity and increase unit operating costs. In continuous operations, inefficiencies such as waiting, delays, or idle time directly reduce production performance and increase costs. Therefore, a key challenge is to balance the high capital cost of new equipment with the increasing operating and production loss costs of aging equipment.

These challenges are especially important in the mining industry, which is one of the most capital-intensive sectors. Mining operations involve large production volumes, long project durations, and high financial risk. Mining production generally consists of extraction, transportation, and processing stages. After extraction, large quantities of material are transported to processing facilities or other dumping locations using expensive mobile equipment. In surface mining, truck–shovel systems are widely used, where trucks repeatedly perform loading, hauling, dumping, and return cycles during daily operations.

Although haulage operations are continuous, production is regularly interrupted by refueling, operator breaks, and planned or unplanned maintenance. Because both capital and operating costs are high, inefficiencies such as long queues at loading or dumping points, low truck availability, or shovel idling can significantly reduce economic performance. While equipment is designed to operate efficiently over its service life, demanding operating conditions, poor maintenance practices, or operational problems can speed up wear and failures. As a result, maintenance needs increase, downtime becomes more frequent, productivity declines, and operating costs rise, leading to the need for replacement decisions.

Equipment replacement decisions are complex because many technical and economic factors must be considered together. These include purchase costs, transportation and installation expenses, depreciation rules, salvage values, age-related operating cost trends, and the availability of new and second-hand equipment. For aging equipment, several options exist: continued operation, retirement, replacement with new equipment, or replacement with second-hand equipment. In replacement cases, equipment may also be sold, salvaged, or transferred within the company. All these decisions must be made in a way that minimizes total life-cycle cost while ensuring that production targets are met throughout the project life.

Early studies on equipment replacement mainly focused on identifying an optimal replacement age by comparing the increasing operating costs of old equipment with the cost of new equipment. These studies highlighted the trade-off between increasing operating expenses and capital investment. However, as systems became more complex, it became clear that equipment performance does not depend only on age but also on usage level, operating conditions, and maintenance quality. In cyclic continuous systems such as mining haulage, equipment condition directly affects productivity and availability, which means replacement decisions cannot be separated from operational performance and production requirements.

Financial evaluation methods have also evolved over time. Modern replacement analysis commonly uses discounted cash flow methods, such as Net Present Value (NPV), to account for the time value of money, depreciation, taxation, and salvage values. These financial factors strongly influence long-term investment decisions. However, combining detailed operational behavior with long-term financial evaluation remains difficult, especially when multiple equipment units and time-dependent decisions are involved.

Another important limitation of traditional replacement models is their inability to capture changing operating conditions. In real mining operations, production targets change, haul distances increase as the mine expands, and operating conditions vary over time. Static models often fail to represent these dynamics. Simulation models are effective in capturing operational details, performance changes, and uncertainty, but they usually do not provide direct guidance on optimal long-term investment decisions.

To address these limitations, integrated approaches are required. By combining simulation and mathematical optimization, it becomes possible to link realistic operational behavior with long-term financial decision-making. In this thesis, a simulation-integrated integer programming framework is developed to support equipment replacement planning in truck-based haulage systems. The framework combines detailed operational outputs from discrete-event simulation with a mathematical optimization model that determines equipment purchase, use, and replacement decisions over time. This approach provides a structured and practical decision-support tool for long-term equipment planning in surface mining operations and other cyclic continuous systems.

1.2 Problem Statement

The effectiveness and availability of mining equipment exhibit a considerable decline over time, which further contributes to increased production losses and rising operating costs. Without the implementation of appropriate remedial actions, mining companies experience adverse conditions such as a decline in unit production profit, an inability to meet demand, and excessive equipment damage. Therefore, it is crucial for mining production to regularly monitor the performance of the equipment and make informed decisions regarding future operating conditions. In compliance with target production rates, aging equipment may be replaced with either brand-new or second-hand ones. Replacing outdated equipment before it has reached the end of its useful life or failing to carefully consider cost flow may result in higher unit production costs. For this reason, these alternative equipment replacement decisions need to have a critical trade-off between capital cost, operational cost, and financial benefits. To determine the most appropriate strategy for deciding which equipment should be replaced and at which period, all effective parameters influencing equipment operations should be considered simultaneously.

1.3 Objectives and Scope of the Study

This research study aims to develop a simulation-integrated integer programming model for an equipment replacement policy to optimize equipment replacement decision in truck-based haulage operations in surface mines by considering variations in unit-level operational cost, ownership cost, and productivity. Sub-objectives of the study are stated as follows:

i. Determining effective parameters in equipment replacement decisions in mining,

ii. Construction of a discrete-event simulation model capable of revealing the productivity and operational cost of individual trucks in a dispatching operation by accounting for variations in route configurations and production rates,

iii. Developing an integer programming model to optimize decisions for equipment replacement, which can involve continued operation, replacement with brand-new equipment, replacement with second-hand equipment, and retirement across multiple periods, in a way that minimizes total ownership cost, operating cost, and production penalties due to reductions in equipment availability or idling time.

iv. Implementation of the model under different scenarios using a real-world dataset from a surface mining operation with a 15-year planning horizon.

Under the scope of the study, the developed framework will be applicable to any cyclic continuous transportation system in which material dispatching operations are performed across multiple loading and dumping destinations with route networks varying in junction information, road segment lengths, and segment gradients. The case study will consider truck fleet operations that reflect the real operating conditions of mining systems.

1.4 Research Methodology

The methodological work packages to be followed in the current study are illustrated in Figure 1.1 and detailed as follows:

i. Conceptualization (WP01): Following an extensive literature review, parameters and variables to be covered in the simulation of joint operation for excavating and hauling systems and the integer programming model to optimize discrete decisions for challengers and defenders will be determined.

ii. Construction of the Event Simulation Algorithm (WP02-WP04): Kinematic and motion model formulations are developed to evaluate assistive and resistive forces in equipment movement so as to determine acceleration, deceleration, and constant-speed decisions along sequential and connected road segments of different routes with varying operational intentions and route configurations. In this manner, the mathematical background for estimating cycle time and fuel consumption at the individual truck level is established so that the resulting productivity and operating cost measures can be forecasted. These interactions are transferred into a discrete-event simulation environment called Arena Simulation. Multi-period and multi-route dispatching simulation model is created in which multi-location loading and dumping points can be defined throughout the mine life. In brief, the developed simulation is capable of revealing the operating cost and productivity of trucks with different ages in different periods under varying route information and uncertain precipitation conditions.

iii. Data Integration (WP05): The simulation model reads operation-, production-, and equipment-based information from a data logging file and writes the equipment-level productivity and cost estimations into the same file. These simulation outcomes will be directly utilized by the integer programming model together with financial parameters, including capital expenditures, cost and production adjustment factors, and salvage values for brand-new and second-hand equipment in different periods.

iv. Development of the Integer Programming Model (WP06): The model will optimize decisions related to equipment replacement, which can involve continued operation, replacement with brand-new equipment, replacement with second-hand equipment, or retirement, in a way that minimizes the overall cumulative operating, ownership, and production penalty costs, while also considering benefits such as salvage values or revenues from second-hand sales. The model is formulated and solved in the IBM ILOG CPLEX solver embedded in the AMPL software.

v. Testing and Validation (WP07): The developed framework is implemented using a real-world dataset under various scenarios, including different production rates, production location and haul road advances, for a truck dispatching operation in a surface mine.

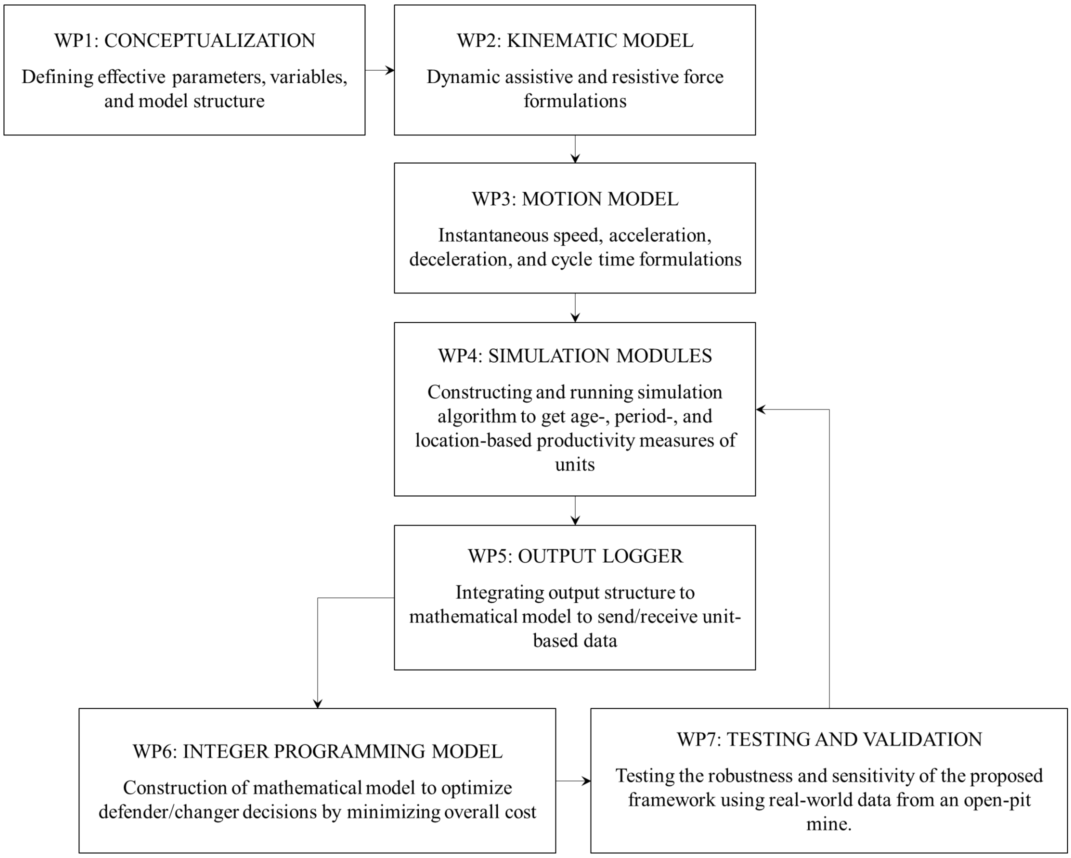


Figure 1.1 Methodological Work Packages

1.5 Expected Industrial Contributions of the Study

The current research study is expected to make the following contributions to the industry on capital equipment replacement and mining system optimization:

i. It proposes an integrated decision-support framework that explicitly combines discrete-event simulation with dynamic integer programming to address long-term capital equipment replacement and fleet configuration decisions in cyclic continuous operations. In this way, industries that employ truck dispatching systems may develop different financial scenarios to determine best- and worst-case outcomes for different production periods, thereby improving their preparedness for capital expenditures.

ii. It incorporates age-dependent operational performance, including productivity, availability, and operating cost deterioration, into the optimization process through simulation-generated inputs, enabling a realistic representation of equipment aging effects over the mine life. On this basis, relevant industries can analyze what-if scenarios to gain insight into the levels of production that can be achieved with their current fleet.

iii. It extends classical defender–challenger replacement modeling by jointly optimizing acquisition, utilization, and retirement decisions for excavating and hauling equipment fleets under time-varying production targets and haul road advancements. Accordingly, tolerance levels for idle equipment in different periods, or the relocation of aging equipment to operational routes with lower cycle times, that is, the flexibility of heterogeneous fleets with respect to age, productivity, and operational location, can be re-evaluated for each future production year.

CHAPTER 2

LITERATURE REVIEW

To establish a solid background for the methodology employed in this study, Section 2.1 first introduces the equipment replacement problem in a general context. Section 2.2 then reviews the variability in existing equipment replacement models, focusing on their adaptation to different production strategies, multi-location availability requirements of fleet equipment, applied modeling approaches, and solution methods. Section 2.3 explicitly discusses the key parameters and decision variables commonly used in equipment replacement models. Section 2.4 concentrates on replacement studies specifically developed for mining systems, while Section 2.5 presents representative examples from other application areas. Finally, Section 2.6 highlights the limitations identified in the existing literature and explains the motivation for the current study.

2.1 Introduction

When the direct and indirect economic losses caused by aging equipment can no longer be balanced, a decision process is required to determine the future condition of the equipment. Mathematical models for capital equipment replacement consider a wide range of economic, technological, and operational factors, which can be grouped into the categories shown in Figure 2.1. These categories are closely related to cost items that are commonly classified as capital costs, operating costs, and general and administrative costs.

Capital costs are usually one-time expenses incurred when equipment is purchased. Operating costs are related to the use of equipment during its service life. For example, the purchase cost of a haul truck is treated as a capital cost, while expenses such as operator wages, fuel, lubricants, and spare parts are classified as operating costs. General and administrative costs include expenses related to administration, engineering, and project management activities. The breakdown of mining cost items into these categories is illustrated in Figure 2.2.

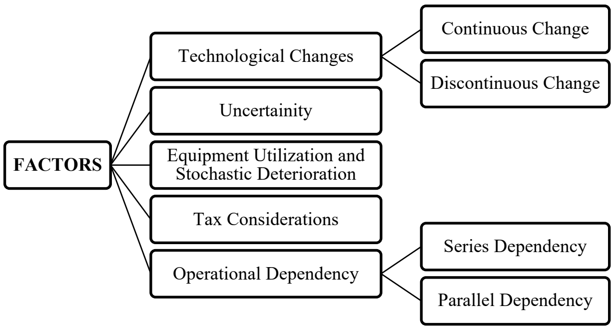


Figure 2.1 Considerations in Mathematical Equipment Replacement Models (Golbasi and Dagdelen, 2017)

In mining operations, production activities are expected to be carried out in line with long-term production schedules and without interruptions, while operating costs are expected to be kept at the lowest possible level. Operating costs in haulage-intensive mining operations are not only influenced by equipment age and maintenance requirements, but also by route geometry, payload characteristics, idling behavior, and environmental conditions such as weather variability. Recent simulation-based studies have shown that these operational factors can lead to significant variability in fuel consumption and overall operating expenditures, even for equipment of the same age operating under nominally similar conditions (Golbasi and Kina, 2022). This highlights the importance of representing operating cost drivers at a detailed operational level rather than relying solely on aggregate or static cost assumptions. Over time, usage-related wear and tear reduces equipment performance, which leads to lower active availability and an increase in unplanned maintenance stops. These unplanned stops can disrupt daily operations and cause delays in production schedules. As a result, maintaining reliable equipment performance becomes a critical concern for mine operations.

Equipment replacement decisions in mining are mainly influenced by factors such as equipment age, accumulated operating distance or hours, and mechanical condition. Age and usage measures, such as km or operating hours, are generally easy to observe and can be directly represented as system states in decision models. In contrast, mechanical condition is more difficult to assess and predict, as it is affected by uncertain operating conditions and varying maintenance practices.

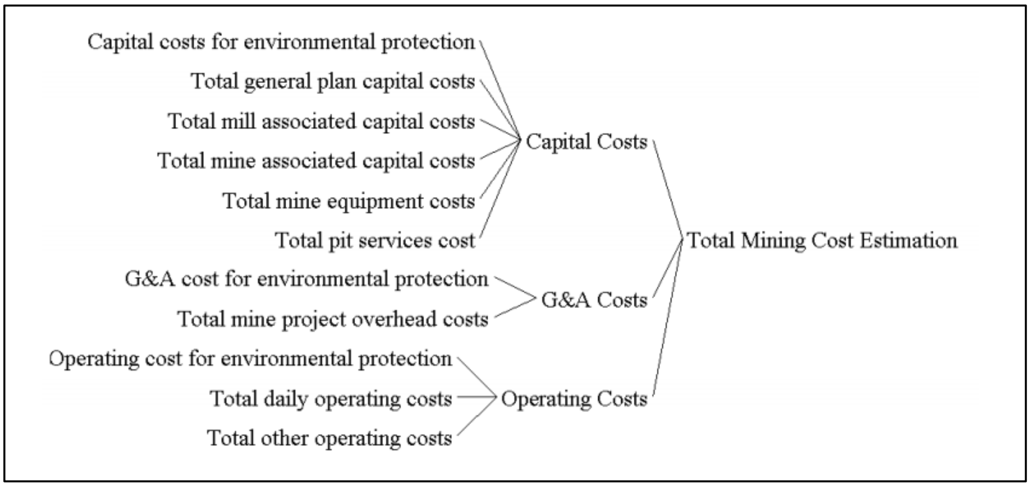


Figure 2.2 Mining Cost Estimation Items

Standard approaches to determining the economic timing of equipment replacement are generally based on discounted cost analysis, with the objective of minimizing total life-cycle costs over the active operating period of an asset. Classical replacement models often assume that equipment is replaced by a continuous sequence of identical assets once the end of its economic life is reached. Within this framework, Yatsenko and Hritonenko (2005, 2009) examined lifetime optimization under conditions of technological change and showed that the economic life of equipment may become shorter when new technologies are introduced more frequently.

In practice, equipment typically goes through an initial period in which it generates positive economic value, followed by a later stage in which its economic contribution declines as operating costs increase. This later stage is commonly associated with wear-out behavior, during which failure rates and the severity of failures rise due to component deterioration. The transition from the useful life phase to the wear-out phase therefore requires careful monitoring in order to keep life-cycle costs within acceptable limits. This situation creates financial trade-offs between actions aimed at improving or extending equipment life and decisions related to replacement planning (Gransberg and O'Connor, 2015).

Life-cycle cost analysis generally groups the main cost elements into operating costs and ownership costs, together with the decision rules used for repair, overhaul, or replacement. Operating costs include maintenance activities, spare parts, fuel, operator labor, and other consumable items. Ownership costs reflect changes in book value, depreciation, and salvage value over time. As a result, decisions on whether to continue operating, refurbish, or replace equipment are shaped by the balance between rising operating costs and ownership-related cost effects. In mining operations, changes in commodity prices may further affect how cost trends are interpreted and evaluated (Gransberg and O'Connor, 2015).

Within this framework, the replacement of a defender asset, representing aging equipment, with a challenger asset, representing new equipment, becomes appropriate when the accumulated cost of continuing to operate the existing asset exceeds an acceptable level. Such decisions depend on the purchase cost of new equipment and the remaining value of the old equipment. New equipment prices generally increase with higher capacity, improved technology, and enhanced productivity, while aging equipment may be sold in the second-hand market, transferred to other operations within the company, or disposed of for salvage value. Therefore, decision makers must evaluate expected cash inflows and outflows together with equipment performance, design characteristics, and capital and labor requirements when planning changes to fleet composition.

2.2 Equipment Replacement Modelling Dimensions

Equipment replacement problems are inherently multi-dimensional and require modelling frameworks that can represent production behavior, spatial structure, uncertainty, and computational limits in a consistent manner. In the literature, equipment replacement models can be examined along four main and complementary dimensions:

i. Production-related characteristics, such as equipment type, output variability, cycle time, and production targets;

ii. Spatial structure, including single-location and multi-location systems and the possibility of reallocating equipment between locations;

iii. Methodological perspective, ranging from deterministic and case-based approaches to stochastic models, where some studies apply well-known methods to different systems, while others develop new approaches and validate them through case studies; and

iv. Solution methods, including mathematical programming, heuristic optimization, and simulation-supported techniques.

This classification provides a structured basis for comparing different modelling approaches and helps clarify how modelling choices influence applicability and decision outcomes. These four dimensions are not intended to define strict or mutually exclusive categories. Instead, they highlight the dominant modelling features that shape problem formulation and solution behavior. Each dimension captures a different aspect of real replacement decision-making. Production-related characteristics determine how equipment contributes to output and how deterioration affects operational performance. Spatial structure defines the flexibility of fleet deployment and the feasibility of moving equipment across locations. The methodological perspective determines how uncertainty, variability, and system dynamics are treated, while the choice of solution method affects computational feasibility and practical implementation. Taken together, these dimensions provide a coherent framework for reviewing and comparing equipment replacement models across different application areas.

A large body of research focuses on general-purpose replacement and investment decision models. For instance, Vander Veen and Jordan (1989) proposed an investment decision framework for multiple machines based on utilization levels, product types, and output requirements. Jones et al. (1991) examined optimal replacement schedules for groups of machines with similar ages under a fixed total fleet size. Scarf and Bouamra (1999) studied discounted cost criteria over a finite planning horizon and developed a flexible approach that allows fleet size changes following replacement decisions. Hartman and Murphy (2006) analyzed finite-horizon replacement problems with stationary costs and related these solutions to the classical infinite-horizon economic life concept. Sethi et al. (2008) addressed shovel-related decisions by jointly considering operating life, acquisition of additional units, and production and maintenance rates. Hartman and Tan (2014) reviewed single-asset replacement strategies under taxation, variable utilization, uncertainty, and technological change, and identified several open research directions. The literature is examined in detail in Sections 2.2.1 to 2.2.3, organized according to four main research dimensions.

In mining applications, uncertainty can appear in several forms. These include changes over time in the size of the mining area and the associated haul road networks, equipment-related variability in cash flows per unit of production, uncertainty in the effective planning horizon, and changes in equipment performance or deterioration behavior. When replacement decisions involve multiple interacting assets, additional factors such as usage intensity, deterioration patterns, tax effects, and fleet-level operational dependencies become increasingly important. These characteristics make mining systems a demanding environment for the development and evaluation of advanced equipment replacement models. Section 2.4 therefore focuses specifically on previous studies related to mining systems.

2.2.1 Production

Production performance is a key dimension in the evaluation of equipment replacement policies because the contribution of an asset to the production cycle directly affects both operational efficiency and economic results. A primary consideration is whether the equipment directly contributes to production, meaning that it determines production time and output volume. In mining operations, haulage and excavation equipment are part of the main production–processing loop and therefore fall into this category. Production-based replacement analysis is also widely applied in other fields, including mining-related studies (Rajabian et al., 2021; Corsetti et al., 2024; Ansaripoor and Oliveria, 2018; Kirstein and Visser, 2017), electric vehicle systems constrained by battery capacity (Othman et al., 2024; Fresia and Bracco, 2023; Longo et al., 2016), agricultural and livestock equipment evaluated by production contribution (Sønnervik et al., 2024; Nævdal, 2022; Grano and Abensur, 2017; Etti et al., 2020), and energy systems assessed through output-related performance measures (Abreu et al., 2025; Aittahar et al., 2023; Huzaifa et al., 2023; Pukala et al., 2021; Pragaspathy and Baskaran, 2017).

A second production-related modelling aspect concerns whether changes in production quantity over time are represented. As equipment ages, downtime typically increases and availability decreases, which reduces output per unit of time and may require either fleet expansion or earlier replacement to meet production targets. Several studies account for these effects. Rajabian et al. (2021) modelled age-dependent changes in haulage capacity; Corsetti et al. (2024) considered short-term variability in renewable energy output; Longo et al. (2016) integrated production from multiple renewable sources; Redmer (2022) represented time-dependent capacity in transport systems; and Zhao et al. (2021) incorporated time-varying minimum transport frequency constraints in container fleet renewal problems.

In cyclic continuous operations, production capacity is closely linked to cycle time, which determines how many operating cycles can be completed within the available working hours. As cycle time increases, unit-time output decreases, which may require additional capacity to maintain production levels. Over long planning horizons, factors such as system expansion, longer transport distances, and increasing operational complexity tend to increase cycle times. In mining, cycle time consists of loading, hauling, dumping, and return activities. Despite its operational importance, explicit representation of cycle time effects is relatively limited in replacement models. For example, Riechi et al. (2017) conducted annual cost analyses based on mileage and age-related measures without directly modelling the effect of cycle time on production. Othman et al. (2024) represented transport capacity as time-dependent in electric vehicle systems. Redmer (2016) assumed declining utilization intensity together with rising variable costs, which indirectly reflects changing production behavior. Manojlovic et al. (2011) analyzed fuel consumption per kilometre and environmental impacts for bus fleets, while Ansaripoor et al. (2016) represented changing operational cycles through variations in km, fuel consumption, and task structure.

Finally, production targets are commonly included in long-term cyclic operations because service and production levels are planned over time and often increase due to mine expansion, demand growth, or regulatory requirements. Rajabian et al. (2021) incorporated time-varying market demand; Redmer (2022) modelled increasing annual transport demand; Ansaripoor et al. (2016) represented changing annual demand structures across vehicle types and tasks; and Ansaripoor and Oliveria (2018) included evolving production targets related to electrification and emission reduction goals. Li et al. (2025) also showed that under different technology development scenarios, changing sustainability objectives can influence replacement decisions over time.

2.2.2 Multi Location

Spatial variability across operational areas within the same planning periods plays an important role in equipment replacement and allocation decisions in cyclic continuous operations. Multi-locational conditions affect operational performance and influence how flexibly equipment can be assigned across the system. When equipment can be moved between locations, reallocation may be used to respond to uneven demand, changing operating conditions, or differences in equipment performance across sites. In mining, equipment allocation is often influenced by geological conditions, such as material hardness, the separation of ore and waste zones, and the presence of multiple working areas with different production requirements. These spatial differences may require different fleet sizes or compositions at different locations.

Some studies have addressed multi-location structures explicitly. Othman et al. (2024) examined dynamic reallocation of buses across multiple cities and routes, integrating route-level decisions into both replacement and deployment planning. Similarly, Abreu et al. (2025) analyzed geographically distributed energy assets operating across several wind farms and solar plants using time-series operational data, while accounting for differences in location-specific conditions and performance. Despite their practical relevance, many equipment replacement studies still assume a single, fixed operating location over periods.

2.2.3 Methodology and Solution Methods

Equipment replacement studies use a wide range of methodological approaches. Some studies rely on deterministic or case-based analyses, where replacement alternatives are evaluated under fixed operating and cost conditions. These approaches are commonly applied in cost-focused evaluations (Škrinjar et al., 2020; Manojlovic et al., 2011) and in studies examining environmental or emission-related outcomes (Osei et al., 2021; Gnap et al., 2024; Etti et al., 2020). Other studies explicitly represent uncertainty by applying stochastic modelling and simulation techniques, including Monte Carlo simulation. In these cases, uncertainty in costs, emissions, or operating conditions is introduced through probabilistic inputs, and replacement strategies are assessed under varying scenarios (Corsetti et al., 2024; Li et al., 2025; Teixeira and Sodre, 2016; Momani et al., 2024).

Reliability-based stochastic models represent another important group of replacement approaches, particularly in preventive replacement planning. The effectiveness of these models depends on accurate identification of failure modes and an understanding of how failures interact within the system. For example, Demirel and Gölbası (2016) applied stochastic reliability modelling to dragline components using catalogue data, expert input, and maintenance records from a Turkish coal mine. Their age-replacement analysis showed that preventive replacement becomes economically reasonable only when the cost of preventive actions exceeds a certain level relative to corrective actions. They also found that higher wear rates and cost ratios lead to shorter optimal replacement intervals, although limited data restricted the application of the method for some components. While this type of component-level replacement based on reliability has been studied extensively, the integration of system-level reliability and availability behavior into equipment replacement models is still limited.

Other modelling approaches include Markov chain models, which describe equipment condition through probabilistic state transitions under uncertainty (Rahimdel and Ghodrati, 2023). These models are often used within maintenance planning frameworks such as Reliability-Centered Maintenance (RCM) (Florea et al., 2022). Renewal process models are commonly applied to non-repairable components with independent failure behavior; for example, drill bits are frequently modelled using Weibull distributions to support replacement timing decisions (Ugurlu and Kumral, 2019). More recent studies have explored data-driven maintenance approaches that use structured operational data and analytical methods to support replacement decisions (Antomarioni et al., 2023), as well as condition-based maintenance strategies that rely on monitoring data and anomaly detection to identify failure risks (Hiruta and Umeda, 2020).

Some studies extend replacement modelling to energy systems used in mining equipment. Liu et al. (2017) examined optimal sizing and life-cycle replacement of hybrid energy storage systems for underground load–haul–dump vehicles by combining degradation modelling, multi-objective optimization, and dynamic programming-based energy management. In addition, reliability and remaining-life estimation models have been developed for electromechanical components. For instance, Martyushev et al. (2023) estimated the remaining service life of motor brushes based on wear limits and monitored condition indicators.

Beyond the modelling approach itself, the choice of solution method determines whether replacement models can be applied at a realistic scale. Many studies use classical mathematical programming techniques, such as linear programming (LP), integer programming (IP), and mixed-integer linear programming (MILP), to optimize replacement, allocation, or investment decisions. Other approaches have been developed to address complexity, uncertainty, or nonlinear relationships, including evolutionary algorithms, machine learning-based methods, and simulation techniques such as Monte Carlo simulation, discrete-event simulation (DES), and continuous-event simulation (CES). Several studies emphasize the importance of explicit mathematical formulations that can represent diverse cost components and operational characteristics in a consistent manner (Cao et al., 2012; Yatsenko and Hritonenko, 2010; Nævdal, 2022; Abdallah and Lasserre, 2016; Zambujal-Oliveira, 2011). The wide range of solution methods reflects the multi-dimensional nature of equipment replacement problems and the need for flexible tools that can be adapted to different operational settings.

2.3 Key Parameters in Equipment Replacement Decisions

Reliability, availability, and safety are widely accepted as key performance indicators in production systems, as they reflect both operational effectiveness and system stability. At the same time, the high maintenance costs associated with heavy mining equipment impose practical limits and encourage the development of more effective maintenance and replacement strategies. Within this setting, the concept of Remaining Useful Life (RUL) plays an important role in reliability-based and condition-based maintenance studies. RUL refers to the estimated period during which a component or system can continue to operate satisfactorily before failure. It supports improved maintenance planning, better cost control, and more effective life-cycle management of assets. RUL-based approaches may also contribute to sustainability goals by supporting decisions related to life extension, reuse, and recycling (Ghomghaleh et al., 2020).

For instance, RUL-based and data-driven replacement decisions are particularly relevant in drilling operations. Drill bits may be replaced either after sudden failure, such as when a bit is lost in the drill hole, or based on operator judgment triggered by increased vibration or reduced penetration rates. Subjective replacement decisions can result in early replacement and unnecessary cost, while delayed replacement may reduce drilling performance and overall productivity. For this reason, the use of objective life data analysis combined with cost-based decision models has been proposed to balance drilling efficiency and operating cost (Uğurlu and Kumral, 2019).

Equipment replacement decisions are influenced by several interrelated parameters that describe technical performance, economic behavior, and operational reliability. In the literature, these parameters are commonly discussed under four main categories: availability, equipment life, cost analysis, and maintenance-related factors. Together, these elements determine when continued operation becomes less attractive than repair, overhaul, or replacement. These parameters are generally utilized as constraint and/objective function parameters, or variables in the models of relevant research studies.

2.3.1 Availability

Availability represents the proportion of administratively scheduled time during which equipment is operational and capable of contributing to production. In mining, downtime can cause significant production losses; therefore, availability modelling is critical in evaluating replacement strategies and fleet performance.

Dos Santos Silva et al. (2016) proposed a statistical methodology to predict off-highway truck availability in open-pit mining using historical service hours and maintenance data. Their approach used probabilistic distributions (binomial, Weibull, and exponential) to estimate maintenance needs and project availability without explicitly separating preventive and corrective actions. Availability is also embedded within composite measures such as Overall Equipment Effectiveness (OEE), combining availability, utilization, and performance efficiency. Samatemba et al. (2020) developed a stochastic algorithm to assess OEE for multiple mining equipment types, identifying cycle time, utilization, and performance efficiency as drivers of low OEE. Elevli and Elevli (2010) applied OEE-based analysis for shovels and trucks and showed that time-based calculation choices can strongly affect estimated metrics. Paraszczak (2005) emphasized the role of data quality and complementary indicators in reliable equipment assessment.

However, improved availability does not always imply productivity gains. Boudreau-Trudel et al. (2014) found that introducing new equipment across underground projects did not consistently yield productivity improvements, highlighting the need to interpret availability within operational context. In safety-critical systems, deterministic availability modelling may be insufficient; Rahimdel and Ghodrati (2023) used Markov chain modelling for compressed air systems in underground mines and showed probabilistic state-transition models better represent availability under uncertainty.

For an equipment replacement model, it is essential to assess whether the total effective operating time of the fleet is sufficient to meet production targets and to identify the weakest parts of the fleet where capacity declines due to equipment aging. Reductions in availability and the resulting penalties from production interruptions create a trade-off between rising operating and penalty costs on one hand and the capital investments required for new equipment on the other.

2.3.2 Equipment Life

Equipment life refers to the period during which an asset can operate effectively before replacement becomes economically or technically justified. In the literature, equipment life is commonly evaluated using reliability models, Remaining Useful Life (RUL) estimation, and deterioration mechanisms that reflect physical, functional, and environmental wear. In addition, depreciation rules defined by the tax regulations of the relevant countries offer useful guidance on the useful lifetimes of different asset types.

Ghodrati et al. (2012) applied a proportional hazard model to estimate RUL by incorporating operational conditions, allowing reliability to vary with equipment usage. Ghomghaleh et al. (2020) compared classical reliability models with frailty-based approaches for an excavator operating in an open-pit mine and showed that accounting for unobserved variability improves RUL estimation and performance evaluation. From a valuation perspective, Turek and Michalak (2012) introduced the concept of operational potential to describe an asset's ability to perform its intended function over time and distinguished between technical, functional, and environmental wear. These forms of wear capture both physical deterioration and external influences such as technological change or regulatory constraints.

Life-cycle considerations also include environmental impacts. Balboa-Espinoza et al. (2023) compared conventional diesel trucks with battery-electric trucks using life-cycle assessment and showed that operational energy sources strongly influence environmental performance, linking equipment life decisions with sustainability evaluation.

In industrial practice, equipment life is commonly described by practical lower and upper lifetime limits within which acceptable availability and operational performance can be maintained. Heavy-duty sectors such as mining and construction should continuously monitor key performance indicators of the operating fleet and analyze the conditions that may cause an asset's service life to fall below expectations.

2.3.3 Cost Analysis

Cost analysis links technical performance and operational behavior to economic outcomes and is a central element of equipment replacement decisions. Replacement timing is often driven by the balance between capital investment and increasing operating and maintenance costs as equipment ages, which motivates the use of life-cycle cost analysis.

For instance, Cebesoy (1997) introduced linear break-even models for surface mining equipment replacement based on discounted cash flow principles. Later studies expanded cost analysis toward total cost of ownership (TCO) and life-cycle costing (LCC), incorporating acquisition, operation, maintenance, and disposal costs (Kirstein and Visser, 2017). These studies emphasize that increasing maintenance cost by equipment aging has a dominant role in determining replacement timing.

Costs are commonly grouped into capital and operating categories. Capital costs include purchase and installation, while operating costs cover maintenance, repair, fuel, and labor, which typically rise with equipment deterioration (Bugaric et al., 2022; Uğurlu and Kumral, 2019). More detailed approaches, such as activity-based life-cycle costing, provide a closer representation of real operations but require extensive data and often handle uncertainty in a limited way (Kirstein and Visser, 2017). As a result, many studies continue to rely on deterministic assumptions despite the presence of stochastic failures and maintenance behavior.

Recent studies have applied cost analysis to alternative equipment technologies. Ahluwalia et al. (2023) compared hydrogen fuel cell and diesel haul trucks using TCO and showed that alternative propulsion systems can be competitive when investment, operating, and replacement costs are evaluated together. Similar analyses have been conducted for electric and alternative-fuel fleets (Othman et al., 2024; Fresia and Bracco, 2023; Kontou et al., 2017).

Depreciation and salvage value also influence replacement decisions by affecting cash flows over time. Different depreciation methods and salvage value assumptions are used to balance ownership and operating costs (Redmer, 2016; Riechi et al., 2017; Rajabian, 2021; Alp et al., 2022). Discounted indicators such as Net Present Value (NPV) are widely applied in long-horizon replacement studies (Corsetti et al., 2024; Redmer, 2022; Sønnervik et al., 2024).

2.3.4 Maintenance

Maintenance is critical for equipment life-cycle management and strongly affects replacement decisions, particularly in capital-intensive industries such as mining. Maintenance costs can represent a large portion of operating expenses, and unplanned failures may lead to substantial production losses.

Holmberg et al. (2017) reported that maintenance costs can account for up to 32% of total operating costs in deep underground mines, with labor and spare parts contributing nearly equally. They also estimated that production losses due to downtime may represent around 20% of total maintenance-related costs, highlighting the economic importance of reducing unplanned failures.

To address these challenges, predictive and condition-based maintenance approaches have received increased attention. Morad and Sattarvand (2013) applied neural networks to predict tire wear and remaining service life, showing the potential of data-driven methods. Hiruta and Umeda (2020) emphasized the role of condition monitoring and anomaly detection in improving availability and reducing maintenance costs within a life-cycle engineering framework. Reliability-based maintenance and replacement policies further link maintenance actions with economic trade-offs. Demirel and Gölbası (2016) showed that preventive replacement becomes economically favorable when production losses from corrective failures exceed certain threshold levels. Florea et al. (2022) applied Reliability-Centered Maintenance (RCM) to frequently failing components and demonstrated how reliability parameters and failure modes influence maintenance and replacement intervals.

Maintenance modelling has also been extended to structural and fatigue-related applications. Grabowski et al. (2021) proposed a fatigue lifetime correction method to update life estimates of welded structures based on actual loading conditions, supporting economically justified interventions. Martyushev et al. (2023) modelled brush wear and remaining life to support timely replacement and reduce operational disruptions. In general, maintenance records and observed trends in failure rates and costs provide essential inputs for end-of-life assessment and replacement timing decisions (Uğurlu and Kumral, 2019).

2.4 Equipment Replacement Research in Mining

Equipment replacement research in mining has been developed mainly due to the sector's high capital intensity, long project durations, and strong dependence on reliable equipment performance. Mining operations require large upfront investments, while equipment operates under harsh and changing conditions that accelerate wear and reduce availability over time. As a result, replacement decisions play a key role in controlling costs, maintaining production continuity, and ensuring long-term economic performance.

A major group of studies focuses on determining economically optimal replacement timing by balancing increasing operating and maintenance costs against the capital cost of new equipment. Al-Chalabi (2022) developed an economic replacement time model for underground drill rigs and showed that maintenance cost is the dominant factor influencing replacement decisions. Sensitivity and regression analyses highlighted how rapidly rising maintenance expenses can outweigh the benefits of extending equipment life, supporting the use of optimization-based decision tools for repairable mining assets.

Decision-oriented frameworks have also been applied to mining replacement problems. Abbaspour and Maghaminik (2016) used a decision-tree approach to evaluate whether equipment should be retained or replaced and demonstrated that replacement outcomes are highly sensitive to whether discounted measures such as Net Present Value are included. Their findings emphasize that replacement decisions based only on direct cost comparisons may be misleading if the time value of money is not explicitly considered.

Another important research stream compares alternative equipment technologies within mining systems. Varaschin and De Souza (2015) evaluated diesel and electric load–haul–dump machines by jointly considering capital and operating costs. Their results showed that replacement outcomes depend strongly on site-specific factors such as energy prices, maintenance practices, and operational constraints. This confirms that technology substitution decisions in mining cannot be generalized without detailed consideration of local conditions.

Several studies highlight that replacement decisions are closely linked with equipment selection and fleet-level interactions. Santelices et al. (2017) proposed a stochastic optimization model that jointly addressed equipment selection and replacement under production assurance constraints, explicitly capturing availability interactions between trucks and loaders. Their results showed that stochastic approaches can provide more robust solutions than deterministic models. Burt (2015) similarly emphasized the complexity of multi-period replacement and selection in surface mining with multiple loading and dumping locations, noting that operating cost, utilization, availability, and age are strongly interconnected in heterogeneous fleets.

System-level replacement studies often combine optimization with simulation to better represent operational behavior. Teplická and Straka (2020) examined efficiency improvements through better integration and distribution of mobile and stationary equipment using simulation and decision-tree analysis. Their findings showed that replacement decisions are frequently linked to broader system configuration and allocation issues rather than being isolated asset-level choices.

Sustainability and energy efficiency considerations have also gained importance in mining replacement research. Kawalec et al. (2020) compared diesel trucks, trolley-assisted haulage systems, and belt conveyors using energy consumption indicators and found that electrified and conveyor-based systems can offer advantages in energy use and maintenance requirements. These studies link equipment replacement decisions with long-term sustainability and environmental performance objectives.

At a more detailed level, component-based replacement problems are commonly studied using reliability and cost-based models. Ugurlu and Kumral (2019) analyzed drill bit replacement using statistical life data, Monte Carlo simulation, and optimization to reduce total replacement costs under uncertainty. While such studies provide valuable insight into localized decisions, their direct application to fleet-level planning remains limited unless supported by additional integration mechanisms.

Recent research has increasingly incorporated data-driven and predictive approaches. Antomarioni et al. (2023) proposed a decision-support system combining data analysis techniques and integer programming to identify dependencies among component failures and reduce downtime. Hiruta and Umeda (2020) introduced a framework that estimates equipment deterioration by comparing observed operational data with simulated behavior, supporting more informed maintenance and replacement planning.

Replacement research in mining also extends to auxiliary systems. Gladysiewicz et al. (2016) optimized conveyor idler replacement by jointly evaluating energy consumption and replacement costs, showing that design and replacement decisions influence both efficiency and cost. Geological and operational variability further affects replacement strategies; Tyulenev et al. (2021) analyzed equipment selection under varying seam conditions and demonstrated how operating schemes influence productivity and unit cost.

At the asset and fleet level under uncertainty, Kirstein and Visser (2017) proposed a risk-based method to estimate optimal replacement age for heavy mobile equipment approaching end-of-life, using expert judgment when historical failure data are limited. Their work highlights the importance of uncertainty and risk representation in long-term mining replacement decisions.

Overall, mining replacement studies often distinguish between stationary processing equipment and mobile haulage fleets. While stationary equipment generally operates under more stable conditions, mobile fleets are exposed to changing environments, increasing haul distances, and age-related availability losses. As a result, haulage fleets require periodic renewal, expansion, or reconfiguration over the mine life. Reflecting this, many recent studies focus on truck–shovel systems and fleet renewal strategies integrating economic, operational, and sustainability considerations (Rajabian, 2021; Corsetti et al., 2024; Aiello et al., 2024; Ansaripoor and Oliveria, 2018; Alp et al., 2022; Škrinjar et al., 2020; Ansaripoor et al., 2016; Castanon et al., 2024).

In summary, although significant progress has been made in modeling replacement timing, fleet interactions, and sustainability in mining systems, much of the existing literature remains fragmented. Many studies focus either on component-level decisions or rely on simplified representations of operational performance. This gap highlights the need for integrated frameworks that jointly address operational dynamics, spatial structure, and long-term investment planning at the system level.

2.5 Equipment Replacement Research in Other Sectors

Equipment replacement has been widely studied in sectors outside mining, especially in systems with high capital requirements, repetitive operating cycles, and long planning horizons. In these sectors, a key challenge is determining appropriate replacement timing under uncertainty, limited data availability, and ongoing technological change. Although the operating environments differ, these challenges are comparable to those observed in mining systems.

Yatsenko and Hritonenko (2016) examined serial asset replacement when information on technological change is incomplete. They proposed a discrete-time method that adjusts the annual capital recovery factor used in the Economic Life approach. Their results showed that traditional replacement rules may perform poorly when technological progress reduces the cost of new assets over time, even when only limited data are available. This study highlights the need to consider technological change in long-term replacement analysis.

In manufacturing and industrial applications, replacement decisions are often handled within broader asset management practices rather than as isolated economic problems. Gandini Panegossi and Da Silva (2021) studied replacement decision-making in a medium-sized manufacturing company and showed that limited access to detailed performance and cost data can restrict the use of analytical replacement models. To address this, they developed an asset management policy aligned with ISO standards to guide replacement decisions for critical equipment. Similarly, Madusanka (2016) reviewed repair and replacement practices and emphasized the trade-off between replacing equipment too early and extending asset life excessively. That study identified deterioration, obsolescence, and economic constraints as the main drivers of replacement decisions, while also noting the limited availability of strong empirical data.

Infrastructure and energy distribution systems face similar challenges related to aging assets and long-term replacement planning. Wijnia et al. (2006) analyzed replacement strategies for aging energy distribution assets using a system dynamics approach that included workforce limitations and preventive replacement actions. Their results showed that even cost-efficient replacement strategies may fail to control rising failure rates if staffing constraints prevent timely implementation. This finding highlights the role of organizational limits in practical replacement planning.

Financial and stochastic approaches have also been applied to replacement problems. Zambujal-Oliveira and Duque (2011) investigated replacement timing under different tax and depreciation rules using real options theory with uncertain salvage values. Their results showed that deterministic models may overestimate replacement activity and that uncertainty can change optimal replacement timing in complex ways. This work illustrates how financial uncertainty can strongly influence long-term investment decisions.

Transport systems represent one of the most studied application areas outside mining. Replacement and renewal of vehicle fleets have been widely examined for buses, rail systems, taxis, and commercial vehicles operating under cyclic conditions. In these systems, equipment deterioration, productivity loss, and cost increases are closely connected. Life-cycle costing combined with stochastic simulation is commonly used to represent uncertainty in operating costs and demand (Riechi et al., 2017; Raposo et al., 2017). Other studies include emissions, service reliability, and performance degradation in replacement analysis (Manojlovic et al., 2011; Castel-Branco et al., 2015; Macian et al., 2017; Bai et al., 2019; Ribeiro and Mendes, 2022; Gnap et al., 2024; Teixeira and Sodre, 2016). These studies show that replacement decisions in transport systems often involve balancing cost efficiency with service and environmental requirements.

The transition toward electrification has further expanded replacement research by linking fleet renewal decisions with energy infrastructure and environmental targets. Several studies examined adoption processes, interactions between transport and energy systems, and long-term emission impacts under renewable electricity conditions (Longo et al., 2016; Fresia and Bracco, 2023; Tang et al., 2023; Bayani et al., 2022; Giliomee and Booysen, 2023; Li et al., 2024; Caban et al., 2024). Prediction-based approaches have been proposed to jointly determine fleet size, replacement timing, and reserve capacity during electrification (Othman et al., 2024), while policy-oriented studies assessed the long-term economic and environmental effects of alternative renewal strategies (Li et al., 2025).

Replacement problems are also addressed in energy systems and renewable resource management, where asset renewal is closely linked to the operation of generation, storage, and consumption units. Examples include risk-based economic analysis (Pukala et al., 2021), machine learning–supported performance estimation combined with multi-objective optimization (Sagawa and Tanaka, 2023), and optimal control models for renewable energy communities (Aittahar et al., 2023). Similar long-horizon cyclic decision problems are observed in shipping and maritime transport, where uncertainty in fuel prices, demand, and regulations motivates the use of real options and robust optimization methods (Zheng and Chen, 2018; Zhao et al., 2021). Comparable structures are also present in renewable resource systems such as fisheries (Nævdal, 2022).

Overall, studies from other sectors show that equipment replacement problems share common structural features across different applications. These include cost increases due to deterioration, uncertainty in demand and operating conditions, and long-term financial trade-offs. At the same time, many studies indicate that replacement decisions are increasingly linked to broader system-level issues such as asset management practices, energy system integration, workforce limits, and environmental objectives. While this literature provides useful methodological insight, direct application to mining often requires adjustments to reflect cyclic production behavior, spatial variation, and the specific wear mechanisms of heavy mobile equipment.

2.6 Summary and Study Motivation

The review of equipment replacement studies in mining and other capital-intensive sectors reveals a clear gap between detailed operational modelling and long-term, system-level replacement decision-making. Although individual aspects such as cost analysis, reliability, maintenance, and sustainability are widely studied, these elements are often addressed individually. Integrated decision-support frameworks that jointly consider operational performance, production requirements, and long-term investment planning remain limited, particularly for cyclic continuous operations.

In many existing studies, operational performance and strategic replacement planning are treated separately. Simulation-based approaches are effective in representing operational variability, equipment aging, and performance degradation; however, they are frequently applied as independent analysis tools without being linked to optimization models capable of producing optimal long-term replacement strategies. In contrast, optimization-based replacement models often rely on simplified or static assumptions regarding equipment productivity, cycle times, and availability. Such assumptions restrict their ability to represent age-dependent productivity loss, evolving haul road networks, time-varying production targets, and changing operational conditions over the life of a mine.

Another important limitation concerns spatial representation. While real mining operations are commonly distributed across multiple locations with distinct production targets and route characteristics, most replacement models adopt a single-location perspective. As a result, they rarely allow dynamic allocation or reallocation of equipment among different operational areas, even though spatial flexibility plays a critical role in fleet utilization and replacement decisions in practice.

A comparative summary of the research studies reviewed in the previous sections is provided in Table 2.1, organized according to the classification criteria illustrated in Figure 2.3.

Table 2.1 Comparison of the Equipment Replacement Literature

#	Study	Framework Items	#	Study	Framework Items
1	Rajabian (2021)	A1, C4, P1, P3, L1, M3, S1	41	Ansaripoor and Oliveria (2018)	A1, C3, P3, L1, M3, S1
2	Alp et al. (2022)	A1, C4, M1, S1	42	Aiello et al. (2024)	A1, C3, P3, L1, M3, S1
3	Škrinjar et al. (2020)	A1, C3, M2	43	Raposo et al. (2017)	A2, C4, C5, L1, M1
4	Zacharaki et al. (2021)	A1, C3, M1, S6	44	Osei et al. (2021)	A4, L1, M2
5	Sharpe et al. (2018)	A6, C3, M3	45	Abdallah and Lasserre (2016)	A6, C3, C5, P1, P2, M1, S1
6	Carvalho et al. (2023)	A1, C3, L1, M2	46	Castel-Branco et al. (2015)	A2, C4, P2, L1, M3, S5
7	Sønnervik et al. (2024)	A5, C3, C5, L1, M3, S1	47	Li et al. (2025)	A2, P1, P2, P3, L1, M2, S2
8	Riechi et al. (2017)	A2, C4, P2, L1, M3, S2	48	Teixeira and Sodre (2016)	A2, C3, C5, L1, M2, S2
9	Othman et al. (2024)	A4, C3, P1, P2, P3, L2, M3, S6	49	Gnap et al. (2024)	A2, C3, P3, L1, M2
10	Redmer (2016)	A4, C4, C5, P2, L1, M3, S1	50	Etti et al. (2020)	A1, P1, L1, M2
11	Ansaripoor et al. (2014)	A4, C3, P2, L1, M3, S1	51	Andreacchio et al. (2019)	A1, C3, L1, M3, S1
12	Zheng and Chen (2018)	A5, C3, C5, P2, P3, L1, M3, S2	52	Castanon et al. (2024)	A1, C3, P1, P2, L1, M3
13	Manojlovic et al. (2011)	A2, C3, P2, L1, M2	53	Huzaifa et al. (2023)	A3, P1, P2, P3, L1, M3, S5
14	Ribeiro and Mendes (2022)	A2, C3, L1, M1	54	Boomen et al. (2018)	A6, C3, C5, M1, S1
15	Tanh et al. (2023)	A4, C3, L1, M3	55	Boomen et al. (2019)	A6, C3, C5, M3, S1
16	Bai et al. (2019)	A2, C3, L1, M3, S1	56	Sagawa and Tanaka (2023)	A3, C2, P1, P2, P3, L1, M3, S6
17	Bayani and Wang (2022)	A4, L1, M3, S6	57	Brito et al. (2022)	A6, C1, L1, M3
18	Fresia and Bracco (2023)	A4, C3, P1, L1, M3, S1	58	Armstrong et al. (2024)	A6, C3, C5, L1, M3
19	Sousa et al. (2019)	A6, C3, L1, M3, S1	59	Mkandawire et al. (2021)	A6, C3, P3, L1, M3, S1
20	Aittahar et al. (2023)	A3, C3, P1, L1, M3, S1	60	Oliveira and Duque (2011)	A6, C4, C5, M1, S1
21	Lynch et al. (2022)	A3, P3, M3, S1	61	Azevedo et al. (2020)	A6, C3, P2, M3, S5
22	Giliomee and Booysen (2023)	A4, L1, M3, S2	62	Momani et al. (2024)	A6, C4, C5, P2, P3, M2, S2
23	Cao et al. (2012)	A6, C1, L1, M1, S1	63	Fan et al. (2011)	A6, C4, C5, P2, L1, M1, S1
24	Kontou et al. (2017)	A4, C3, C5, P1, P3, L1, M3, S1	64	Kirstein and Visser (2017)	A1, C3, P1, L1, M3, S2
25	Viri et al. (2021)	A4, C3, P3, L1, M3, S2	65	Huang et al. (2024)	A6, C2, L1, M3, S1
26	Li et al. (2024)	A4, L1, M3, S6	66	Sahu et al. (2016)	A6, C4, C5, M3, S1
27	Longo et al. (2016)	A4, C2, P1, P3, L1, M2	67	Palladino and Turi (2023)	A6, C3, C5, L1, M2, S2
28	Yatsenko and Hritonenko (2010)	A6, C4, C5, P3, L1, M1, S1	68	European Society of Radiology (2014)	A6, C3, L1, M1,
29	Macian et al. (2017)	A2, C4, L1, M3, S2	69	Coronas et al. (2022)	A3, P3, L1, M3, S2
30	Zhao et al. (2021)	A5, C4, P1, P2, P3, L1, M3, S1	70	Afanasiev et al. (2024)	A1, M1
31	Jakovics and Horváth (2023)	A2, C3, P3, L1, M1	71	Hakkim et al. (2022)	A4, P3, L1, M2, S2
32	Pragaspathy and Baskaran (2017)	A3, P1, P2, L1, M1	72	Bouoiyour et al. (2023)	A3, M2
33	Nævdal (2022)	A5, C2, C5, P1, L1, M1, S1	73	Nam and Lee (2022)	A6, M3, S1
34	Grano and Abensur (2017)	A1, C4, C5, L1, M3, S1	74	Goodell et al. (2023)	A6, M2
35	Abreu et al. (2025)	A3, P1, P2, L2, M1, S6	75	Rovny et al. (2017)	A6, L1, M3
36	Pukala et al. (2021)	A3, C3, C5, P1, L1, M1	76	Kayani et al. (2024)	A6, M2
37	Caban et al. (2024)	A4, C3, L1, M3, S1	77	Steuer (2016)	A6, M2
38	Redmer (2022)	A4, C4, C5, P1, P2, P3, L1, M3, S5	78	Somerville and Nagy (2025)	A6, M2
39	Ansaripoor et al. (2016)	A4, C3, P1, P2, P3, L1, M3, S1	79	Gerotto et al. (2025)	A6, M1, S2
40	Corsetti et al. (2024)	A1, C3, C5, P1, P2, P3, L1, M2, S2	80	Dutta and Dutta (2022)	A3, M2

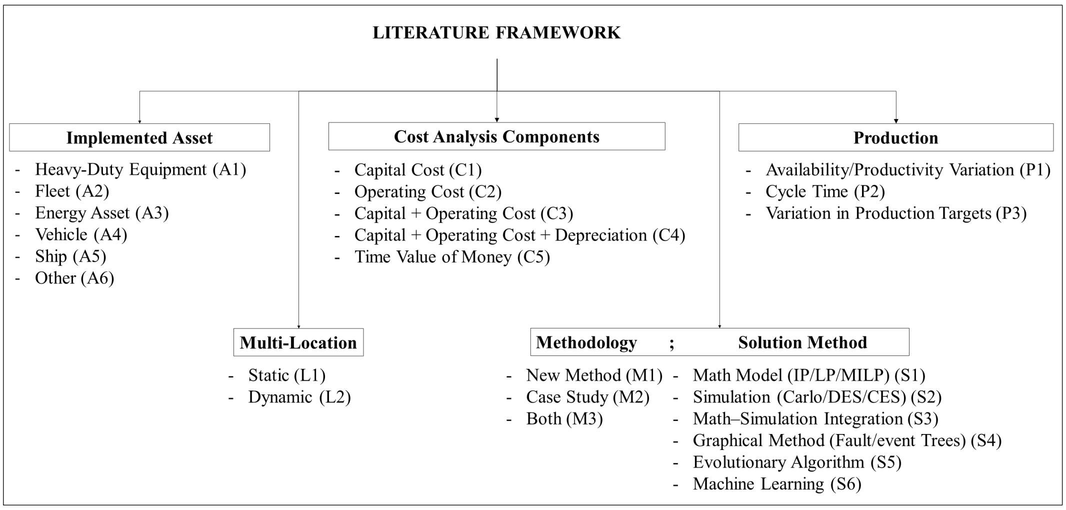


Figure 2.3 Literature Comparison Framework

To overcome the identified shortcomings, this thesis develops a simulation-integrated dynamic integer programming framework that explicitly connects operational behavior of individual trucks in fleet with long-term investment and equipment replacement decisions. A dynamic material dispatching model is constucuted in a discrete-event simulation enviroment to model route-specific operations, age-related changes in productivity and availability, the evolution of cycle times, and fuel or energy consumption. The resulting simulation outputs are then transferred into the integer programming optimization model as time-, age-and location-dependent productivity and cost parameters of trucks, allowing replacement decisions to be evaluated using an NPV criterion under realistic and time-varying operating conditions. In addition, the framework incorporates changing production targets and multi-location deployment requirements within a single, coherent decision structure.

Based on the gaps identified in the literature, the main contributions of this study are summarized as follows:

i. Implemented Asset: The framework is designed for truck-based haulage systems in which multiple capital-intensive equipment units, each with different ages and productivity levels, must collectively satisfy periodic production targets. While mining is adopted as the main application domain, the underlying model structure is generic and can be adapted to other cyclic production systems.

ii. Cost Analysis: Investment costs, operating costs, depreciation, and salvage values are combined within a unified cash-flow formulation. The resulting cash flows are influenced by fleet heterogeneity in terms of equipment age, route characteristics across periods, and expected cost increases over time. The time value of money is explicitly represented through an interest rate, and replacement decisions are assessed using Net Present Value (NPV).

iii. Production Representation: Equipment deterioration is captured through availability-based productivity loss, such that haulage capacity declines with age in line with effective operating availability. The framework allows user-defined availability profiles, period-specific route configurations, and production targets specified independently for each planning period.

iv. Multi-Location Capability: Spatial structure is directly represented by allowing multiple operational locations with different production targets and route characteristics. Allocation and reallocation constraints enable flexible deployment of equipment across locations, supporting realistic fleet planning over time.

v. Solution Methodology: The proposed approach combines discrete-event simulation with dynamic mathematical optimization. The simulation component represents detailed operational behavior and fuel consumption, while the optimization model identifies cost-minimizing acquisition, utilization, replacement, and allocation decisions subject to production constraints across locations and periods.

Overall, the proposed framework addresses key limitations in existing replacement studies by combining operational detail with long-term economic optimization. This integration provides a practical and consistent basis for supporting equipment replacement decisions in mining operations characterized by long planning horizons, spatial complexity, and capital-intensive fleets.

CHAPTER 3

DEVELOPMENT OF THE DISCRETE-EVENT SIMULATION MODEL

3.1 Introduction

In surface mining, truck dispatching systems are essential for transporting ore or waste between various operational points such as loaders, excavators, crushers, dumpsites, or stockpiles. The number and capacity of trucks play a crucial role in evaluating the key performance indicators of these systems. To use dispatching systems effectively, it is important to allocate trucks to excavators or loaders in a way that maximizes productivity and minimizes operational costs.

As previously discussed, operating costs increase as equipment ages and wears over time. Maintenance intervals become shorter, and operational performance factors like fuel consumption add extra costs. Decision-makers must therefore determine the optimal timing for equipment replacement while accounting for the high capital costs associated with mining equipment. Favorable economic conditions are required to justify replacement decisions, which inherently involve balancing increasing operational costs against substantial capital investment costs.

To address this challenge, a mathematical modeling framework that simultaneously considers operational costs, investment costs, and financial benefits is required in order to identify optimal scenarios that minimize total costs while satisfying production targets. In this context, the present study proposes two models that are integrated with each other. The first model is a truck dispatching model formulated in the form of a discrete-event simulation. This simulation model accounts for the geometric and operational characteristics of transportation roads and evaluates kinematic forces and motion parameters accordingly. Truck characteristics, route and location information for each period, and other relevant operational conditions are introduced as model inputs, while the simulation produces yearly transported material quantities for trucks with varying ages, together with fuel consumption values, as outputs. The simulation outputs are then used as inputs to the second model, which is an integer programming model. This optimization model aims to minimize total costs, including equipment-level operational costs, investment costs, and penalty costs related to production losses caused by reduced equipment availability or idling, while also accounting for benefits obtained from salvaging and selling aging equipment, and ensuring that production targets are satisfied.

This chapter explains the logic behind the developed dispatching algorithm and its implementation within a discrete-event simulation software environment. The model requires several sub-models to compute effective forces during truck movement, generate dynamic speed profiles, and determine fuel consumption required to counteract resistive forces at various speeds. These sub-models employ both deterministic and stochastic approaches, performing time-based (dynamic) calculations and decisions at discrete intervals. The model evaluates system status changes at specific event times and incorporates random variables as model inputs.

3.2 Algorithm Logic

The transported material in a dispatching system may vary across different operational contexts; for example, it may represent a manufactured product awaiting dispatch from a factory, a container to be transported in logistics operations, passengers in commercial aviation, or commuters in urban transportation systems. Depending on the type of material handled, the configuration of hauling and loading equipment can be defined accordingly. Multiple alternatives can also be designed for the matching of hauling and loading units. In this study, scenarios with different numbers of hauling and loading units operating at multiple locations are simulated. In addition, alternative routes that hauling units can follow within a single working day are incorporated into the system. When the periodic operations of a hauling unit are examined in detail, the following operational steps are defined:

i. Hauling units initiate their operational cycles from predefined parking stations designated for the system.

ii. During each relevant operating period, every hauling unit operates in coordination with a specific loader to which it is assigned.

iii. Upon reaching the assigned loading point, the hauling unit undergoes the process and may enter a queue if the loading point is currently occupied.

iv. Following completion of the loading process, hauling units proceed to the designated dumping location based on the material type being transported and the corresponding operational assignment.

v. At the dumping locations, hauling units unload their payloads and may wait in a queue if unloading points are temporarily occupied.

vi. When the fuel level of a hauling unit drops below a predefined threshold, the unit is directed to the fuel station for refueling, which is always carried out after the dumping process; therefore, hauling units travel to the fuel station without a payload.

vii. At the end of the working period, all hauling units unload any remaining material, if applicable, and return to the parking station to complete their operational cycle.

The simulation model incorporates a comprehensive set of parameters required to sustain operational activities, and these parameters are directly applied within the operational steps defined above. Since parameter values differ depending on the types of hauling and loading units employed, the simulation input files are designed in a user-friendly manner, thereby allowing straightforward adaptation to alternative equipment configurations. Both the simulation model and the mathematical optimization model include endogenous and exogenous parameters. Endogenous parameters are those directly associated with the transportation medium and the characteristics of the road network on which it operates, and variations in these parameters directly influence operational efficiency and, consequently, the investment policy determined in this study. Exogenous parameters are not directly related to the equipment itself; however, they may still affect operational performance through variability arising from factors such as weather conditions or other external influences. The algorithm indices are provided in Table 3.1, and the variables, input parameters and probability density (distribution) functions are summarized in Table 3.2. The computational procedure of the discrete-event simulation model is summarized as follows.

i. The simulation model operates at a microscopic level, explicitly tracking the behavior of each hauling unit T_k throughout daily operations over the entire simulation horizon. The primary performance output of the simulation is the transported material amount Mat_{T_k}, which is derived from dynamically calculated cycle times and operational constraints. These outputs constitute an input for the mathematical optimization model discussed in Section 4.

ii. At the start of the simulation, an initial fleet configuration is specified. For each hauling unit T_k, the operational day is initialized by setting the day counter to $d = 1$ and assigning the initial location as the parking station in Step 1. At the beginning of each operational day, the rainfall probability W^{Month} is evaluated using predefined monthly precipitation data (Step 2). If rainfall is realized, rolling resistance R^{Rol} and, where applicable, the maximum attainable speed V^{max} are adjusted to reflect deteriorated road-surface conditions.

iii. For each equipment unit T_k, initial operational attributes are assigned in Step 3. These include the selected route r, the initial segment index $s = 1$, initial and maximum speeds V^{ini} and V^{max}, gross vehicle weight EVW_k, and fuel tank capacity FTC_k. Based on these attributes and the characteristics of the current route segment, force calculations are performed in Step 4. The net force F^{Net} is computed by combining available rimpull R^R, grade resistance R^G, and rolling resistance R^{Rol}.

Table 3.1 Indices Used in the Simulation Model

Indices	Explanation
r	route indices represent the road between two stations, where $r \in \{1 \dots R\}$
s	section indices represent the segment of road, where $s \in \{1 \dots S\}$
k	truck type indices, where $k \in \{1 \dots K\}$

Table 3.2 The Algorithm Variables and Inputs

Input Parameter/PDF	Description
$\mathrm{Av}_{k,a}$	Availability estimates of equipment type k with age a (%)
EVW_{k}	Empty vehicle weight of equipment type k (ton)
FTC_{k}	Fuel tank capacity of equipment type k (lt)
$\mathrm{FL}^{\mathrm{critical}}$	Critical Fuel Level (lt)
$\mathrm{G}_{r,s}$	Gradient of the segment s of the route r (°)
$\mathrm{i}_{r,s}$	Intersection information of the segment s of the route r, where $\in\ (0,1,2)$
$\mathrm{L}_{r,s}$	Length of the segment s of the route r (m)
$\mathrm{Month}^{\mathrm{Target}}$	Target month that the simulation must stop
P_{k}	Payload density function of equipment type k (ton)
$\mathrm{Time}_{k}^{\mathrm{Load}}$	Loading time density function of equipment type k (min)
$\mathrm{Time}_{k}^{\mathrm{Dump}}$	Dumping time density function of equipment type k (min)
$\mathrm{Time}_{k}^{\mathrm{Fuel}}$	Refueling time density function of equipment type k (min)
$\mathrm{T}^{\mathrm{daily}}$	Daily working hours (h)
$\mathrm{W}^{\mathrm{Month}}$	Precipitation probability of operating day in a month (%)

Variables	Description
acc	Acceleration (m/s^2)
CT	Total Cycle Time (sec)
d	Day number
dec	Deceleration (m/s^2)
$\mathrm{FC}^{\mathrm{Acc}}$	Fuel consumption function of acceleration distance
$\mathrm{FC}^{\mathrm{Cons}}$	Fuel consumption function of constant distance
$\mathrm{FC}^{\mathrm{Dec}}$	Fuel consumption function of deceleration distance
$\mathrm{FC}^{\mathrm{Idle}}$	Fuel consumption function of idle
FL	Fuel Level (lt)
$\mathrm{F}^{\mathrm{Net}}$	Net Force (kN)
GVW_{k}	Gross vehicle weight of equipment type k (ton)
Mat_{T_k}	The amount of material transported by the equipment T_k (ton)
$\mathrm{Month}^{T_{now}}$	Current month of the simulation
R^{G}	Grade Resistance (kN)
$\mathrm{R}^{\mathrm{Rol}}$	Rolling Resistance (kN)
R^{R}	Available Rimpull (kN)
$\mathrm{V}^{\mathrm{ini}}$	The initial speed (km/h)
$\mathrm{V}^{\mathrm{max}}$	The maximum speed (km/h)
$\mathrm{V}^{\mathrm{fin}}$	The final speed (km/h)
$\mathrm{T}^{\mathrm{now}}$	Simulation time (h)
T_{k}	Equipment ID for equipment type k
TFC	Total Fuel Consumption (lt)
TW	Total equipment weight (tons)
$\mathrm{x}^{\mathrm{Acc}}$	Acceleration distance (m)
$\mathrm{x}^{\mathrm{Dec}}$	Deceleration distance (m)
$\mathrm{x}^{\mathrm{Cons}}$	Distance traveled at V_{max} (m)

iv. Using the net force, kinematic variables are derived in Step 5. Acceleration acc, deceleration dec, and attainable speeds are calculated, followed by the determination of acceleration and deceleration distances (x^{Acc} and x^{Dec}) and final speed V^{fin} in Step 6. A consistency check is applied in Step 7 to verify whether the segment length $L_{r,s}$ is sufficient to accommodate both acceleration and deceleration phases. If $x^{Acc} + x^{Dec} > L_{r,s}$, is satisfied, the kinematic variables are recalculated to fit within the segment length; otherwise, the constant-speed distance x^{Cons} is computed.

v. Once the motion profile for the corresponding route segment is finalized, segment-level travel time, fuel consumption, and associated state variables are calculated (Step 8). Fuel consumption is evaluated using regime-specific functions corresponding to FC^{acc}, constant-speed travel FC^{Cons}, deceleration FC^{Dec}, and idling FC^{Idle}. These calculations are used to update the total cycle time CT, total fuel consumption TFC, and fuel level FL.

vi. After completion of the current road segment, the intersection attribute $i_{r,s}$ is evaluated (Step 9). A value of $i_{r,s} = 0$ indicates that no intersection is present where the hauling unit is required to decelerate, whereas $i_{r,s} = 1$ denotes junctions at which the hauling unit must estimate a safe braking distance in order to ensure that its velocity becomes zero at the intersection. If $i_{r,s} \neq 2$, the hauling unit proceeds to the subsequent road segment by incrementing the segment index to $s = s + 1$, and the simulation returns to the force calculation stage (Step 4) for the newly entered segment. This procedure continues iteratively until a segment with $i_{r,s} = 2$ is encountered, which indicates arrival at an operational station.

vii. When a hauling unit arrives at a loading point (Step 10), it may enter a first-in–first-out queue if the assigned loader/excavator is occupied. Once loading is completed, payload P_k, loading time $Time_k^{Load}$, total equipment weight TW, and idling fuel consumption $FC^{Idle}$are applied. The hauling unit is subsequently assigned a new route from the loading point to the appropriate dumping location, and the segment index is reset to $s = 1$.

viii. Upon arrival at a dumping point in Step 11, a queuing logic similar to that applied at the loading point is implemented. During this stage, dumping time $\mathrm{Time}_k^{\mathrm{Dump}}$, idling fuel consumption, and payload reset operations are executed. Subsequent routing decisions are determined based on the current fuel level FL and the remaining daily working time $\mathrm{T}^{\mathrm{now}}$. If $\mathrm{FL} < \mathrm{FL}^{\mathrm{critical}}$, the hauling unit is routed to the fuel station. If sufficient working time remains, the hauling unit is routed back to a loading point; otherwise, it is directed to the parking station.

ix. If the hauling unit arrives at a fuel station (Step 12), refueling time $\mathrm{Time}_k^{\mathrm{Fuel}}$ and idling fuel consumption are applied, and the fuel level FL is replenished accordingly. Following completion of the refueling process, the hauling unit is routed either to a loading point or to the parking station, depending on the remaining daily working time $\mathrm{T}^{\mathrm{now}}$.

x. Parking stations act as both scheduled and unscheduled interruption points (Step 13). During pre-scheduled administrative breaks, such as lunch breaks or at the end of the daily working period, hauling units complete their current operational cycle and return to the parking station. If the simulation time satisfies the condition $\mathrm{Month}^{\mathrm{T_{now}}} = \mathrm{Month}^{\mathrm{Target}}$, the simulation is terminated. Otherwise, a new operational day is initialized by incrementing $\mathrm{d} = \mathrm{d} + 1$, and the procedure resumes from the rainfall evaluation step.

xi. Throughout the simulation horizon, the total cycle time CT determines the number of trips that a hauling unit can complete within the daily working period and, consequently, its periodic hauling capacity $\mathrm{Mat}_{\mathrm{T_k}}$. Age-dependent deterioration is incorporated through an availability parameter $\mathrm{Av}_{\mathrm{k,a}}$ that progressively reduces effective operating time as equipment ages. By iterating the procedure across all hauling units, operational days, and planning periods, the simulation aggregates cycle times, fuel consumption, and transported material volumes into age- and period-specific measures.

The developed simulation framework follows a microscopic modeling approach, explicitly representing the behavior of individual equipment units within a cyclic continuous operation. Equipment-specific characteristics, including model type, load or service capacity, and acceleration and braking capabilities, are employed as input data. The model generates speed and performance profiles at fine temporal resolutions in order to estimate instantaneous energy consumption rates, which are subsequently aggregated to obtain total energy consumption for each operating period. In addition, network-based routes connecting defined operational points are incorporated into the model, and interactions among equipment units are represented through queuing mechanisms. The algorithm logic flows between the simulation modules are presented in Figure 3.1 while the pseudo-flow is given in Table 3.3.

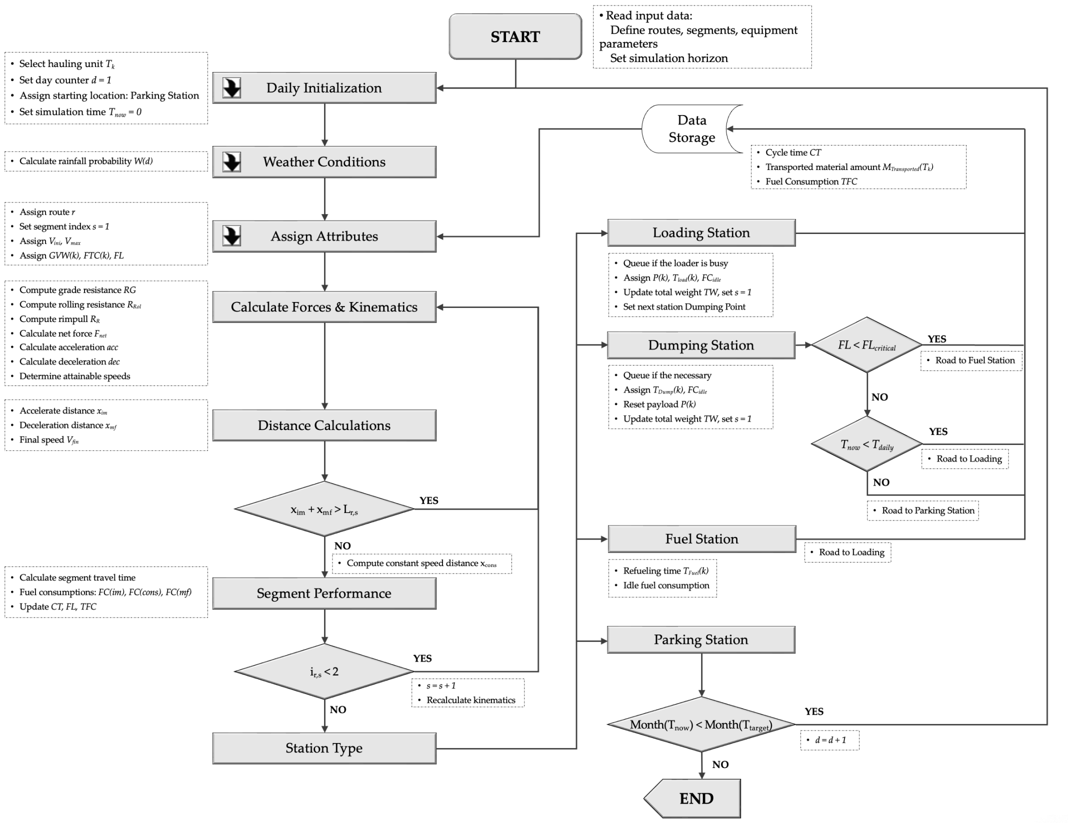


Figure 3.1 Modules of the Developed Simulation Model

Table 3.3 Pseudo-Flow of the Algorithm Logic

Step 1:	For each equipment T_k, assign a new day. d=1
Step 2:	Calculate rain probability for day d. W^{Month}
Step 3:	For each equipment T_k, assign initial attributes. r, s, V^{ini}, V^{max}, EVW_k, FTC_k
Step 4:	Calculate forces. R^{Rol}, R^{G}, R^{R}, F^{Net}
Step 5:	Compute kinematic variables. acc, dec, V^{max}
Step 6:	Calculate distance and final speed variables. x^{Acc}, x^{Dec}, V^{fin}, FC^{Acc}, FC^{Dec}
Step 7:	Check if the segment distance is sufficient. If $\mathbf{x^{Acc} + x^{Dec} > L_{r,s}}$, then recalculate x^{Acc}, x^{Dec}, V^{fin}, FC^{Acc}, FC^{Dec} according to $L_{r,s}$ If $\mathbf{x^{Acc} + x^{Dec} \leq L_{r,s}}$, then go to Step 8
Step 8:	Calculate; x^{Cons}, FC^{Cons}, CT, TFC, FL
Step 9:	Check intersection count $i_{r,s}$; If $i_{r,s} \neq 2$, increase segment s=s+1, and proceed to Step 3 If $i_{r,s} = 2$, proceed with Step 10, Step 11, Step 12, and Step 13 according to station information
Step 10:	If the equipment T_k is in the **Loading Point ;** Assign: P_k, T_k^{load}, TW, FC^{Idle}, FL Assign new route to **Dumping Point** , and segment s = 1 Go to Step 3
Step 11:	If the equipment T_k is in the **Dumping Point ;** Assign: P_k, T_k^{dump}, TW, FC^{Idle}, P(k), FL If FL < $FL^{critical}$, then assign a new route to the **Fuel Station**, and segment s = 1 Else: $T^{now} < T^{daily}$, then assign a new route to **Loading Point**, and segment s = 1 Else if: Assign new route to **Parking Station**, and segment s = 1 Go to Step 3
Step 12:	If the equipment T_k is in the **Fuel Station ;** Assign: T_k^{fuel}, FC^{Idle}, FL If $T^{now} < T^{daily}$, then assign a new route to the **Loading Point**, and segment s = 1 Else: Assign new route to **Parking Station**, and segment s = 1 Go to Step 3
Step 13:	If the equipment T_k is in the **Parking Station ;** If $Month^{T_{now}} = Month^{Target}$, then simulation stops, **END** Else: assign the next day d = d+1, and Go to Step 2

3.3 Simulation Modeling in Arena Software

The developed model is implemented using the Arena simulation software to represent all feasible routes within a cyclic continuous operation under varying operational objectives and operating conditions. The model captures dynamic interactions between equipment units and their operating environment, thereby allowing acceleration and deceleration decisions to be determined based on route-specific characteristics, environmental conditions, and task dependencies. An integrated algorithm enables the simultaneous tracking of energy consumption at both the individual equipment level and the fleet level throughout the simulation horizon. In order to accurately represent the complete operational cycle, the simulation model is structured into several interconnected subcomponents, including Transporting, Loading, Unloading, Refueling or Recharging, and Parking processes, thereby providing a detailed and realistic representation of cyclic continuous operations.

The model is structured as dynamic, stochastic, and discrete in nature. Arena Simulation is a discrete-event simulation software developed based on the SIMAN language. The simulation models are constructed using flowchart modules and data modules to represent the processes of the system. Flowchart modules consist of objects that describe the logical flow of the simulation process, whereas data modules define the characteristics of process elements, including the values and expressions associated with entities and resources.

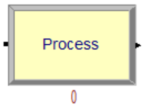
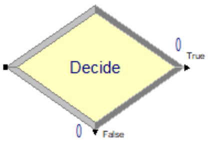
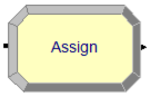
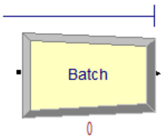
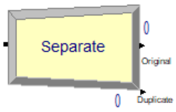
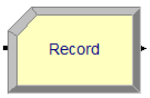
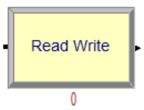
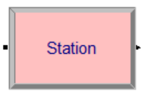
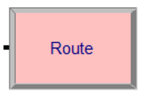
- Entity: They represent the dynamic objects within the simulation environment. The simulation process begins with the creation of these entities, and they remain active throughout the simulation until the termination condition is reached.
- Variable: They represent the specifications and state-related values of the overall system that govern model behavior during the simulation.
- Attribute: They are defined within the model and are assigned to each entity in order to specify the individual characteristics of entities.

- Resource: They are utilized by entities and influence their behavior over the observation period. Due to their limited capacities, when an entity requires a resource that is unavailable, it must wait in a queue until the resource becomes available.
- Queue: A queue represents the location where entities wait when their progression is constrained by limited or unavailable resources. Queue conditions may be defined using various ranking rules, with First In, First Out (FIFO) serving as the default rule in Arena.
- Schedule: A schedule is defined to represent the operating schedule of resources over time.

In this research study, trucks are employed as active entities within the mine haulage system. They are categorized into different groups according to their operational partners, namely excavators and crushers. Excavators and crushers are modeled as resources that trucks can seize, utilize for loading and dumping operations, and subsequently release to proceed to the next station. The fuel station and parking station are also modeled as resources and are used for refueling and parking activities, respectively. System variables include segment properties, truck characteristics, and weather and road conditions. Attributes such as forces, kinematic variables, including acceleration, deceleration, and speed levels, cycle times, payload, and fuel consumption are monitored and recorded for each truck throughout the simulation. The flowchart modules that are extensively used during the modeling phase are listed in Table 3.4.

Simulation runs are executed based on user-defined input parameters, thereby enabling scenario-based analyses. The model operates on a time-based structure in which the occurrence time of each event within the operational processes is computed by the system using user-provided stochastic data. The calculated time is stored as an attribute of the corresponding entity, after which the simulation model facilitates the transition of the entity to the subsequent operational step. The selection of the subsequent step is determined based on user-defined decision criteria.

Table 3.4 Flowchart modules and Definitions

Symbol	Flowchart Modules	Description
	Create	Starting point of entities
	Dispose	Ending point of entities
	Process	Main processing method. It contains the seize, delay, and release processes
	Decide	Decision making process based on conditions or probabilities.
	Assign	Assigning new values to variables, entity attributes/
	Batch	Grouping entities based on the number of entering entities or attribute
	Separate	Splitting batched entities or duplicating entities
	Record	Collection of statistics
	Read/Write	Reading data from an input file and writing data to an output file
	Station	Physical or logical location where processing occurs
	Route	Transferring entities between stations

For a specified time period, the model calculates, on a per-truck basis, the amount of material transported by a given fleet within the corresponding timeframe. In order to accomplish this, the model utilizes the characteristics of both the trucks and the mine road profile to compute acceleration, constant-speed travel, and deceleration durations. Based on the input parameters, the model determines the durations of operational activities and repeats this cycle continuously throughout the simulation horizon. At the end of each operational day, activities are suspended, and the simulation resumes on the subsequent day. In addition, the model incorporates a fuel consumption calculation that is implemented using a predefined fuel consumption formulation embedded within the system. Figure 3.2 illustrates the simulation algorithm modules in Arena Simulation environment.

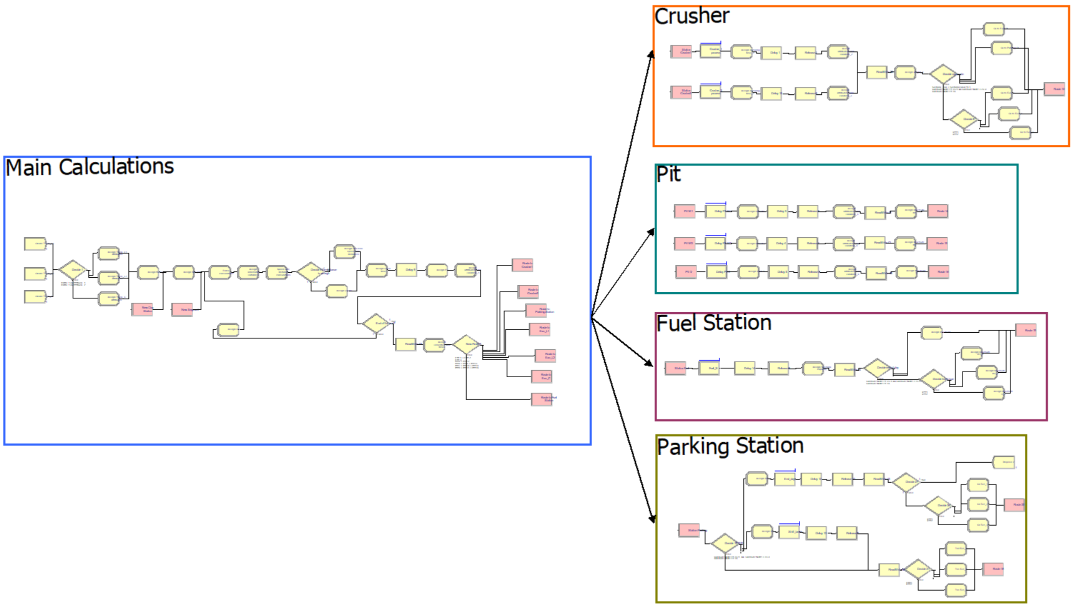


Figure 3.2 General View of the Simulation Model in Arena Simulation

The simulation begins with the creation of truck entities using the *Create* module. Different specifications for trucks are generated through separate Create modules. In this study, as default, three main types of excavators are used, two of which operate in waste hauling and one of which operates in ore extraction; therefore, three Create modules are employed. These allocations can be modified according to location-based production requirements. Truck entities generated from the different Create modules are subsequently combined, and their cumulative information is transferred to the *Decide* module in order to initiate the truck cycle toward the assigned excavator for loading. Assign modules are utilized to allocate specific attributes to entities and system variables, namely truck type k, route r, intersection $i_{r,s}$, V^{ini}, V^{max}, and V^{fin}. Figure 3.3 illustrates the truck creation and variable assignment components of the simulation model.

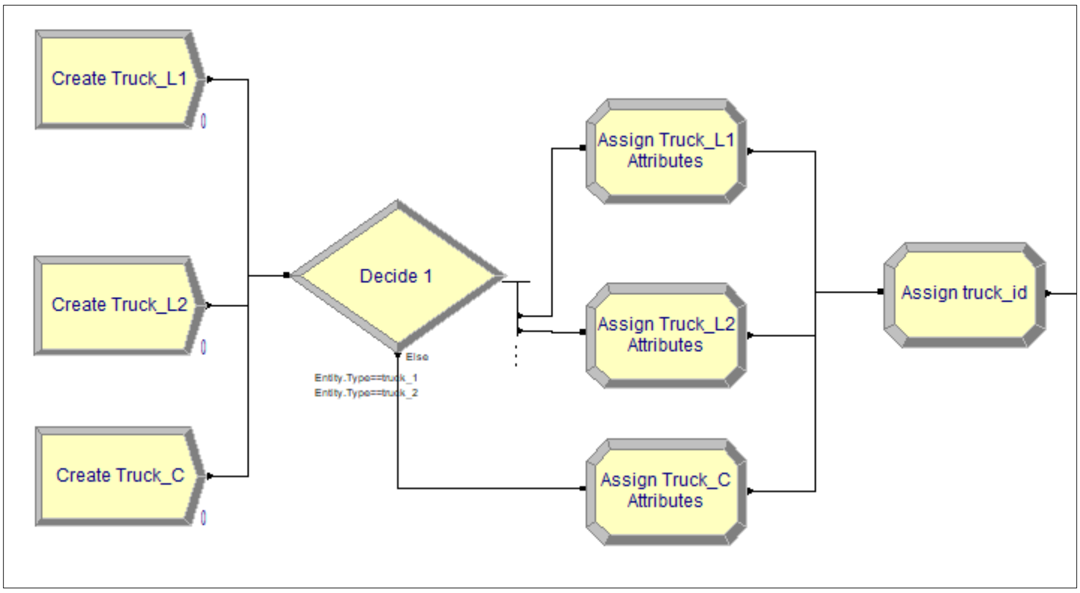


Figure 3.3 Creation of Truck Entities

Each truck entity is assigned a unique identification number in order to enable the simultaneous monitoring of individual trucks along their respective routes and road segments. At the beginning of the simulation, all trucks are located in the parking area and subsequently travel from this location to the next operational station. The road network between stations is divided into segments based on gradient variations and the presence of intersections. Since the traveling characteristics of each truck differ, the segment number is treated as an attribute associated with each truck entity. Route- and segment-specific attributes are assigned to each truck as it passes through the corresponding *Assign* modules.

The initial part of the *Hauling* Submodule is illustrated in Figure 3.4. Within this submodule, speed levels and hauling time are determined based on segment-specific information, including route length, grade, and intersection locations. The process begins with weather forecasting through the precipitation probability density function W^{Month} derived from monthly rainfall input data. If rainy conditions are detected, the rolling resistance coefficient is adjusted accordingly to reflect deteriorated road conditions. For each operational day, a new precipitation probability is generated. Subsequently, the simulation proceeds with the calculation of forces, namely grade resistance R^{G}, rolling resistance R^{Rol}, available Rimpull R^{R}, and net force F^{Net}, as well as kinematic variables such as acceleration acc, deceleration dec, and maximum truck speed V^{max}, using the relevant governing equations.

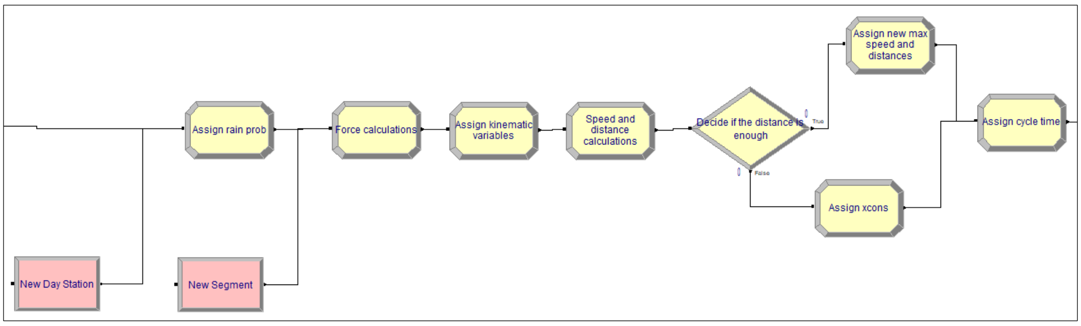


Figure 3.4 Hauling Submodule - Part 1

Within the *Assign* modules, these computations vary depending on whether road gradient are uphill or downhill, as both force calculations and kinematic variables are strongly influenced by road gradients and travel direction. The algorithm evaluates the maximum speed level by simultaneously considering the mechanically achievable speed limit of the trucks under the prevailing road segment conditions and the applicable mine speed limits. At each segment, the algorithm selects the minimum of these two values to determine the effective final speed within the segment. Subsequently, speed profiles for individual road segments are generated by computing initial and final speed levels based on the segment length, denoted as length $L_{r,s}$ and the intersection between consecutive road segments $i_{r,s}$. If a segment intersection point corresponds to a point where the truck is required to reduce its speed to zero, the truck adjusts all acceleration and deceleration decisions accordingly. Otherwise, the final speed attained in the current segment is transferred to the next sequential segment and used as the initial speed.

The *Decide* module evaluates whether a truck can reach its calculated maximum speed level V^{max} by assessing the required acceleration and braking distances. If the combined distance needed for acceleration and braking is less than or equal to the length of the road segment, two conclusions are established: i) sufficient distance exists to reach the calculated maximum speed, and ii) the truck can safely decelerate to the required final speed within the segment length. However, if the combined achievable acceleration and braking distance exceeds the segment length, the model adjusts the maximum achievable speed level within the segment to ensure that adequate acceleration and braking can be performed. This submodule also computes the travel time associated with each road segment and determines the corresponding fuel consumption components, namely FC^{Acc},FC^{Dec} , and FC^{Cons}.

Once the speed levels and fuel consumption for a given segment are estimated, the model verifies whether the route has been completed. If the route is not yet finished, the model returns to the New Segment Station, incrementing the segment number by one within the Assign module until the end of the route is reached. This incrementation occurs after all required truck-related calculations for the active segment are completed. Upon completion of the route, truck entities exiting the Hauling Submodule proceed to their designated destination stations.

Figure 3.5 illustrates the second part of the Hauling Submodule, which determines the subsequent station to be travelled. Route modules are used to facilitate entity transfers between predefined stations, enabling trucks to move initially from the parking area to the excavator stations. Station modules define the physical locations of excavators, crushers, parking areas, and fuel stations, and serve as reference points both within and around the pit.

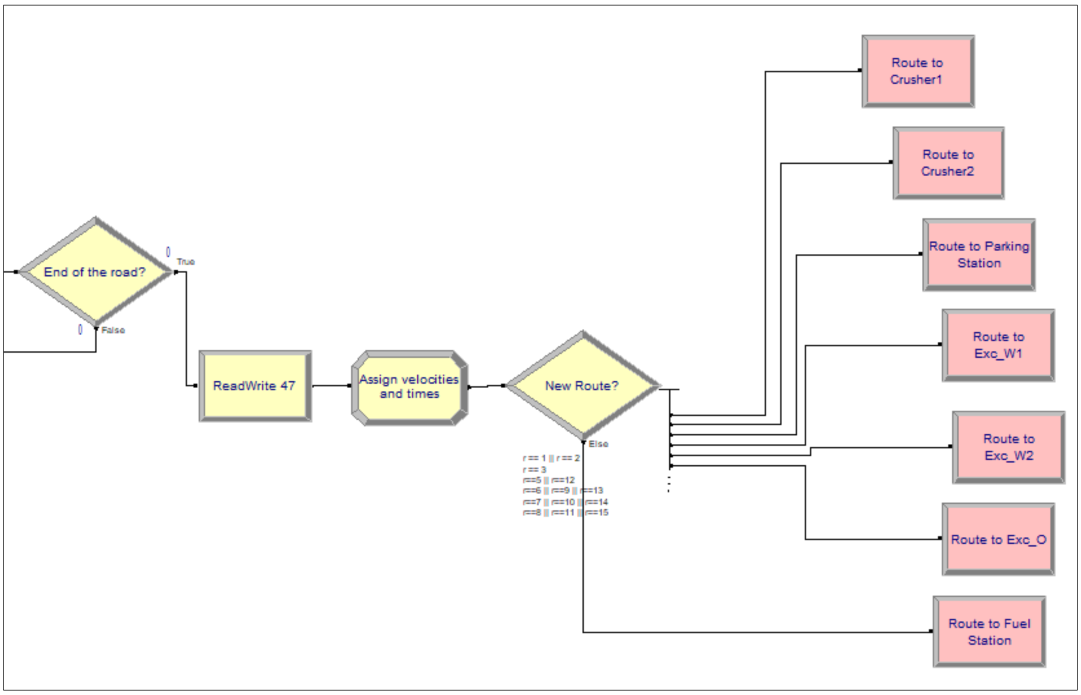


Figure 3.5 Hauling Submodule - Part 2

Figure 3.6 illustrates the loading processes conducted by two excavators operating in waste material handling at Pit W1 and Pit W2, and one excavator operating in ore extraction at Pit O. By default, three loading points are defined in the model, which can be modified in accordance with operational requirements. Each loading submodule associated with these excavators adheres to the same operational principles. The submodule begins with a *Station* module, which indicates the physical location of the excavator. Upon the arrival of a truck entity at an excavator, the model places the truck directly into the excavator queue. If the excavator is occupied by loading another truck, the arriving truck entity waits in the loading queue. The queue follows a First In, First Out (FIFO) ranking rule, meaning that each newly arriving truck entity joins the end of the queue and waits until all previously queued trucks have been loaded. Once the excavator becomes available, it initiates the loading process for the truck entity located at the front of the queue after a designated truck maneuvering time.

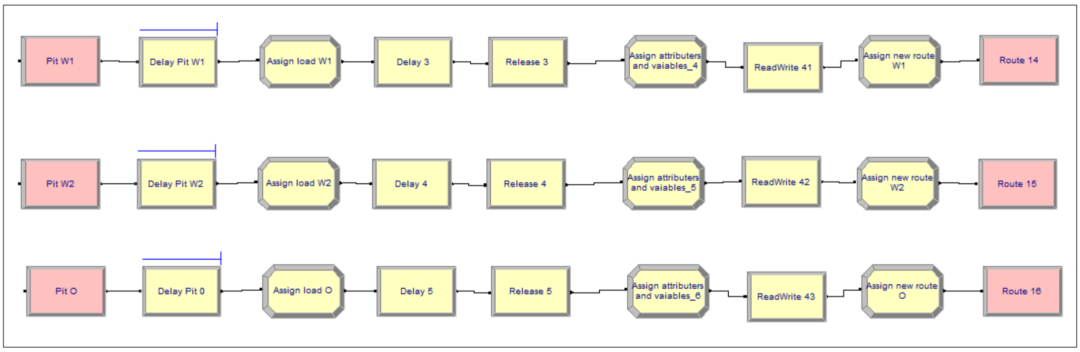


Figure 3.6 In Pit Loading Processes

Loading time is assigned within the Process module to control and initiate the loading procedure. Once the loading operation is completed, the truck is identified as loaded within the algorithm. Following the completion of the loading process, a new truck weight is randomly assigned based on the probability distribution of the material load. The Assign module also computes the truck's fuel consumption during the loading operation. During this stage, the fuel consumption rate is estimated under the assumption that truck engines operate in an idling condition throughout the loading and queueing periods. Loaded trucks are restricted to traveling exclusively on routes between excavators and designated dumping destinations. The algorithm prevents any route changes until the hauled material has been dumped. Consequently, the *Route* module is used to transfer loaded truck entities to either the crusher station or the waste dumpsite station.

The *Hauling* Submodule illustrated in Figures 3.4 and 3.5 is employed to assign truck entities from excavators to crushers or dumpsites. Speed levels and hauling times for each road segment are recorded in order to generate detailed speed profiles and to determine cycle times. In addition, cumulative fuel consumption is calculated for each segment and for the entire route in order to represent both segment-level and total fuel consumption profiles for individual trucks.

The dumping process flowchart in the crusher area is presented in Figure 3.7. Trucks whose loading operations may be carried out by multiple excavators must be assigned to a dumping station, such as dumpsite, stockpile, and crusher. Upon arrival along the designated route, if a dumping point is already occupied by another truck, the arriving truck must wait at the end of the queue. The dumping time is incorporated into the cycle time calculations of trucks undergoing the dumping operation. Once the dumping process is completed, trucks are designated as empty within the simulation framework.

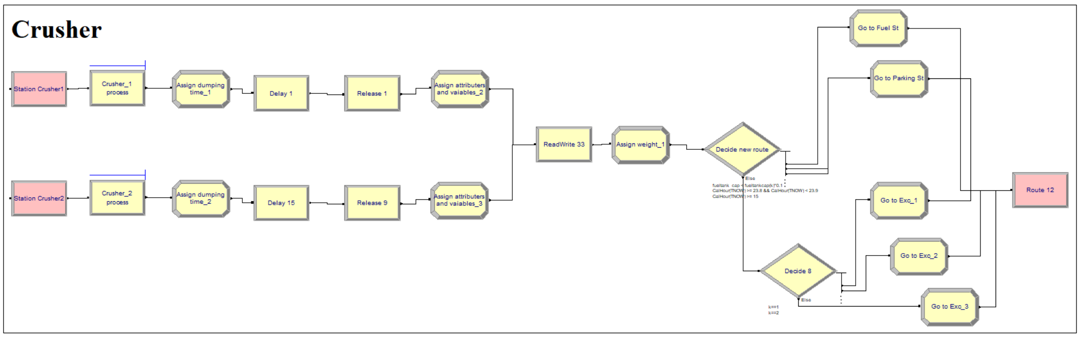


Figure 3.7 Dumping Process in Crusher

Similar to the loading process, fuel consumption during dumping operations is calculated within the *Assign* module by accounting for truck idling conditions. Immediately following the dumping operation, the model evaluates the possible subsequent destinations and corresponding routes. Three potential destinations are considered as default: returning to an excavator for the next loading operation, traveling to a fuel station for refueling, or proceeding to a parking station for administrative purposes. Initially, the model evaluates the fuel tank level and initiates a refueling process if the fuel level falls below 10 percent of the total fuel tank capacity, which is defined as an adjustable threshold within the algorithm. The queue status at the fuel station is also evaluated, and trucks are required to wait if a queue is present. Upon completion of the refueling process, the fuel tank capacity is replenished, and trucks proceed to the subsequent station. The control logic governing fuel tank levels and refueling decisions is illustrated in Figure 3.8.

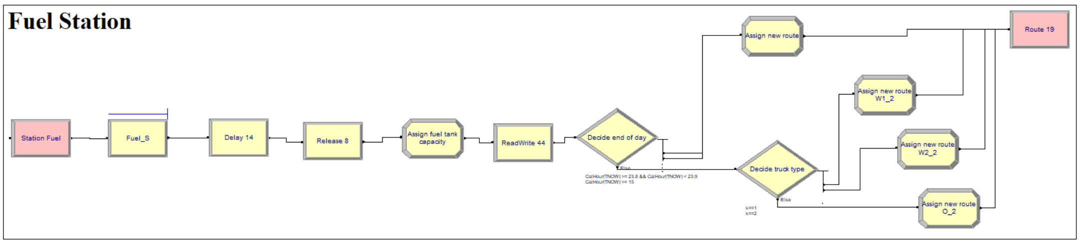


Figure 3.8 Refueling Process

If the *Decide* module determines that refueling is not required, administrative breaks are managed as illustrated in Figure 3.9. Initially, the model evaluates whether a shift break is scheduled. If a break is detected, truck entities are directed to the parking station. The *Batch* module then recalls all empty truck entities, and no hauling or loading operations are permitted during the break period. However, truck entities carrying a payload are not allowed to take a break before completing the dumping process. Once the shift break concludes, truck entities are transferred from the parking station to their respective excavator stations through the Hauling Submodule.

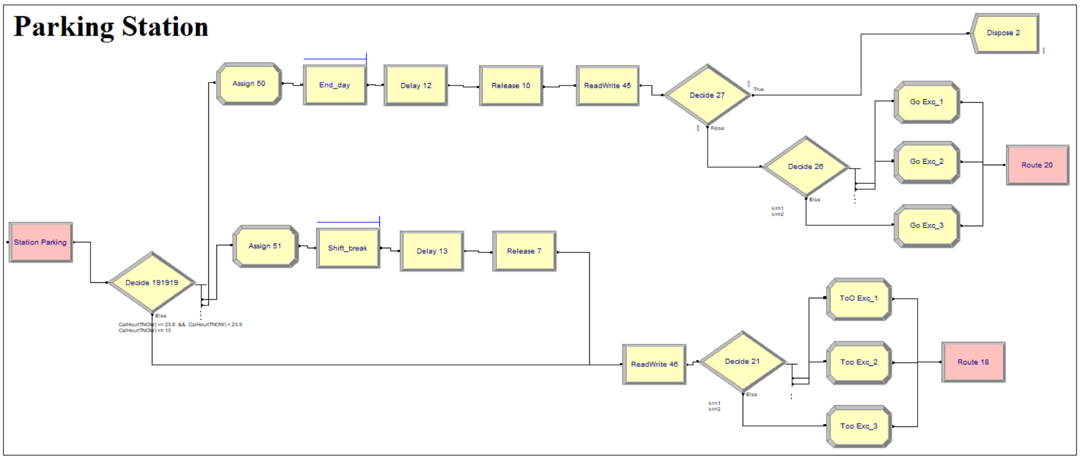


Figure 3.9 Break Time and End of the Day Control

If no shift break is identified, the model evaluates whether the current shift is approaching its end. If the shift is still ongoing, truck entities continue their scheduled production cycles by following newly assigned routes. However, if the shift is expected to end shortly, the algorithm verifies whether a full year has elapsed since the start of the simulation. By default, the model simulates operations over a one-year period, although this target observation period can be modified by the user. If the target period has not yet been completed, truck entities are relocated to the parking station at the conclusion of the final shift and remain there until the next operational day begins. Detailed simulation outputs, including daily production quantities and fuel consumption values, are systematically recorded and reported, accounting for both individual and cumulative fuel consumption rates for each truck as well as for the entire fleet across all segments and routes. At the start of a new operational day, truck entities travel to their assigned loading points and resume their production schedules based on the prevailing daily weather conditions.

If the simulation determines that the default one-year target observation period has been completed, the simulation is terminated. The simulation procedure is repeated until a balance point is reached in the simulation outcomes. At the end of each simulation replication, an output data file is generated, containing results reported on a shift-, day-, and period-based structure. Figure 3.9 illustrates the control mechanism of the model with respect to shift termination and the target observation period.

Arena Simulation software is utilized to model all feasible routes that trucks may travel between various operational points within the mining area under different operational objectives. This modeling approach enables the incorporation of dynamic interactions between vehicles and the operating environment, thereby allowing acceleration and deceleration decisions to be determined based on route segment characteristics, weather conditions, and precedence dependencies. The developed algorithm allows for the simultaneous monitoring of fuel consumption rates at both the individual vehicle level and the fleet level. The algorithm consists of several interconnected submodules, including Hauling, Loading, Dumping, Refueling, and Parking.

The Arena-based simulation model was developed iteratively to ensure operational realism and reliable outputs. Arena was selected due to its suitability for discrete-event modeling and its modular structure, which enabled transparent representation and verification of complex queue-based haulage operations. While open-source simulation platforms provide greater flexibility for full code-level customization, the chosen approach prioritized model clarity, robustness, and efficient integration with the optimization framework. From a computational standpoint, the simulation model does not constitute the primary performance bottleneck, as simulation outputs are generated offline and computational efficiency is mainly governed by the optimization stage. Although dynamic, self-generating simulation structures based on SIMAN code and real-time data inputs are technically feasible, the model structure in this study was intentionally kept fixed, with scenario-based parameter updates, to maintain repeatability, transparency, and consistency in long-term replacement analysis.

3.4 Summary

The simulation model developed in Chapter 3 provides a detailed representation of the operational dynamics of the mining haulage fleet by incorporating key factors such as vehicle speed, fuel consumption, and material transportation efficiency. By integrating user-defined probability distributions and operational parameters, the model represents real-world decision-making processes within the mining operation. This framework enables a comprehensive evaluation of system performance under varying operational conditions, ensuring that key operational constraints and performance metrics are accurately represented.

To support informed capital equipment replacement decisions, the outputs of the simulation model are directly utilized as inputs to the mathematical model presented in Chapter 4. Performance indicators generated through simulation, including fleet utilization levels, fuel efficiency measures, and age-dependent productivity profiles of trucks, are incorporated into the dynamic integer programming formulation as key constraints and objective function components. Through this integration, the mathematical model evaluates the trade-offs among operating costs, penalty costs arising from reductions in truck availability or excessive idling, and capital investment requirements in order to identify optimal equipment replacement schedules.

Chapter 4 details the formulation of this mathematical optimization model and explains the solution approach employed to integrate simulation-derived data into a coherent decision-support framework. In brief, the model determines optimal binary decisions regarding equipment retention or replacement over the planning horizon, thereby enabling cost-effective fleet management while maintaining the required levels of operational efficiency.

CHAPTER 4

DEVELOPMENT OF THE INTEGER PROGRAMMING MODEL

4.1 Introduction

The current section aims to introduce an integer programming model capable of optimizing truck replacement planning for truck-based dispatching operations by accounting for variations in production rates, evolving haul road networks, and multiple destination points, all of which directly influence haulage cycle times. The model explicitly considers heterogeneous truck fleets characterized by different ages and availability levels, while minimizing cumulative capital costs, operating costs, and penalty costs associated with production losses. To support this objective, the mathematical formulation incorporates location- and period-based production targets over the planning horizon. Accordingly, the model structure is designed to satisfy variable production requirements across multiple locations on a period-by-period basis. Age-dependent operating cost variations across different periods, including changes in maintenance, fuel, and labor costs, are incorporated into the mathematical model. In addition, revenues obtained from truck salvage values and the sale of second-hand trucks at the end of the project period are also considered. In this context, Section 4.2 presents the problem statement of the mathematical model in a more explicit manner, Section 4.3 introduces and discusses the objective function and constraints in detail, and Section 4.4 summarizes the chapter.

4.2 Model Problem Statement

The selection of capital equipment for mining operations depends on multiple interrelated parameters. First, the type of mining method plays a critical role in equipment selection, as truck–shovel systems are typically employed in open-pit mining, whereas continuous mining systems may be preferred in certain opencast operations. Furthermore, as the mine life progresses, extensions of the mining area lead to longer haul distances and increased cycle times, which reduce the time-based production rates of individual hauling units and thereby necessitate adjustments in the composition and configuration of the equipment fleet. In addition, increases in the total volume of material to be extracted during different production periods require adjustments in the fleet configuration, which may involve adding brand-new or second-hand equipment to increase the overall hauling capacity.

Mining equipment generally consists of large-scale machinery that requires substantial capital investment. In surface mining operations, trucks function as the primary haulage units, while shovels or excavators are responsible for material extraction. If annual production targets remain constant, the number of shovels required over the mine life is expected to remain relatively stable. However, as haul distances increase and cycle times become longer, the number of trucks required to sustain production increases over time. Therefore, an optimized equipment acquisition and replacement strategy can provide significant financial benefits for mining companies. Achieving such optimization requires a careful evaluation and comparison of investment costs and operating expenses to ensure cost-effective fleet management.

In an equipment replacement decision model, financial parameters must be incorporated as model inputs in order to capture the effects of fluctuating economic conditions over the planning horizon, whether favorable or unfavorable. Accordingly, the proposed model establishes an optimization framework that simultaneously accounts for investment costs, operating expenses, revenues, and financial returns, while ensuring that annual production targets are satisfied under specified operational constraints. Finally, the model is solved with integer programming (IP) through the IBM CPLEX solver implemented within the AMPL interface.

4.3 Formulation

This section presents the mathematical formulation of the integer programming model developed to support optimal truck replacement planning over the defined planning horizon. The formulation converts the operational characteristics and decision context described in the previous sections into a structured optimization problem composed of decision variables, an objective function, and a set of constraints that collectively define the feasible solution space.

The model is formulated within a discrete, multi-period framework in which replacement-related decisions are evaluated for each planning period. In each period, decisions are taken regarding whether individual trucks are continued in operation, replaced with brand-new units, replaced with second-hand units, or retired from the fleet. These decisions are represented through binary variables that explicitly track the operational status and age progression of trucks across successive periods. By modeling equipment age evolution explicitly, the formulation allows replacement decisions to be evaluated dynamically across the planning horizon rather than independently for each period.

Production feasibility is ensured through period- and location-specific constraints that require the available fleet capacity to satisfy predefined production targets. The effective hauling capacity of the fleet in each period is determined using productivity parameters obtained from the simulation model, which reflect both route-dependent operational conditions and age-related performance degradation of trucks. In this way, the mathematical formulation maintains consistency between simulated operational performance and optimization-based decision-making.

The objective function is constructed to capture the cumulative economic impact of replacement decisions over the planning horizon. Cost components included in the formulation consist of capital investment costs associated with the acquisition of brand-new and second-hand trucks, age-dependent operating costs such as maintenance, fuel, and labor expenses, and penalty costs associated with production losses arising from reduced truck availability or excessive idling. In addition, economic benefits resulting from truck retirement, including salvage values and revenues from second-hand equipment sales, are incorporated into the objective function as cost-offsetting terms.

A set of logical and operational constraints is introduced to ensure feasible fleet evolution over time. These constraints govern the allowable transitions between operational states, enforce consistency between acquisition, operation, and retirement decisions, and prevent infeasible age progressions of equipment units. Additional constraints ensure that production requirements are satisfied in every planning period while respecting the capacity limitations implied by the available fleet configuration.

To sum up, the integer programming formulation seeks to minimize the cumulative system cost over the planning horizon while ensuring that all operational and production-related constraints are satisfied. The complete mathematical model, including the definition of sets, indices, parameters, decision variables, the objective function, and the associated constraints, are presented below.

Indices, input parameters and decision variables of the mathematical model are tabulated in Table 4.1. The mathematical formulation of the proposed framework is defined as a mixed-integer programming (MIP) model with the objective of minimizing the NPV of all fleet-related costs over the planning horizon. The objective function aggregates all relevant cost and revenue components, including capital investments, operating expenses, idle capacity penalties, and salvage revenues, and discounts them using an annual discount rate r (Table 4.2). This formulation enables a consistent economic evaluation of long-term replacement and investment decisions while explicitly accounting for equipment aging, utilization patterns, and retirement behavior.

Table 4.1 Mathematical Model Input Parameters and Variables

Indices	
l	Period index (integer, $l \in \{1 \dots \text{Life}\}$)
a	Age index (integer, $a \in \{1 \dots \text{Age}\}$)
c	Location index (integer, $c \in \{1 \dots \text{Location}\}$)
Input Parameters	
Life	Operation period
Age	The maximum equipment age that can be used in the mine
Age_SH	Set of allowable ages for second-hand purchases
Location	The number of locations where equipment can work
min_usage	Minimum required operating age
R	Discount rate
$T_{l,c}$	Production target of period l and location c
$P_{a,l,c}$	Transportation amount by equipment at age a, period l, and location c
$OC_{a,l}$	Operational cost of a equipment at age a and period l
$CC_{a,l}$	Capital cost of a equipment at age a and period l
$S_{a,l}$	Salvage value of a equipment at age a and period l
Z_l	Penalty cost for idle in period l
$SCC_{a,l}$	Capital cost of a second-hand equipment at age a and period l
$SS_{a,l}$	Salvage value of a second-hand equipment at age a and period l
Adj^{Pro}	Productivity adjustment factor for second-hand equipment
Adj^{Cost}	Operating cost adjustment factor for second-hand equipment
Decision Variables	
Equipment purchased as brand-new	
$buyN_l \in Z_+$	number of equipment just purchased in period l
$nN_{l,a} \in Z_+$	number of stock equipment with age a in period l
$rtrN_{l,a} \in Z_+$	number of retired equipment with age a in period l
$uN_{l,a,c} \in Z_+$	number of equipment with age a used at location c in period l
$idleN_{l,a} \in Z_+$	number of equipment with age a kept idle in period l
Equipment purchased as second-hand	
$buySH_{l,a} \in Z_+$	number of second-hand equipment just purchased in period l with age a
$nSH_{l,a} \in Z_+$	number of second-hand stock equipment with age a in period l
$rtrSH_{l,a} \in Z_+$	number of retired second-hand equipment with age a in period l
$uSH_{l,a,c} \in Z_+$	number of second-hand equipment with age a used at location c in period l
$idleSH_{l,a} \in Z_+$	number of second-hand equipment with age a kept idle in period l

Table 4.2 Objective Function

	$\textbf{Minimize NPV} = \sum_{l=0}^{Life} \{$
Operating Costs	$+\sum_{a=0}^{Age} (OC_{a,l} * uN_{l,a,c} + Adj^{Cost} * OC_{a,l} * uSH_{l,a,c})$
Idle Penalty for Average Productions of Locations	$+\sum_{a=0}^{Age} \sum_{c=0}^{Location} (\frac{P_{a,l,c}}{Location} * idleN_{l,a} * Z_l + \frac{P_{a,l,c}}{Location} * idleSH_{l,a} * Z_l)$
Capital Costs	$+\sum_{a=0}^{Age} (CC_{a,l} * buyN_l + SCC_{a,l} * buySH_{l,a})$
Salvage Revenue	$-\sum_{a=0}^{Age} (S_{a,l} * rtrN_{l,a} + SS_{a,l} * rtrSH_{l,a})$
Discount to Present Value	$\} * (1 + r)^{-l}$
Revenue from Sales of End-of-Project Assets	$-\{\sum_{a=0}^{Age} (S_{a,life} * (nN_{l,a} - rtrN_{l,a}) + SS_{a,life} * (nSH_{l,a} - rtrSH_{l,a})\} * (1 + r)^{-life}$

The operational and logical feasibility of the optimization problem is ensured through a set of constraints in Table 4.3, which are summarized and explained as follows:

- **Constraint C1:** The constraint enforces that, for each planning period l and operational location c, the total material transported by the available fleet meets the specified production requirement $T_{l,c}$. The contribution of each equipment unit to total production is calculated using the simulation-based capacity parameter $P_{a,l,c}$, which represents productivity variations with respect to equipment age, time period, and location. For second-hand units, the effective production capacity is reduced by the factor Adj^{Pro} to account for diminished operational efficiency. Therefore, the constraint maintains the operational feasibility of the fleet configuration and replacement decisions.

Table 4.3 Mathematical Model Constraints

C1	$\sum_{l=0}^{Life} \sum_{c=0}^{Location} (P_{a,l,c} * uN_{l,a,c} + Adj^{Pro} * P_{a,l,c} * uSH_{l,a,c}) \geq T_{l,c} \quad \text{for } \forall a \in \{1 \dots Age\}$
C2	$nN_{l=1,a=1} = buyN_{l=1}$ $nN_{l=1,a} = 0 \text{ for } \forall a \in \{2 \dots Age\}$
C3	$nN_{l,a} = \sum_{c=0}^{Location} (uN_{l,a,c}) + idleN_{l,a} + rtrN_{l,a} \quad \text{for } \forall\, l \in \{1 \dots Life\}, \text{and } a \in \{1 \dots Age\}$
C4	$nN_{l+1,a=1} = buyN_{l+1} + idleN_{l,a=1} \quad \text{for } \forall\, l \in \{1 \dots (Life-1)\}$ $nN_{l+1,a=1} = idleN_{l,a} + \sum_{c=0}^{Location} (uN_{l,a-1,c}) \quad \text{for } \forall\, l \in \{1 \dots (Life-1)\}, \text{and } a \in \{2 \dots Age\}$
C5	$nSH_{l=1,a} = 0 \quad \text{for } \forall a \in \{1 \dots Age\}$ $buySH_{l=1,a} = 0 \quad \text{for } \forall a \in \{1 \dots Age\_Sh\}$
C6	$nSH_{l,a} = \sum_{c=0}^{Location} (uSH_{l,a,c}) + idleSH_{l,a} * rtrSH_{l,a} \quad \text{for } \forall\, l \in \{1 \dots Life\}, \text{and } a \in \{1 \dots Age\}$
C7	$nSH_{l,a=1} = idleSH_{l-1,a=1} \quad \text{for } \forall\, l \in \{2 \dots Life\}$ $nSH_{l,a} = idleSH_{l-1,a} + \sum_{c=0}^{Location} (uSH_{l-1,a-1,c}) + buySH_{l,a} \text{ for } \forall\, l \in \{2 \dots Life\}, \text{and } a \in \{1 \dots Age\}$ $nSH_{l,a} = idleSH_{l-1,a} + \sum_{c=0}^{Location} (uSH_{l-1,a-1,c}) \quad \text{for } \forall\, l \in \{2 \dots Life\}, \text{and } a \in \{2 \dots Age\}$
C8	$rtrN_{l,a} \leq nN_{l,a} \quad \text{for } \forall\, l \in \{1 \dots Life\}, \text{and } a \in \{1 \dots Age\}$ $rtrSH_{l,a} \leq nSH_{l,a} \quad \text{for } \forall\, l \in \{1 \dots Life\}, \text{and } a \in \{1 \dots Age\}$ $rtrN_{l,a} = 0 \quad \text{for } \forall\, l \in \{1 \dots Life\}, \text{and } a \in \{1 \dots min\_usage\}$ $rtrSH_{l,a} = 0 \quad \text{for } \forall\, l \in \{1 \dots Life\}, \text{and } a \in \{1 \dots min\_usage\}$
C9	$rtrN_{l,a=Age} \geq \sum_{c=0}^{Location} (uN_{l,a=Age,c}) \quad \text{for } \forall\, l \in \{1 \dots Life\}$ $rtrSH_{l,a=Age} \geq \sum_{c=0}^{Location} (uSH_{l,a=Age,c}) \text{ for } \forall\, l \in \{1 \dots Life\}$

- **Constraint C2:** This constraint defines the initial fleet composition by restricting system entry in the first period to brand-new equipment only. All new units are initialized at age $a = 1$, while higher age classes are fixed to zero at $l = 1$. In this way, the model prevents introducing pre-aged equipment and establishes a consistent baseline for tracking equipment life cycles over the planning horizon.

- **Constraint C3:** This constraint maintains keeping brand-new purchased equipment across each period and age category. The total number of available units $nN_{l,a}$ is required to be entirely assigned to one of the mutually exclusive states, namely operation $uN_{l,a,c}$, idle status $idleN_{l,a}$, or retirement $rtrN_{l,a}$. By enforcing this balance, the model ensures that each unit occupies a single operational state and avoids any duplication in equipment accounting.

- **Constraint C4:** This constraint regulates the inter-period transition of brand-new equipment across age classes. Equipment units acquired in period $l + 1$ enter the system at age $a = 1$, while units already in the fleet progress to the next age category based on their utilization or idling status in period l. This dynamic formulation links decisions across consecutive periods and ensures a realistic and consistent representation of equipment aging over the planning horizon.

- **Constraint C5:** This constraint prevents the system from being initialized with second-hand equipment and restricts second-hand acquisitions in the first planning period. Second-hand units are allowed to enter the fleet only through purchase decisions in subsequent periods and at allowable age levels, thereby ensuring consistency with assumed market availability conditions and operational assumptions of the model.

- **Constraint C6:** This constraint extends the stock conservation logic defined in Constraint C3 to second-hand equipment. For each period and age category, the available second-hand inventory $nSH_{l,a}$ must be fully distributed among utilization, idling, or retirement decisions. By enforcing this allocation, the constraint ensures feasibility and internal consistency in the management of second-hand fleet units.

- **Constraint C7:** This constraint specifies the inter-period aging mechanism for second-hand equipment. Second-hand units enter the system at their corresponding initial ages upon purchase, while units already in operation advance to subsequent age classes according to their utilization or idling status in the preceding period. In this way, the constraint ensures consistent and coherent lifecycle tracking of challenger equipment throughout the planning horizon.

- **Constraint C8:** This constraint limits retirement decisions by ensuring that the number of units retired in any given period and age class does not exceed the available equipment stock. Furthermore, it prevents early retirement by prohibiting the disposal of units that have not yet reached the minimum required usage ag min_usage e, thereby reflecting practical, contractual, and economic constraints associated with equipment life cycles.

- **Constraint C9:** This constraint ensures that equipment units do not operate beyond the maximum allowable age age. If a unit is utilized at this maximum age in period l, it is required to be retired within the same period. By enforcing this condition, the model prevents infeasible aging in subsequent periods and ensures that end-of-life requirements are satisfied for all operating equipment units.

The integer programming formulation presented in this study establishes a comprehensive decision framework for determining optimal equipment acquisition, utilization, and retirement actions over a multi-year planning horizon. The model is designed to minimize the net present value of total fleet-related costs while ensuring that annual production requirements are met at each operational location, and it achieves this by explicitly embedding operational performance parameters within the optimization structure. Productivity and energy consumption estimates generated by a discrete-event simulation model are used as external inputs, allowing the formulation to reflect the influence of route characteristics, equipment aging, and operating conditions on both technical performance and economic outcomes.

Investment-related parameters form the first major input category and represent the capital expenditures associated with procuring brand-new and second-hand equipment units. These costs vary over time due to economic factors such as inflation, market conditions, and potential technological developments, and therefore play a decisive role in evaluating lifecycle costs in capital-intensive cyclic systems. The acquisition of new equipment is represented by the parameter $CC_{a,l}$, while second-hand purchases are modeled using $SCC_{a,l}$, enabling the model to compare alternative strategies across periods. In addition, age- and period-specific salvage values, denoted by $S_{a,l}$ and S $SS_{a,l}$, are incorporated to represent the residual value recovered upon equipment retirement. Together, these parameters govern the variation of equipment book values and strongly influence the identification of economically optimal replacement timing.

The second group of inputs consists of operating cost parameters, which arise from routine equipment usage and exhibit a strong dependence on operating age. Operating costs $OC_{a,l}$ increase as equipment accumulates service time, reflecting rising maintenance needs, higher failure likelihoods, and increased fuel or energy consumption. Because fuel usage typically constitutes the dominant share of operating expenditures in cyclic continuous haulage systems, the simulation model estimates fuel consumption at a detailed level by accounting for route geometry, segment-level speeds, grade resistance, and loading conditions. These simulation-derived fuel consumption values are subsequently converted into age-dependent operating cost parameters and introduced into the mixed-integer programming formulation, enabling a clear distinction between younger, more efficient units and older, less productive ones. For second-hand equipment, operating costs are adjusted using an additional cost multiplier $\mathrm{Adj}^{\mathrm{Cost}}$ to reflect increased maintenance burdens and fuel consumption. Furthermore, idle capacity penalties Z_l are incorporated to discourage economically inefficient fleet configurations by assigning an explicit cost to underutilized assets. Z_l starts to dominate the objective function if unit time-value of production is critical and fleet utilization drops due to unavailability drops of ageing equipment.

Production-related inputs constitute the third category of model parameters and are defined through annual production targets $T_{l,c}$ specified for each operational location, together with age- and location-dependent capacity parameters $P_{a,l,c}$ obtained from the simulation model. These capacity parameters implicitly capture the combined effects of equipment aging, haul road extensions, operational delays, and evolving cycle times over the planning horizon. By incorporating simulation-based productivity estimates, the formulation determines the number of equipment units required in each period to satisfy production commitments. In this respect, production requirements serve not only as binding constraints but also as a direct link between fleet operational performance and economic contribution, thereby enabling the evaluation of feasibility and cost-effectiveness for alternative fleet configurations.

The objective function is constructed to minimize the discounted sum of all capital and operating costs, penalties of under-utilized hauling capacity and net of salvage revenues, over the planning horizon. Annual operating costs are computed by aggregating the expenditures incurred by all actively utilized units, with new and second-hand equipment treated separately to reflect differences in performance and maintenance characteristics. Idle capacity is penalized through period-specific coefficients Z_l, which convert unused equipment into an economic loss and discourage excessive fleet sizing. Capital expenditures associated with equipment acquisitions are added in the corresponding periods, while salvage revenues from retired units are deducted from total costs. A final revenue is also estimated to account for the remaining book value of equipment that remains in the fleet at the end of the planning horizon. All cash flows are discounted using the factor $(1+r)^{-l}$, ensuring that decisions made in different periods are evaluated consistently on a present-value basis.

The periodic evaluation of the fleet is governed by a comprehensive set of stock balance constraints. Initial conditions ensure that all equipment entering the system in the first period is newly purchased and assigned to the youngest age class. Within each period, partitioning constraints allocate the available stock of each age group into mutually exclusive states, active use, idling, or retirement, thereby preventing double counting. Inter-period transition constraints define the aging process by allowing units to advance to subsequent age classes depending on their utilization or idling status in the previous period. A corresponding structure is applied to second-hand equipment, with additional restrictions ensuring that second-hand purchases are permitted only in later periods and only for eligible age categories in compliance with practice. Collectively, these constraints provide a consistent and realistic representation of equipment life cycles.

Retirement behavior is regulated through complementary constraints that govern both eligibility and timing. Equipment units are prohibited from early retirement before satisfying a predefined minimum usage requirement, except in the final period of the planning horizon. Upper-bound constraints further ensure that the number of retired units in any period does not exceed the available stock of the corresponding age class. In addition, units that reach the maximum allowable operating age and remain active in a given period are forced to retire within that same period, thereby preventing infeasible aging and enforcing end-of-life conditions consistent with industry practice.

The overall formulation establishes a clear trade-off between production feasibility, operational efficiency, and investment decisions. An aging or undersized fleet increases operating costs and tightens production constraints, whereas an oversized fleet leads to higher capital expenditures and recurring operating costs. By evaluating all decisions within a unified net present value framework, the model balances escalating age-related operating costs against the substantial upfront investments required for acquiring new or second-hand equipment. In this manner, it identifies cost-effective replacement and acquisition strategies for each planning period while ensuring that production requirements are satisfied.

Finally, the integration of simulation-based operational outputs with a rigorous mixed-integer programming formulation enables the model to capture equipment deterioration, time-dependent productivity changes, and evolving haulage network configurations in a realistic manner. This hybrid structure ensures that optimized replacement and allocation decisions are both economically sound and operationally feasible under realistic working conditions. The model is implemented in the AMPL environment and solved using the CPLEX solver, allowing efficient computation of optimal solutions for large-scale, capital-intensive fleet systems.

4.4 Summary

This chapter presented the development of a comprehensive mathematical framework for optimizing equipment replacement decisions in cyclic continuous operations, with a specific focus on truck-based haulage systems in open-pit mining. The proposed approach integrates operational, production-related, and financial considerations within a unified mixed-integer programming formulation. By coupling simulation-based estimates of productivity, cycle time, and energy consumption with long-term investment and replacement decisions, the framework captures the interaction between short-term operational behavior and long-term economic performance in a consistent and analytically rigorous manner. This integration allows the model to represent equipment deterioration, haulage route evolution, and changing capacity requirements more realistically than traditional static or scenario-based replacement approaches.

The formulation explicitly incorporates key elements of equipment life-cycle management, including capital acquisition costs, age-dependent operating expenses, penalties associated with idle capacity, and salvage values, all of which are evaluated using a net present value criterion. Location-specific production constraints ensure that output requirements are satisfied in every planning period, while stock balance and aging constraints provide a coherent representation of fleet evolution over time. Additional restrictions on equipment usage and retirement enforce realistic life-cycle policies by preventing infeasible early disposal decisions and eliminating the possibility of operating equipment beyond its allowable age. Through these mechanisms, the model establishes a structured trade-off between increasing operating costs associated with aging equipment and the substantial capital expenditures required for fleet renewal.

From an implementation standpoint, the AMPL modeling environment provides a transparent and modular structure in which the objective function, constraints, and decision variables are clearly defined and separated. This structure improves readability, facilitates verification and debugging, and allows efficient adaptation to alternative scenarios, planning horizons, or asset categories. The separation of model, data, and execution files supports systematic data handling and straightforward sensitivity analyses. The mixed-integer programming model is solved using the CPLEX solver, ensuring computational efficiency and robustness for large-scale, multi-period fleet planning problems. The AMPL-based implementation of the model is discussed in more detail in Section 5.

To sum up, the mathematical model developed in this chapter establishes a robust analytical foundation for evaluating equipment replacement strategies under realistic operational and economic conditions. Although the framework is sufficiently general to be applied to a wide range of cyclic continuous systems, its structure and parameterization are particularly well suited to open-pit mining environments characterized by long planning horizons, high capital intensity, and evolving production requirements. The subsequent chapters build upon this formulation by applying the model to a real-world case study, presenting numerical results, and discussing managerial insights derived from the optimized replacement and investment decisions.

CHAPTER 5

APPLICATION OF THE DEVELOPED FRAMEWORK FOR AN OPEN-PIT MINING OPERATION

This chapter highlights the critical importance of optimal equipment replacement planning decisions for mining industry by applying the developed simulation-integrated integer programming model to real-world data from an open-pit mining operation.

5.1 Introduction

Although the hybrid optimization framework developed in this study is applicable to a wide range of cyclic continuous systems, open-pit mining operations constitute an especially appropriate application environment due to their long-term uninterrupted production, spatially complex operating structures, and heavy reliance on capital-intensive mobile equipment fleets.

In surface mining operations, haulage equipment, especially haul trucks, represents one of the largest components of total capital investment. These assets are typically deployed continuously over long service lives, often extending over multiple decades. As trucks accumulate operating hours, their technical condition gradually deteriorates, leading to higher maintenance demands, increasing operating costs, and declining mechanical availability. At the same time, the progressive expansion of an open-pit mine results in longer haulage distances, evolving road networks, and changes in route geometry. These physical changes directly influence haulage cycle times, thereby reducing the material transport capacity of individual trucks over time.

Additional operational complexity stems from the location-specific nature of mining activities. Production is typically distributed among multiple loading areas and dumping destinations, each associated with distinct production targets, material properties, and operational constraints. Moreover, haulage fleets are rarely homogeneous in practice, as phased procurement strategies, partial fleet renewals, and equipment replacements lead to the simultaneous operation of trucks with different ages, capacities, and performance levels. As a result, dispatching decisions, fleet sizing, and replacement timing are closely interrelated and evolve dynamically over the life of the mine.

Under such conditions, simulation-based modeling offers significant advantages for representing long-term haulage operations. By explicitly tracking truck movements, route developments, queuing effects, and age-dependent performance variations, the simulation component captures operational dynamics that cannot be adequately addressed using static assumptions or simplified analytical models. Integrating these detailed operational outputs into the mathematical optimization framework enables a realistic assessment of fleet productivity, cost evolution, and replacement strategies under changing mining conditions.

Accordingly, this chapter applies the proposed simulation-integrated optimization framework to an open-pit mining operation. Dispatch processes are simulated over the planning horizon, and the resulting operational performance measures are incorporated into the optimization model to support investment and replacement decision-making. The results obtained from the integrated application are then examined to assess the validity, robustness, and practical applicability of the proposed framework within a real mining context. The remainder of the chapter is organized as follows: Section 5.2 presents the inputs and resulting outputs of the simulation model, Section 5.3 describes the inputs and outputs of the mathematical optimization model through the integration of the simulation and optimization components, and Section 5.4 discusses and interprets the results obtained from the integrated analysis, including a sensitivity analysis.

5.2 Implementation of the Simulation Model

Inputs

The developed discrete-event simulation algorithm is implemented using Rockwell Arena software. The planning horizon of the mine is defined as 15 years, and end-of-year haul road configurations are adopted in order to obtain conservative productivity estimates. Over the project life, a total of 195 alternative haulage routes, 13 routes per year, are defined to connect excavators, processing facilities, waste dumps, and parking stations. To ensure consistency and comparability across different periods and locations, a single truck model (MAN TGS 41.430 8×4 BB, 2025), $\mathrm{k} = 1$, is employed throughout the analysis. Trucks are scheduled to operate for 22.5 hours per day in three shifts over 300 operating days per year, while operations are suspended for two months annually due to unfavorable weather conditions.

The simulation input parameters are tabulated in Table 5.1. These parameters were defined based on site-specific operating practices. It should be noted that route-specific parameters, including segment gradients $\mathrm{G}_{\mathrm{r,s}}$, segment lengths $\mathrm{L}_{\mathrm{r,s}}$, and intersection priority $\mathrm{i}_{\mathrm{r,s}}$, are given only for period $l = 1$ as a representative example since a total of 195 distinct routes exist over the life of the mine.

The set of 195 haulage routes was systematically generated based on the spatial layout and phased development plan of the open-pit mine. For each planning year, alternative routes connecting loading points, dumping locations, processing facilities, and parking areas were identified according to the evolving pit geometry and haul road network. The resulting route set represents all operationally feasible and practically utilized haulage paths over the life of the mine, rather than hypothetical or artificially generated alternatives. By updating haul road configurations annually, the model captures the progressive expansion of the pit and its direct impact on haul distances, travel times, and fleet productivity.

To represent age-related deterioration, availability values $Av_{k,a}$ were assigned to trucks for a set of age $a \in \{1 \dots 8\}$ since trucks are stated to be retired upon reaching a maximum operating age of eight years. These values are site-specific and reflect the company's past operational experience regarding how truck availability declines across different age categories when full-period utilization is enforced, capturing the combined effects of increasing maintenance requirements, scheduled downtime, and reduced operational reliability. As observed from the $Av_{k,a}$ set, an eight-year-old truck can operate for only approximately two-thirds of the scheduled shift hours in average due to extensive maintenance requirements.

The trucks operating at the mine site are equipped with a fuel tank capacity FTC_k of 400 L, and refueling is initiated whenever the fuel level falls below the critical threshold $FL^{critical} = 40lt$. According to site operating rules, refueling of loaded trucks is not permitted; therefore, trucks are required to unload their payloads before traveling to the refueling station, in compliance with the general practice in mines.

MAN-type trucks have an empty vehicle weight EVW_k of 18.5 tons and are scheduled to operate for 22.5 hours per day across three shifts, denoted as T^{daily}. Based on historical operational records, these trucks typically carry an average payload of 40 tons, with observed variations ranging from 35 to 45 tons. Accordingly, payload assignment in the simulation model is represented using a triangular probability distribution, $P_k = \text{tri.dist}\,(35, 40, 45)$, where the minimum, most likely, and maximum payload values correspond to 35, 40, and 45 tons, respectively.

The traveling component of the haulage cycle time is determined within the simulation by simultaneously evaluating kinematic behavior, motion decisions for each road segment with respect to length $L_{r,s}$ and gradient $G_{r,s}$, and traveling priority between successive segments $(i_{r,s})$. In addition to travel time decisions, loading, dumping, and refueling durations are treated as stochastic variables and are generated using site-specific probability density functions, $Time_k^{Load}$, $Time_k^{Dump}$, $Time_k^{Fuel}$.

Table 5.1 Simulation Model Inputs

Input Parameters/PDFs	Description
$Av_{k,a}$	$\{0.95, 0.91, 0.85, 0.79, 0.75, 0.73, 0.70, 0.66\}$ for $k = 1$, and $a \in \{1 \dots 8\}$
EVW_k	18.5ton
FTC_k	400lt
$FL^{critical}$	40lt
$G_{r,s}$ $(l = 1)$	$G_{1,s} = \{0, 10, -2.5, 8, 0\}$ $s \in \{1 \dots 5\}$
	$G_{2,s} = \{0, 0\}$ $s \in \{1, 2\}$
	$G_{3,s} = \{2, 0, -2.43, 2.06\}$ $s \in \{1 \dots 4\}$
	$G_{4,s} = \{0, -8, 2.50, -10, 0\}$ $s \in \{1 \dots 5\}$
	$G_{5,s} = \{2.43, 0, -1.10, -10, 0\}$ $s \in \{1 \dots 5\}$
	$G_{6,s} = \{2.43, 0, 0\}$ $s \in \{1 \dots 3\}$
	$G_{7,s} = \{2, 0, -1.50, -10, 0\}$ $s \in \{1 \dots 5\}$
	$G_{8,s} = \{0, 10, -2.5, 2.3, 0\}$ $s \in \{1 \dots 5\}$
	$G_{9,s} = \{0, -2.3, 2.5, -10, 0\}$ $s \in \{1 \dots 5\}$
	$G_{10,s} = \{2.43, 0, -1.10, -10, 0\}$ $s \in \{1 \dots 5\}$
	$G_{11,s} = \{2, 0, -1.50, -10, 0\}$ $s \in \{1 \dots 5\}$
	$G_{12,s} = \{0, 0\}$ $s \in \{1, 2\}$
	$G_{13,s} = \{2, 0, -2.43, 2.06\}$ $s \in \{1 \dots 4\}$
$i_{r,s}(l = 1)$	$i_{1,s} = \{1, 1, 1, 0, 2\}$ $s \in \{1 \dots 5\}$
	$i_{2,s} = \{0, 2\}$ $s \in \{1, 2\}$
	$i_{3,s} = \{0, 0, 1, 2\}$ $s \in \{1 \dots 4\}$
	$i_{4,s} = \{1, 1, 1, 1, 2\}$ $s \in \{1 \dots 5\}$
	$i_{5,s} = \{0, 1, 1, 1, 2\}$ $s \in \{1 \dots 5\}$
	$i_{6,s} = \{0, 1, 2\}$ $s \in \{1 \dots 3\}$
	$i_{7,s} = \{0, 0, 1, 1, 2\}$ $s \in \{1 \dots 5\}$
	$i_{8,s} = \{1, 1, 1, 0, 2\}$ $s \in \{1 \dots 5\}$
	$i_{9,s} = \{1, 1, 1, 1, 2\}$ $s \in \{1 \dots 5\}$
	$i_{10,s} = \{0, 0, 1, 1, 2\}$ $s \in \{1 \dots 5\}$
	$i_{11,s} = \{0, 0, 1, 1, 2\}$ $s \in \{1 \dots 5\}$
	$i_{12,s} = \{1, 2\}$ $s \in \{1, 2\}$
	$i_{13,s} = \{0, 0, 1, 2\}$ $s \in \{1 \dots 4\}$
$L_{r,s}(l = 1)$	$L_{1,s} = \{550, 470, 100, 170, 70\}$ $s \in \{1 \dots 5\}$
	$L_{2,s} = \{100, 75\}$ $s \in \{1, 2\}$
	$L_{3,s} = \{50, 75, 100, 25\}$ $s \in \{1 \dots 4\}$
	$L_{4,s} = \{70, 170, 100, 470, 550\}$ $s \in \{1 \dots 5\}$
	$L_{5,s} = \{150, 100, 130, 470, 550\}$ $s \in \{1 \dots 5\}$
	$L_{6,s} = \{125, 100, 50\}$ $s \in \{1 \dots 3\}$
	$L_{7,s} = \{100, 125, 50, 470, 550\}$ $s \in \{1 \dots 5\}$
	$L_{8,s} = \{550, 470, 100, 150, 100\}$ $s \in \{1 \dots 5\}$
	$L_{9,s} = \{100, 150. 100. 470. 550\}$ $s \in \{1 \dots 5\}$
	$L_{10,s} = \{150, 100. 130. 470. 550\}$ $s \in \{1 \dots 5\}$
	$L_{11,s} = \{100, 125. 50. 470. 550\}$ $s \in \{1 \dots 5\}$
	$L_{12,s} = \{100, 75\}$ $s \in \{1, 2\}$
	$L_{13,s} = \{50, 75, 100, 25\}$ $s \in \{1 \dots 4\}$
P_k	Triangular.dist (35,40,45)
$Time_k^{Load}$	Triangular.dist (3.00,3.50,4.00)
$Time_k^{Dump}$	Triangular.dist (1.25,1.75,2.25)
$Time_k^{Fuel}$	Triangular.dist (2.5,3,3.5)
T^{daily}	22.5h (3 shifts)
W^{Month}	$\{0.36, 0.23, 0.25, 0.42, 0.45, 0.30, 0.10, 0.10, 0.14, 0.27, 0.28, 0.30\}$ $m \in \{1 \dots 12\}$

Route	1	2	3	4	5	6	7	8	9	10	11	12	13
From	Exc L1*	Dump Site	Dump Site	Dump Site	Fuel Station	Parking Station	Fuel Station	Parking Station	Fuel Station	Crusher	Crusher	Crusher	Exc L2
To	Dump Site	Exc L1	Fuel Station	Parking Station	Exc L1	Exc L1	Parking Station	Exc L2**	Exc L2	Parking Station	Fuel Station	Exc L2	Crusher

**Excavator in Location-1, operated for waste production only*
***Excavator in Location-2, operated for ore production only*

These distributions are subjectively determined by authorized operational personnel based on minimum, most likely, and maximum expected process times expressed in minutes, and are represented using triangular distributions defined as $\mathrm{tri.dist}\,(3.00, 3.50, 4.00)$, $\mathrm{tri.dist}\,(1.25, 1.75, 2.25)$, and $\mathrm{tri.dist}\,(2.5, 3.0, 3.5)$, respectively. Finally, travel time is strongly influenced by precipitation conditions, as changes in road–tire interaction decrease rolling resistance and lead to additional energy losses and fuel consumption. In the simulation model, precipitation conditions are represented using a monthly binary probability specific to the mining area $\mathrm{W_m^{Day}}$.

Outputs

As outlined previously, the simulation framework generates two main categories of outputs. The first output corresponds to the transported material capacity of an individual truck, expressed as a function of equipment age a, planning period l, and operational location c, denoted as ${\mathrm{Mat}_{\mathrm{T_k}}}^{\mathrm{l,a,c}}$. The second output consists of period-specific operating cost estimates for each truck. Rather than being calculated directly, operating expenditures are inferred from the simulated total fuel consumption values $\mathrm{TFC}^{\mathrm{l,a,c}}$, since fuel expenses constitute a dominant component of overall operating costs and are widely used in industry practice as a proxy for total operating expenditure.

The simulated production outputs for both waste and ore haulage activities are presented in Figures 5.1 and 5.2. The results demonstrate that trucks of identical age can exhibit different transport capacities depending on the material handled, primarily due to variations in haul road geometry, route length, and operating conditions. For instance, during the fifth year of operation, a one-year-old truck assigned to ore haulage is capable of transporting approximately 0.689 million tons, whereas a seven-year-old truck operating under the same conditions achieves only about 0.521 million tons. More broadly, the results reveal a consistent downward trend in hauling capacity over time, driven jointly by equipment aging effects and the progressive extension of haulage routes as the mine expands.

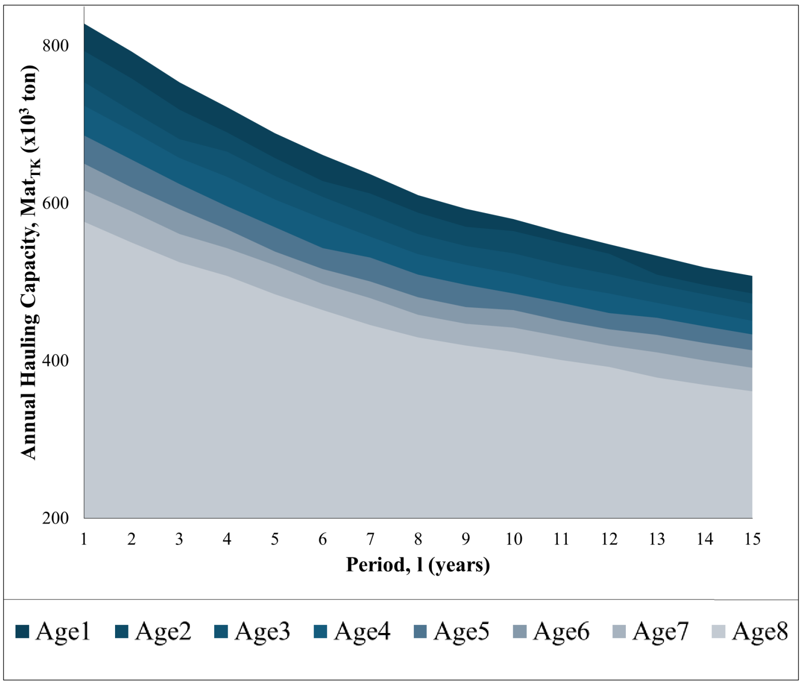


Figure 5.1 Annual Ore Hauling Capacity of Each Truck for Different Production Periods and Equipment Ages($Mat_{T_k}{}^{l,a,c}$)

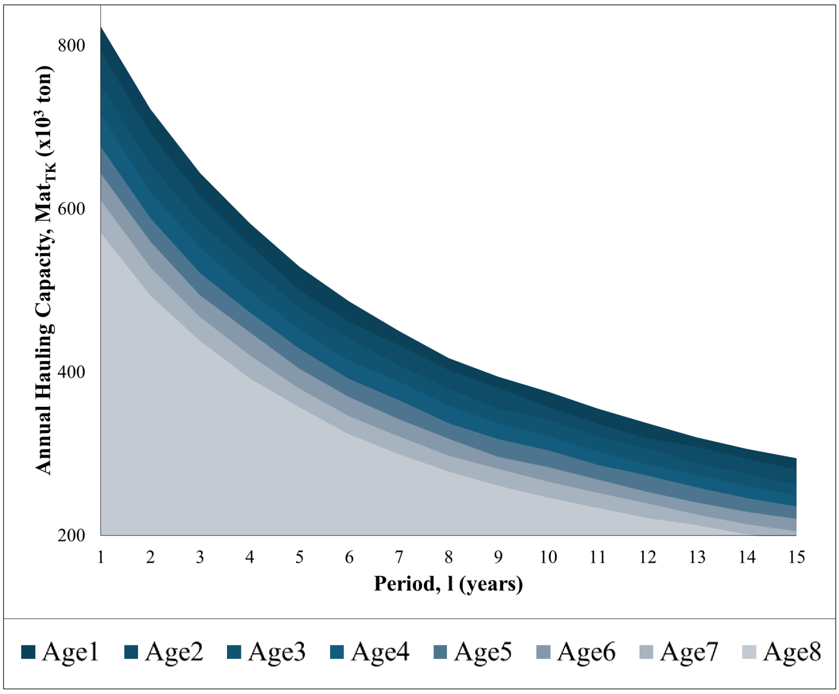


Figure 5.2 Annual Waste Hauling Capacity of Each Truck for Different Production Periods and Equipment Ages($Mat_{T_k}{}^{l,a,c}$)

In truck-based dispatching operations, fuel expenses generally constitute a significant portion of total operating costs, typically ranging between 25% and 40%, depending on factors such as mine geometry, haul distances, and prevailing operating conditions. For the mining operation examined in this case study, fuel consumption represents approximately 30% of total operating expenditures, while the remaining cost components are attributed to maintenance personnel and operators (35%), spare parts (6%), maintenance activities (3%), and ownership-related expenses (26%). Given this cost structure, fuel consumption outputs generated by the simulation model provide a robust and practical basis for estimating age- and period-dependent operating costs of trucks within the optimization framework. The simulation-assisted estimates of annual fuel costs for trucks across different operating ages **a** and planning periods l are illustrated in Figure 5.3.

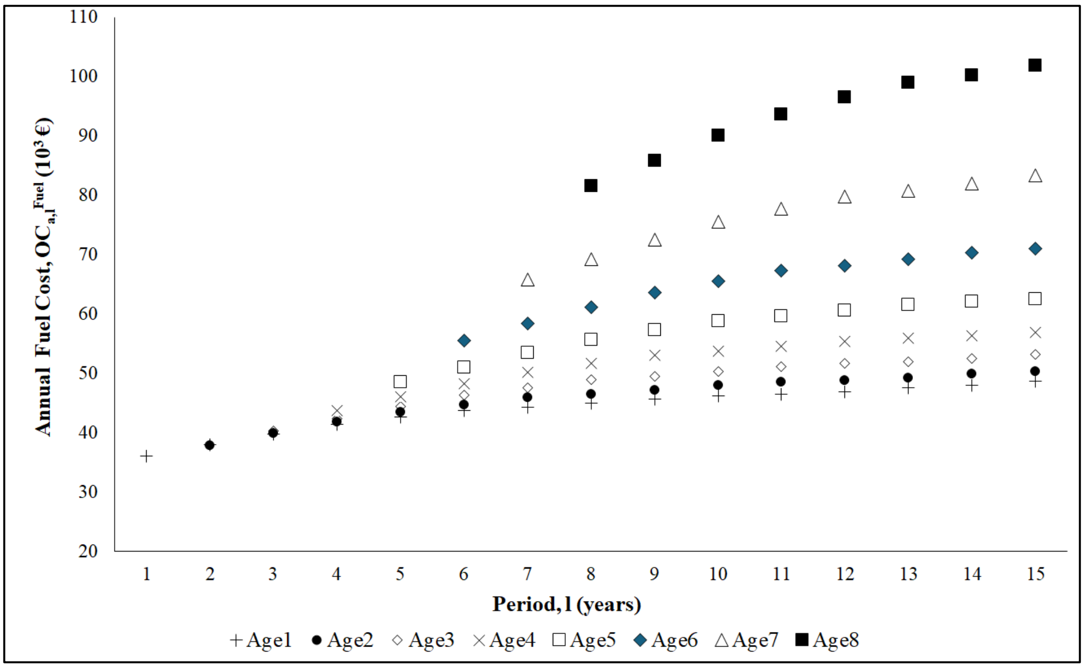


Figure 5.3 Total Fuel Cost of Single Truck with Age a in Period l ($OC_{a,l}^{Fuel}$)

In the developed simulation model, operational performance indicators emerge naturally from system interactions such as queuing at loading and dumping points, refueling operations, route characteristics, and shift-based operational interruptions. The resulting outputs, including cycle times, production levels, fuel consumption, and idling durations, are consistent with industry-reported haulage operations, where waiting times at excavators, crushers, and fuel stations constitute a non-negligible portion of total truck operating time. Rather than being imposed exogenously, these performance measures arise endogenously from resource constraints and dispatch logic, indicating that the simulation framework produces realistic and well-behaved operational outcomes representative of practical mining operations.

5.3 Implementation of the Mathematical Model

The proposed integer programming model was implemented using AMPL (A Mathematical Programming Language), which is a widely used high-level modeling environment for the formulation and solution of mathematical optimization problems. AMPL offers a clear and modular structure in which decision variables, parameters, constraints, and the objective function are defined explicitly, thereby enhancing model transparency, readability, and flexibility. Given the linear and mixed-integer structure of the formulation, the IBM ILOG CPLEX solver was employed to efficiently compute optimal solutions.

The implementation of the model requires a minimum of two core files. The model file (.mod) contains the complete mathematical formulation, including all decision variables, constraints, and the objective function. The run file (.run) is used to control the solution process by specifying solver settings and execution commands. In addition, a separate data file (.dat) was created to store all numerical input parameters, such as cost coefficients, production requirements, and productivity values obtained from the simulation model. This clear separation between model structure and input data improves usability and enables straightforward adaptation of the framework to alternative scenarios or case studies without modifying the underlying mathematical formulation. For the implemented mine case study, the corresponding .dat, .mod, and .run files are provided and examined in detail in Appendices A, B, and C, respectively.

Inputs

A planning horizon of 15 years was considered for the implementation, with two distinct operational locations representing separate production areas for ore and waste haulage. The company aims to maintain a constant stripping ratio of 7 tons of waste to 2 tons of ore; therefore, annual production targets were defined as 2 million tonnes for Location 1 and 7 million tonnes for Location 2. Based on operational experience and common industry practice, the maximum allowable operating age of any truck (Age) was set to eight years and incorporated into the model as an upper age constraint. In addition, a minimum service life requirement (min_usage) of three years was imposed before trucks became eligible for retirement. When second-hand trucks are included in the fleet, the company is allowed to purchase units with operating ages less than six years at the time of acquisition. Annual hauling capacities, operating costs, and salvage values were specified as age- and period-dependent matrices and were defined separately for brand-new and second-hand equipment to capture differences in performance and cost behavior.

- ***Capital Cost Inputs***: The capital cost of brand-new haul trucks was set at €165,000, based on information obtained from the company, and represents the purchase price of a brand-new truck at period $l = 1$. Consistent with sectoral expectations, this cost was assumed to increase annually by 3.6% in €. Accordingly, year-specific capital cost values were calculated over the entire 15-year planning horizon, enabling the model to realistically capture the timing effects of capital expenditures. Capital costs for second-hand trucks were similarly derived from industry-based information and were calculated using the book value of the equipment. As an illustrative example, the acquisition cost of a three-year-old truck purchased in year 5 was obtained by applying three years of depreciation to the initial purchase price of a brand-new truck. A useful economic life of five years was assumed for the purpose of depreciation calculations. From an operational standpoint, trucks exceeding six years of age were considered unsuitable for second-hand acquisition due to increased operating cost and declining availability. Accordingly, as discussed earlier, the model limits second-hand purchases to trucks with ages of six years or less, and the acquisition of seven- or eight-year-old units is not allowed. The resulting capital cost parameters for both brand-new and second-hand equipment are presented in Table 5.2.

- ***Salvage Value Inputs***: Salvage values are specified as parameters that vary with both equipment age and planning period. For brand-new equipment, the salvage value $S_{a,l}$ is calculated as the remaining book value by deducting the accumulated depreciation from the acquisition cost over the interval between the purchase period and the sale period. For second-hand equipment, the salvage value $SS_{a,l}$ is derived from the market value of an equivalent-age unit in the sale period and is further reduced by one additional year of depreciation to account for continued operation prior to disposal. The variation in salvage values for brand-new and second-hand trucks as a function of equipment age a at the salvage period **l** is presented in Table 5.3.

- ***Operating Cost Inputs*****:** As mentioned in Section 5.2, the simulation model produces estimates of total annual fuel consumption $TFC^{l,a,c}$, which vary according to haul distances, cycle times, and idling behavior, and constitute one of the largest shares of operating costs at the mine, representing approximately 30% of total operating expenditures. Age-related performance degradation is reflected through operating cost escalation factors applied across equipment age classes. Based on site-specific operational data, overall operating costs are assumed to increase by $\{0, 5, 6.5, 8.5, 11.0, 14.3, 18.6, 24.1\}$ % for equipment ages $a \in \{1 \ldots 8\}$. The total expected annual operating cost values for brand-new trucks, expressed as functions of equipment age a and planning period l, are presented in Table 5.4. For second-hand trucks, operating cost parameters $OC_{a,l}$ are assumed to be 5% higher than those of equivalent brand-new trucks, represented by the cost adjustment factor $Adj^{Cost} = 1.05$.

Table 5.2 Capital Costs of Brand-New $\left(CC_{a,l}\right)$ and Second-Hand Trucks $\left(SCC_{a,l}\right)$ in 10^6 €

		Project Period in Year, l														
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Brand New Age, a	**1**	0.165	0.171	0.177	0.183	0.190	0.197	0.204	0.211	0.219	0.227	0.235	0.243	0.252	0.261	0.271
Second-Hand Age, a	**2**	0	0.087	0.090	0.093	0.096	0.100	0.104	0.107	0.111	0.115	0.119	0.124	0.128	0.133	0.137
	3	0	0.057	0.063	0.065	0.067	0.070	0.072	0.075	0.078	0.081	0.083	0.086	0.090	0.093	0.096
	4	0	0.038	0.041	0.046	0.047	0.049	0.051	0.053	0.054	0.056	0.058	0.060	0.063	0.065	0.067
	5	0	0.025	0.027	0.030	0.033	0.034	0.035	0.037	0.038	0.039	0.041	0.042	0.044	0.045	0.047
	6	0	0.023	0.025	0.027	0.030	0.033	0.034	0.035	0.037	0.038	0.039	0.041	0.042	0.044	0.045

Table 5.3 Salvage Values of Brand-New $(S_{a,l})$ and Second-Hand Trucks $(SS_{a,l})$ in 10^6 €

		Project Period in Year, l														
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Brand New Age, a	**1**	0.12	0.124	0.128	0.133	0.138	0.143	0.148	0.153	0.159	0.164	0.17	0.177	0.183	0.189	0.196
	2	0	0.087	0.09	0.093	0.096	0.1	0.104	0.107	0.111	0.115	0.119	0.124	0.128	0.133	0.137
	3	0	0	0.063	0.065	0.067	0.07	0.072	0.075	0.078	0.081	0.083	0.086	0.09	0.093	0.096
	4	0	0	0	0.046	0.047	0.049	0.051	0.053	0.054	0.056	0.058	0.06	0.063	0.065	0.067
	5	0	0	0	0	0.033	0.034	0.035	0.037	0.038	0.039	0.041	0.042	0.044	0.045	0.047
	6	0	0	0	0	0	0.033	0.034	0.035	0.037	0.038	0.039	0.041	0.042	0.044	0.045
	7	0	0	0	0	0	0	0.033	0.034	0.035	0.037	0.038	0.039	0.041	0.042	0.044
	8	0	0	0	0	0	0	0	0.033	0.034	0.035	0.037	0.038	0.039	0.041	0.042
Second-Hand Age, a	**2**	0	0.063	0.065	0.067	0.07	0.072	0.075	0.078	0.081	0.083	0.086	0.09	0.093	0.096	0.100
	3	0	0.03	0.033	0.034	0.035	0.037	0.038	0.039	0.041	0.042	0.044	0.045	0.047	0.049	0.051
	4	0	0.014	0.016	0.017	0.018	0.019	0.019	0.02	0.021	0.021	0.022	0.023	0.024	0.025	0.026
	5	0	0.007	0.008	0.008	0.009	0.009	0.01	0.01	0.011	0.011	0.011	0.012	0.012	0.013	0.013
	6	0	0.005	0.005	0.005	0.006	0.007	0.007	0.007	0.007	0.008	0.008	0.008	0.008	0.009	0.009

Table 5.4 Annual Operational Costs of the Brand-New Trucks ($OC_{a,l}$) in 10^6 €

		Project Period in Year, l														
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Age, a	**1**	0.498	0.524	0.549	0.571	0.588	0.604	0.611	0.621	0.631	0.638	0.641	0.648	0.656	0.662	0.671
	2	0	0.523	0.550	0.577	0.600	0.617	0.634	0.642	0.652	0.662	0.669	0.673	0.680	0.689	0.695
	3	0	0	0.557	0.586	0.614	0.639	0.658	0.675	0.683	0.694	0.705	0.713	0.717	0.725	0.734
	4	0	0	0	0.604	0.635	0.666	0.693	0.713	0.732	0.741	0.753	0.765	0.773	0.778	0.786
	5	0	0	0	0	0.670	0.705	0.739	0.769	0.792	0.813	0.823	0.836	0.849	0.858	0.863
	6	0	0	0	0	0	0.766	0.806	0.845	0.879	0.905	0.929	0.940	0.955	0.970	0.981
	7	0	0	0	0	0	0	0.908	0.955	1.001	1.042	1.073	1.101	1.115	1.132	1.150
	8	0	0	0	0	0	0	0	1.127	1.186	1.243	1.293	1.331	1.367	1.384	1.406

The operating cost values presented in Table 5.4 reflect the combined effects of equipment aging and period-dependent operational conditions. As equipment age increases, operating costs rise due to reduced availability, higher maintenance requirements, and declining operational efficiency, which are captured through age-specific cost escalation factors. In addition, for a given equipment age, operating costs may vary across planning periods as haul distances, route geometries, and cycle times evolve with mine expansion, directly influencing fuel consumption and total operating expenditures. It should be noted that zero values appearing in the operating cost table do not indicate zero operating cost; rather, they correspond to age–period combinations in which no equipment is operated or assigned within the simulation framework. Therefore, operating cost values are reported only for feasible and actively utilized equipment configurations generated by the integrated simulation–optimization process.

- ***Penalty Cost Inputs***: Production interruptions resulting from reductions in equipment availability or temporary suspension of equipment operations is penalized in the model in order to represent the economic consequences of underutilized assets. This idling penalty is quantified by the mine as foregone revenue and is expressed in €/m³ per 100 m of haul distance. For each year within the planning horizon, the haul distance between the pit and the processing facility is evaluated together with projected variations in exchange rates, diesel prices, and labor costs to estimate a corresponding unit cost per ton. This cost is incorporated into the objective function as an idle-capacity penalty that is proportional to the unrealized hauling potential of the fleet. The inclusion of this penalty term discourages inefficient idling behavior and promotes effective fleet utilization within the optimization framework. Table 5.5 presents representative average haul distances for different years, illustrating how increasing haulage distances influence the unit revenue per ton of production.

Table 5.5 Idle Penalty Cost Calculation (Z_l)

	Project Period in Year, l							
	1	**2**	**3**	**4**	**5**	**6**	**7**	
Ave. Haul Length (m)	1,020	1,120	1,230	1,290	1,400	1,510	1,570	
Unit Revenue (€/m^3)	0.06	0.08	0.09	0.11	0.13	0.16	0.19	
Unit Penalty (k€/ton)	0.027	0.035	0.046	0.059	0.076	0.099	0.123	
	8	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Ave. Haul Length (m)	1,680	1,740	1,750	1,810	1,870	1,930	1,990	2,050
Unit Revenue (€/m^3)	0.23	0.28	0.33	0.40	0.48	0.57	0.69	0.83
Unit Penalty (k€/ton)	0.158	0.196	0.237	0.294	0.365	0.452	0.559	0.691

Outputs

The integer optimization model yields a cost-minimizing equipment investment and replacement strategy for the open-pit mining operation over the 15-year planning horizon. The optimal solution corresponds to a minimum Net Present Value (NPV) of €27.96 million, which represents the discounted total system cost accumulated over the entire horizon under a discount rate of 10%. This NPV aggregates all relevant economic components, including operating expenditures, capital investments, depreciation effects, salvage revenues, idle capacity penalties, and replacement actions involving brand-new, second-hand, and retired equipment.

From a computational perspective, the solution was obtained efficiently despite the multi-period and combinatorial nature of the problem. Convergence was achieved after approximately 1,000 simplex iterations and 33 branch-and-bound nodes, indicating a tractable solution process for a large-scale, real-world fleet planning problem. The quality of the solution was assessed using standard mixed-integer programming optimality metrics, with an absolute MIP gap of 0.0747 and a relative MIP gap of 0.97%, confirming that the obtained solution lies very close to the theoretical optimum and can be considered reliable for decision-making purposes.

All computational experiments were performed on a standard personal laptop (MacBook) equipped with 8 GB of RAM. The optimization model was solved in around 45 seconds, indicating that the proposed framework can be executed efficiently without requiring specialized high-performance computing resources.

The optimized investment and utilization strategy fully satisfies the annual production requirements specified for both operational locations throughout the planning horizon. The resulting fleet size evolution and period-specific decisions are summarized in Figure 5.4. The optimal solution begins with an initial deployment of twelve brand-new trucks, which remain in continuous operation during the early years of the project. As equipment ages and haulage conditions evolve, the model gradually introduces retirement decisions starting in the mid-horizon, while simultaneously supplementing capacity through selective acquisitions of brand-new and second-hand trucks.

Over the full 15-year horizon, the optimized strategy involves the acquisition of 83 brand-new trucks and 3 second-hand trucks, alongside the retirement of 55 equipment units. Second-hand equipment plays a limited but strategically important role, primarily during periods where production requirements increase while capital expenditure is constrained. Throughout the mid-horizon years, the active fleet size fluctuates within a narrow range, typically between twenty-five and twenty-eight trucks, reflecting the model’s emphasis on avoiding excessive over-investment.

In the thirteenth year of the planning horizon, the model implements a strategic transition by temporarily idling a portion of the existing fleet while simultaneously introducing new trucks. This coordinated decision reflects a forward-looking strategy aimed at securing sufficient haulage capacity for the final two years of operation, while avoiding unnecessary capital expenditures associated with overinvestment in equipment with limited remaining economic life. Assets retired during the project life and equipment remaining at the end of the project generate revenue through second-hand sales and salvage recovery.

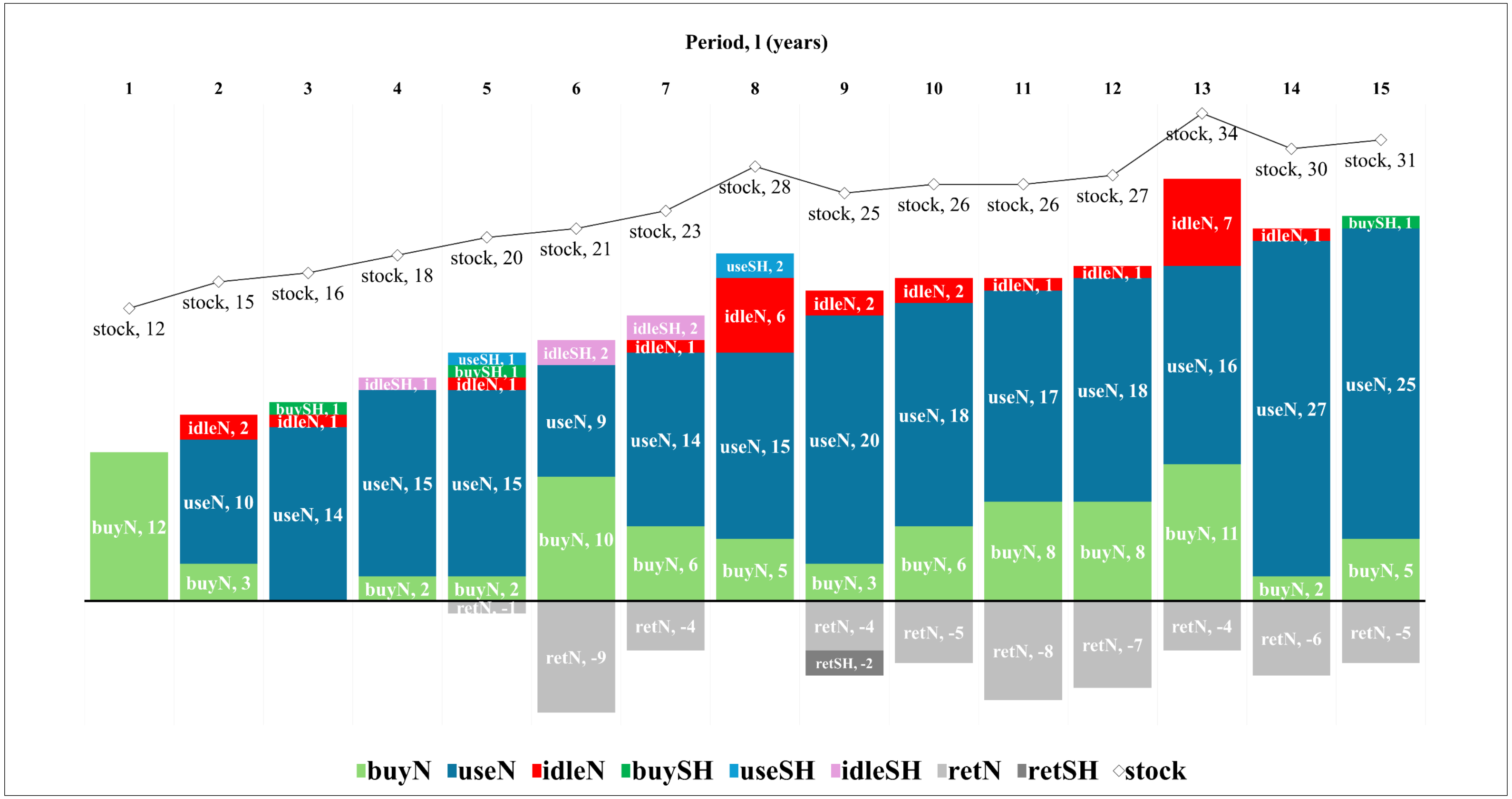


Figure 5.4 Optimized Acquisition, Utilization, and Retirement Decisions for Haul Trucks across Planning Periods over the Mine Life

The observed patterns of acquisition, utilization, and retirement are driven by the interaction of several key mechanisms embedded in the model. Increasing operating costs and declining productivity associated with equipment aging progressively reduce the economic attractiveness of older trucks, triggering retirement decisions at specific periods. At the same time, binding production constraints across multiple locations limit the flexibility of fleet utilization and require timely capacity adjustments through new or second-hand acquisitions. The optimization process balances these opposing forces by trading off higher operating costs of aging units against the substantial capital expenditures associated with fleet renewal, thereby determining replacement timing endogenously rather than through predefined rules.

5.4 Sensitivity Analysis

A sensitivity analyze was conducted to examine how the model responds to changes in key parameters, such as discount rate, operating cost, and production targets. Variations in the discount rate primarily influence the net present worth of decisions (Figure 5.5). While changes in discounting change the value of the objective function, the general structure of the replacement strategy remains consistent. This behavior indicates that the model maintains operational feasibility across different financial perspectives and that discounting mainly affects the relative weighting of early versus late-period decisions rather than the fundamental planning logic.

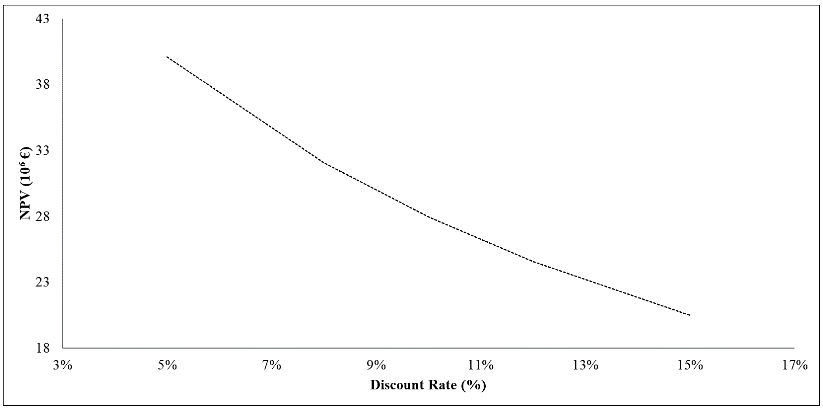


Figure 5.5 Sensitivity of the Model Result to Discount Rate

Second, changes in operating expenses directly affect total costs, which is expected given the importance of haulage costs in mining. However, the overall pattern of fleet replacement and utilization does not change significantly. Higher operating costs increase the incentive to reduce the use of older trucks, while lower costs allow existing equipment to remain in production longer. These adjustments occur gradually and remain consistent with operational constraints. Sensitivity of the model results can be viewed in Figure 5.6.

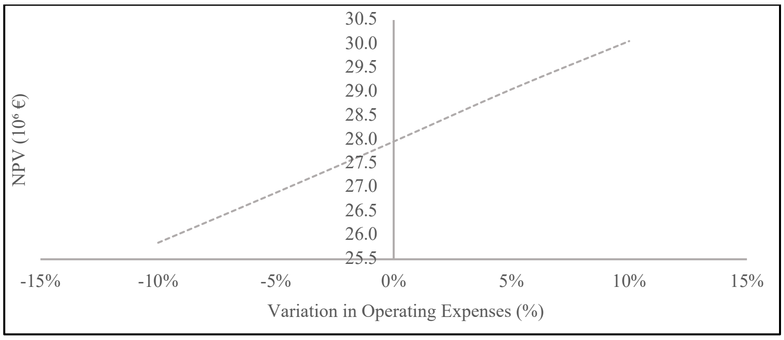


Figure 5.6 Sensitivity of the Model Result to Variation in Operating Cost

On the other hand, changes in production targets have a stronger impact on fleet decisions. For instance, a 10% increase in annual production targets results in a markedly different planning outcome (Figure 5.7). Under this condition, the optimization moves away from a strategy mainly based on replacing aging equipment and instead follows a capacity expansion approach. This requires a rapid increase in fleet size and significantly higher capital investments from the middle of the planning horizon onward. To satisfy the higher haulage demand, idling conditions are postponed and new truck purchases are intensified, even though this leads to higher capital costs. These results indicate that production growth is the dominant factor determining fleet size and investment intensity. From a practical perspective, long-term fleet sizing and replacement decisions should therefore be closely aligned with mine planning activities, including mine expansion, haul road development, route configuration, and destination layout, as these factors directly influence cycle times and the productivity of individual trucks throughout the mine life.

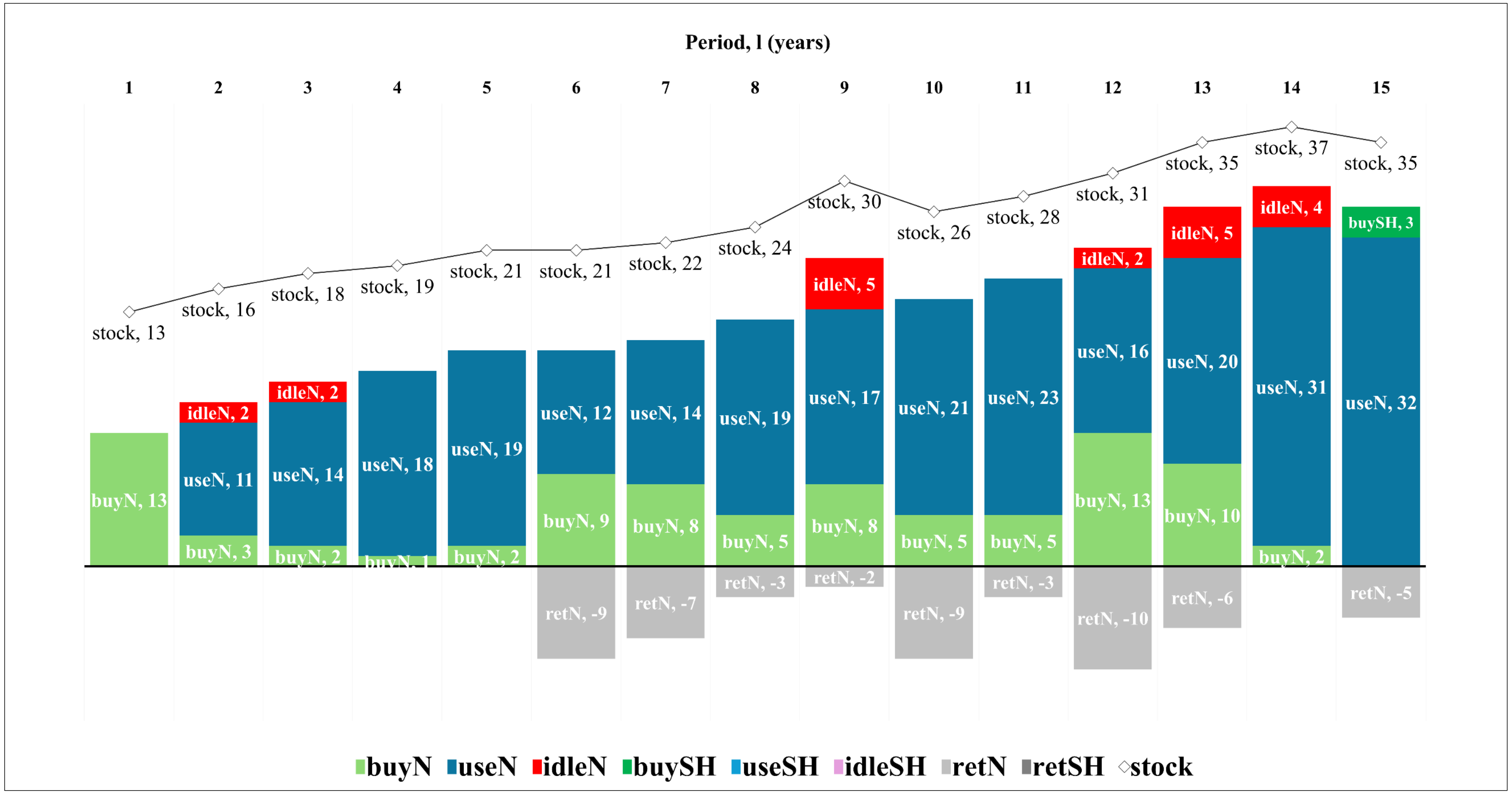


Figure 5.7 Optimized Truck Replacement Decisions when Annual Production Target is Increased by 10%

5.5 Managerial Discussion

A key strength of the proposed framework is the direct link between the simulation model and the mathematical optimization model. The discrete-event simulation reflects how operating conditions change over time, including variations in cycle times, haul distances, and truck performance as equipment ages. These changes are passed to the optimization model through age- and period-based productivity and cost parameters. As a result, replacement and investment decisions rely on realistic operating behavior rather than fixed or simplified assumptions.

The model shows that equipment replacement planning in mining should be addressed as a long-term, integrated decision problem rather than a series of independent annual choices. By jointly considering operational performance, production requirements, and investment decisions within a single framework, fleet planning can be evaluated consistently over the entire mine life. From a management perspective, the analysis indicates that replacement decisions evolve naturally over time: stable fleet use in the early years, gradual adjustments in the middle of the project, and tighter control of capital spending toward the end emerge from the combined effects of equipment aging, changing haulage conditions, and production constraints. This outcome suggests that fixed replacement ages or simple cost-based rules are often insufficient for effective fleet planning in practice.

The analysis also shows that equipment aging and mine expansion together reduce haulage efficiency. As trucks get older, operating costs increase and availability decreases, while longer haul distances lower productivity even for newer units. Decisions based only on equipment age or only on haul distance may therefore underestimate long-term impacts. The integrated framework helps these combined effects be considered at the same time.

Another important observation concerns the role of second-hand equipment. The optimized results indicate that second-hand trucks are mainly useful as short-term capacity support. Although they reduce initial capital requirements, their higher operating costs and limited remaining life reduce their long-term value. This points to the need for careful and limited use of second-hand equipment rather than routine reliance on it.

An important advantage of the proposed framework is its flexibility with respect to equipment characteristics and fleet composition. Although the case study focuses on a single truck model and includes second-hand units, the framework can be readily extended to analyze fleets consisting of multiple truck brands, payload capacities, or equipment types. Incorporating off-highway and on-highway trucks, or comparing alternative truck specifications, does not require structural changes to the simulation or optimization models. Instead, such extensions can be implemented by updating the corresponding input data matrices, including equipment-specific productivity parameters, operating cost functions, availability profiles, and acquisition costs.

More broadly, the proposed framework is not limited to haul trucks and can be applied to other types of cyclic continuous production equipment, such as loaders, conveyors, or mobile material-handling units, provided that their operational cycles can be represented within the simulation environment. In such cases, only the equipment-related data structures need to be adapted, while the overall modeling logic and decision structure remain unchanged. This highlights the user-friendly and modular nature of the framework, making it suitable for comparative equipment studies and technology evaluations beyond the specific case examined in this study.

The inclusion of idle capacity penalties provides useful guidance for fleet planning. Maintaining more trucks than required results in economic losses, particularly as haul distances increase over time. In addition, retaining aging equipment with low availability leads to indirect production losses that are reflected through penalty costs. These results indicate that fleet size should be aligned with realistic production plans and adjusted through timely acquisition and retirement decisions, rather than maintaining underutilized capacity.

Sensitivity results further underline the importance of production planning. Financial parameters mainly affect cost levels, while production targets directly influence fleet size and the timing of investments. This highlights the need to coordinate equipment planning closely with mine planning. Changes in mine layout, haul road development, and destination locations should be reflected in fleet decisions to avoid shortages or unnecessary investments.

Overall, the framework developed in this study provides a practical tool for supporting long-term equipment planning in mining operations. By combining realistic operational modeling with structured optimization, it helps decision-makers assess the trade-off between continuing to operate aging equipment and investing in replacements, while ensuring that production requirements are met throughout the mine life.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This thesis study examined the problem of long-term equipment replacement planning in cyclic continuous operations, with a focus on truck-based haulage systems in mining. Such systems operate over long time horizons and are affected by equipment aging, increasing haul distances, and changing production requirements. These characteristics make replacement decisions closely connected to both operational performance and long-term cost behavior.

To address this problem, the study developed a simulation-integrated dynamic integer programming framework that combines detailed operational modeling with long-term economic optimization. Discrete-event simulation was used to represent haulage operations under realistic conditions, capturing route-dependent cycle times, fuel consumption, and age-related changes in equipment availability and productivity. By transferring these outputs into the integer-programming optimization model as time-, age-, and location-specific parameters, the framework avoids simplified performance assumptions and ensures that replacement decisions are evaluated under realistic operating behavior.

The optimization model determines fleet acquisition, utilization, replacement, and retirement decisions over a multi-period planning horizon. The objective function minimizes the Net Present Value of total fleet-related costs, including capital expenditures, operating costs, idle capacity penalties, and salvage revenues, while enforcing production targets for each operational location and period. The model explicitly allows both new and second-hand equipment options and represents productivity degradation through availability-based capacity constraints.

Application of the framework to a real open-pit mining operation with 195 different haulage routes over a 15-year horizon demonstrates its practical effectiveness. The optimized solution satisfies all production targets while achieving a minimum discounted total cost of €27.96 million. The resulting fleet strategy shows that replacement decisions evolve gradually rather than occurring at fixed ages or uniform intervals. Stable fleet operation is observed in the early years, followed by controlled adjustments through replacement and limited second-hand usage in the middle years, and more conservative investment behavior toward the end of the project life. These patterns emerge from the interaction between equipment aging, mine expansion, and production constraints, rather than from predefined replacement rules.

From a managerial perspective, the results indicate that equipment replacement planning should be treated as a long-term and integrated decision process. Decisions based solely on calendar age, km, or short-term cost comparisons may fail to capture the combined effects of aging equipment and changing haulage conditions. The study also shows that production targets are the primary driver of fleet size and investment timing, while financial parameters mainly influence the overall cost level. This highlights the importance of aligning fleet planning decisions closely with mine planning activities, including mine expansion, haul road development, and destination layouts.

The analysis further suggests that second-hand equipment can be useful as temporary capacity support but has limited long-term value due to higher operating costs and shorter remaining life. In addition, penalizing idle capacity reveals that maintaining excess fleet size can lead to economic losses, especially as haul distances increase and availability declines. Efficient fleet management therefore requires timely acquisition and retirement decisions that closely follow realistic production plans.

Overall, the study confirms that integrating discrete-event simulation with dynamic optimization provides a consistent and reliable basis for long-term equipment replacement planning. The proposed framework enables decision-makers to evaluate trade-offs between operating aging equipment and investing in replacements while ensuring production targets are met throughout the project life. Although demonstrated for an open-pit mining operation, the framework is applicable to other cyclic continuous haulage systems where capital-intensive fleets operate under evolving conditions.

6.2 Recommendations

Based on the findings of this study, several directions for future research and practical extensions can be identified:

- Incorporation of Uncertainty: Future studies could extend the deterministic optimization framework by incorporating uncertainty in key parameters such as fuel prices, maintenance costs, production targets, and equipment availability. Stochastic or robust optimization approaches could enhance the model's applicability under volatile economic and operational conditions.
- Integration of Environmental Objectives: The framework may be extended to include environmental performance indicators such as fuel efficiency, emissions, energy consumption, or carbon-related costs. This would enable multi-objective optimization and support decision-making that balances economic performance with sustainability considerations, which are becoming increasingly important in mining operations.
- Coupling with Mine Planning Models: Integrating the equipment replacement framework with long-term mine planning or production scheduling models would allow investment and replacement decisions to co-evolve with mine expansion strategies, haul road development, and production sequencing. Such integration could provide a fully unified decision-support system for strategic mine planning.
- Rolling-Horizon and Adaptive Planning Applications: The model could be adapted to a rolling-horizon structure, allowing periodic re-optimization as

new operational data and updated production plans become available. This extension would increase the practical relevance of the framework by supporting adaptive fleet management rather than one-time strategic planning.

- Extension to Other Cyclic Industries: Although the case study focused on open-pit mining, the framework is readily transferable to other continuous cyclic systems such as logistics hubs, port operations, construction fleets, and industrial material handling systems. Applying the model to these sectors would further demonstrate its generality and practical value.

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APPENDICES

A. Mathematical Model: AMPL Input Data File (.dat)

```
param life       :=  15;
param age        :=   8;
param loc        :=   2;
param min_usage  :=   5;
param r          := 0.1;

# yearly production target (T[life, location])
param T :
   1 2 :=
1   2 7
2   2 7
3   2 7
4   2 7
5   2 7
6   2 7
7   2 7
8   2 7
9   2 7
10  2 7
11  2 7
12  2 7
13  2 7
14  2 7
15  2 7
;

# transportation by truck (P[age, year, loc])
param P :=
# Location 1
[*,*,1] :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0.828513 0.792798 0.753322 0.722013 0.689001 0.661232 0.636883 0.610322 0.593115 0.580155 0.563161 0.548061 0.533461 0.518365 0.507625
2 0        0.758124 0.718524 0.689829 0.657446 0.628230 0.612543 0.587885 0.570135 0.564743 0.549807 0.536168 0.509367 0.496269 0.485526
3 0        0        0.681105 0.665464 0.634756 0.608231 0.584726 0.561169 0.545675 0.536374 0.521933 0.510150 0.496595 0.484250 0.472557
4 0        0        0        0.633490 0.605021 0.580462 0.557653 0.535403 0.521820 0.510267 0.495564 0.485583 0.473709 0.462107 0.451060
5 0        0        0        0        0.569575 0.542817 0.530832 0.509356 0.496189 0.485668 0.473356 0.460432 0.454486 0.443719 0.433461
6 0        0        0        0        0        0.516377 0.500676 0.480552 0.468156 0.464331 0.451061 0.439935 0.432884 0.422692 0.413613
7 0        0        0        0        0        0        0.479519 0.458444 0.446888 0.441883 0.430497 0.419238 0.410880 0.400211 0.391398
8 0        0        0        0        0        0        0        0.429534 0.419492 0.411092 0.401149 0.391987 0.378441 0.369644 0.361150

# Location 2
[*,*,2] :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0.823136 0.722302 0.644096 0.582108 0.528879 0.486693 0.450574 0.417181 0.394253 0.376157 0.355206 0.337521 0.320097 0.305891 0.294743
2 0        0.692233 0.616538 0.555909 0.500121 0.461884 0.432740 0.402757 0.380918 0.357033 0.336983 0.318830 0.308703 0.294099 0.280929
3 0        0        0.583255 0.530283 0.479244 0.440987 0.408448 0.379722 0.355571 0.341350 0.321953 0.306787 0.289160 0.275157 0.262561
4 0        0        0        0.499020 0.452212 0.414190 0.388437 0.358536 0.337676 0.321801 0.302981 0.286988 0.273800 0.261113 0.249328
5 0        0        0        0        0.428466 0.391974 0.365473 0.337738 0.318230 0.304192 0.286351 0.273374 0.258648 0.245898 0.235785
6 0        0        0        0        0        0.369637 0.342494 0.318741 0.296350 0.283987 0.268472 0.253643 0.240275 0.228877 0.220379
7 0        0        0        0        0        0        0.321477 0.297939 0.281850 0.266041 0.252184 0.239579 0.225956 0.213838 0.205432
8 0        0        0        0        0        0        0        0.278649 0.261031 0.246505 0.233807 0.221406 0.212994 0.201359 0.192260
;

# capital cost of a truck (CC[age, year])
param CC :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0.165000 0.170940 0.177094 0.183469 0.190074 0.196917 0.204006 0.211350 0.218959 0.226841 0.235007 0.243468 0.252232 0.261313 0.270720
;

# salvage of a truck (S[age, year])
param S :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0.119625 0.123932 0.128393 0.133015 0.137804 0.142765 0.147904 0.153229 0.158745 0.164460 0.170380 0.176514 0.182869 0.189452 0.196272
2 0        0.086728 0.089850 0.093085 0.096436 0.099908 0.103504 0.107231 0.111091 0.115090 0.119233 0.123526 0.127973 0.132580 0.137353
3 0        0        0.062878 0.065141 0.067487 0.069916 0.072433 0.075041 0.077742 0.080541 0.083440 0.086444 0.089556 0.092780 0.096120
4 0        0        0        0.045586 0.047228 0.048928 0.050689 0.052514 0.054404 0.056363 0.058392 0.060494 0.062672 0.064928 0.067266
5 0        0        0        0        0.033050 0.034240 0.035473 0.036750 0.038073 0.039443 0.040863 0.042334 0.043858 0.045437 0.047073
6 0        0        0        0        0        0.033050 0.034240 0.035473 0.036750 0.038073 0.039443 0.040863 0.042334 0.043858 0.045437
7 0        0        0        0        0        0        0.033050 0.034240 0.035473 0.036750 0.038073 0.039443 0.040863 0.042334 0.043858
8 0        0        0        0        0        0        0        0.033050 0.034240 0.035473 0.036750 0.038073 0.039443 0.040863 0.042334
;

# operational cost of a truck (OC[age, year])
param OC :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0.112715 0.118586 0.124322 0.129367 0.133161 0.136734 0.138388 0.140585 0.142836 0.144349 0.145192 0.146707 0.148526 0.149926 0.152044
2 0        0.118351 0.124515 0.130539 0.135835 0.139819 0.143571 0.145307 0.147615 0.149978 0.151566 0.152451 0.154043 0.155952 0.157422
3 0        0        0.126044 0.132608 0.139024 0.144664 0.148908 0.152903 0.154752 0.157209 0.159726 0.161418 0.162361 0.164055 0.166089
4 0        0        0        0.136695 0.143814 0.150771 0.156889 0.161490 0.165823 0.167829 0.170494 0.173223 0.175058 0.176080 0.177918
5 0        0        0        0        0.151711 0.159612 0.167333 0.174123 0.179230 0.184039 0.186265 0.189222 0.192251 0.194288 0.195423
6 0        0        0        0        0        0.173376 0.182405 0.191229 0.198988 0.204825 0.210321 0.212865 0.216244 0.219706 0.222033
7 0        0        0        0        0        0        0.205562 0.216268 0.226730 0.235930 0.242850 0.249366 0.252382 0.256389 0.260494
8 0        0        0        0        0        0        0        0.255173 0.268462 0.281449 0.292869 0.301460 0.309548 0.313292 0.318266
;

# penalty of a truck (S[age, year])
param Z :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0.000026 0.000035 0.000046 0.000057 0.000075 0.000097 0.000121 0.000155 0.000193 0.000233 0.000289 0.000358 0.000443 0.000549 0.000678
;
```

```
# capital cost of a second hand truck (SCC[age, year])
param SCC :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0        0        0        0        0        0        0        0        0        0        0        0        0        0        0
2 0        0.086728 0.089850 0.093085 0.096436 0.099908 0.103504 0.107231 0.111091 0.115090 0.119233 0.123526 0.127973 0.132580 0.137353
3 0        0.057162 0.062878 0.065141 0.067487 0.069916 0.072433 0.075041 0.077742 0.080541 0.083440 0.086444 0.089556 0.092780 0.096120
4 0        0.037675 0.041442 0.045586 0.047228 0.048928 0.050689 0.052514 0.054404 0.056363 0.058392 0.060494 0.062672 0.064928 0.067266
5 0        0.024831 0.027314 0.030046 0.033050 0.034240 0.035473 0.036750 0.038073 0.039443 0.040863 0.042334 0.043858 0.045437 0.047073
6 0        0.022574 0.024831 0.027314 0.030046 0.033050 0.034240 0.035473 0.036750 0.038073 0.039443 0.040863 0.042334 0.043858 0.045437
;

# salvage of a second hand truck (SS[age, year])
param SS :
  1        2        3        4        5        6        7        8        9        10       11       12       13       14       15 :=
1 0        0        0        0        0        0        0        0        0        0        0        0        0        0        0
2 0        0.062878 0.065141 0.067487 0.069916 0.072433 0.075041 0.077742 0.080541 0.083440 0.086444 0.089556 0.092780 0.096120 0.099581
3 0        0.030046 0.033050 0.034240 0.035473 0.036750 0.038073 0.039443 0.040863 0.042334 0.043858 0.045437 0.047073 0.048768 0.050523
4 0        0.014357 0.015793 0.017372 0.017997 0.018645 0.019317 0.020012 0.020732 0.021479 0.022252 0.023053 0.023883 0.024743 0.025633
5 0        0.006860 0.007546 0.008301 0.009131 0.009460 0.009800 0.010153 0.010519 0.010897 0.011290 0.011696 0.012117 0.012553 0.013005
6 0        0.004522 0.004974 0.005471 0.006018 0.006620 0.006858 0.007105 0.007361 0.007626 0.007901 0.008185 0.008480 0.008785 0.009101
```

B. Mathematical Model: AMPL Main File (.mod)

```
# ========================
# PARAMETERS and SETS
# ========================
param life;
param age;
param loc;
param min_usage integer >= 1;
param r;

set LIFE := 1..life;
set AGE  := 1..age;
set LOC  := 1..loc;
set AGE_SH := 2..6;

param T  {LIFE, LOC};
param P  {AGE, LIFE, LOC};
param OC {AGE, LIFE};
param CC {AGE, LIFE};
param S  {AGE, LIFE};

param Z  {LIFE};
param SCC {AGE, LIFE};
param SS  {AGE, LIFE} default 0;

# ========================
# DECISION VARIABLES
# ========================

# --- Yeni (sıfır) kamyonlar ---
var buyN   {l in LIFE}                      >= 0, integer;
var nN     {l in LIFE, a in AGE}            >= 0, integer;
var rtrN   {l in LIFE, a in AGE}            >= 0, integer;
var uN     {l in LIFE, a in AGE, c in LOC} >= 0, integer;
var idleN  {l in LIFE, a in AGE}            >= 0, integer;

# --- İkinci el kamyonlar ---
var buySH  {l in LIFE, a in AGE_SH}         >= 0, integer;
var nSH    {l in LIFE, a in AGE}            >= 0, integer;
var rtrSH  {l in LIFE, a in AGE}            >= 0, integer;
var uSH    {l in LIFE, a in AGE, c in LOC} >= 0, integer;
var idleSH {l in LIFE, a in AGE}            >= 0, integer;

# ========================
# STOCK BALANCE and FLOW – NEW TRUCKS
# ========================

s.t. InitYoungN:
    nN[1,1] = buyN[1];

s.t. InitOlderN {a in AGE: a >= 2}:
    nN[1,a] = 0;

s.t. PartitionN {l in LIFE, a in AGE}:
    sum {c in LOC} uN[l,a,c]
  + idleN[l,a]
  + rtrN[l,a]
  = nN[l,a];

s.t. FlowAge1N {l in LIFE: l <= life-1}:
    nN[l+1,1] = buyN[l+1] + idleN[l,1];
```

```
s.t. FlowAgesN {l in LIFE, a in AGE: l <= life-1 && 2 <= a && a <= age}:
    nN[l+1,a] = idleN[l,a] + sum {c in LOC} uN[l,a-1,c];

# =========================
# STOCK BALANCE and FLOW - SECOND HAND TRUCKS
# =========================

s.t. InitSH {a in AGE}:
    nSH[1,a] = 0;

s.t. NoSH_Year1 {a in AGE_SH}:
    buySH[1,a] = 0;

s.t. FlowSH_Age1 {l in LIFE: l >= 2}:
    nSH[l,1] = idleSH[l-1,1];

s.t. FlowSH_SH {l in LIFE, a in AGE_SH: l >= 2}:
    nSH[l,a] = idleSH[l-1,a]
             + sum {c in LOC} uSH[l-1,a-1,c]
             + buySH[l,a];

s.t. FlowSH_Others {l in LIFE, a in AGE diff AGE_SH: l >= 2 && a >= 2}:
    nSH[l,a] = idleSH[l-1,a]
             + sum {c in LOC} uSH[l-1,a-1,c];

s.t. PartitionSH {l in LIFE, a in AGE}:
    sum {c in LOC} uSH[l,a,c] + idleSH[l,a] + rtrSH[l,a] = nSH[l,a];

# =========================
# RETIREMENT LOGIC
# =========================

s.t. RetireUpperN  {l in LIFE, a in AGE}:
    rtrN[l,a]  <= nN[l,a];

s.t. RetireUpperSH {l in LIFE, a in AGE}:
    rtrSH[l,a] <= nSH[l,a];

s.t. NoEarlyRetireN  {l in LIFE, a in AGE: l < life && a < min_usage}:
    rtrN[l,a]  = 0;

s.t. NoEarlyRetireSH {l in LIFE, a in AGE: l < life && a < min_usage}:
    rtrSH[l,a] = 0;

s.t. RetireMaxAgeN {l in LIFE}:
    rtrN[l,age] >= sum {c in LOC} uN[l,age,c];

s.t. RetireMaxAgeSH {l in LIFE}:
    rtrSH[l,age] >= sum {c in LOC} uSH[l,age,c];

# =========================
# PRODUCTION CAPACITY
# =========================

s.t. Prod {l in LIFE, c in LOC}:
    sum {a in AGE} (
          P[a,l,c]        * uN[l,a,c]
        + 0.95 * P[a,l,c] * uSH[l,a,c]
    ) >= T[l,c];

# =========================
# OBJECTIVE (NPV)
# =========================

minimize Total_NPV:
```

```
sum {l in LIFE}

  (
     sum {a in AGE, c in LOC}
         (        OC[a,l] *  uN[l,a,c]
         + 1.05 * OC[a,l] * uSH[l,a,c] )

           + sum {a in AGE}
               Z[l] * (
                   sum {c in LOC} P[a,l,c] * idleN[l,a] / 2
                 + 0.95 * sum {c in LOC} P[a,l,c] * idleSH[l,a] /2
               )

   + CC[1,l] * buyN[l]

   + sum {a in AGE_SH} SCC[a,l] * buySH[l,a]

   - sum {a in AGE}
         ( S[a,l]  * rtrN[l,a]
         + SS[a,l] * rtrSH[l,a] )
  ) / (1 + r)^l

- ( sum {a in AGE}
      ( S[a,life]  * ( nN[life,a]  - rtrN[life,a] )
      + SS[a,life] * ( nSH[life,a] - rtrSH[life,a] ) )
  ) / (1 + r)^life;
```

C. Mathematical Model: AMPL Run File (.run)

```
reset;

model model_final.mod;
data  model_final.dat;

option solver cplex;
option cplex_options 'timelimit=900 mipgap=0.01 mipdisplay=4';

solve;

printf "\n========================================\n";
printf "Optimal solution found\n";
printf "Total_NPV = %.6f\n", Total_NPV;
printf "========================================\n\n";


printf "Yearly Aggregated Fleet Events\n";
printf "%6s %8s %8s %8s %8s %8s %8s %8s %8s\n",
    "Year",
    "buyN",   "buySH",
    "useN",   "useSH",
    "retN",   "retSH",
    "idleN",  "idleSH";

for {l in LIFE} {
    printf "%6d %8.0f %8.0f %8.0f %8.0f %8.0f %8.0f %8.0f %8.0f\n",
        l,
        buyN[l],
        sum {a in AGE_SH} buySH[l,a],
        sum {a in AGE, c in LOC} uN[l,a,c],
        sum {a in AGE, c in LOC} uSH[l,a,c],
        sum {a in AGE} rtrN[l,a],
        sum {a in AGE} rtrSH[l,a],
        sum {a in AGE} idleN[l,a],
        sum {a in AGE} idleSH[l,a];
}
printf "\n\n";

printf "Matrix: NEW USED by Age and Year\n";
printf "%6s", "Age";
for {l in LIFE} printf "%6d", l;
printf "\n";

for {a in AGE} {
    printf "%6d", a;
    for {l in LIFE} {
        printf "%6.0f",
            sum {c in LOC} uN[l,a,c];
    }
    printf "\n";
}
printf "\n\n";

printf "Matrix: SH USED by Age and Year\n";
printf "%6s", "Age";
for {l in LIFE} printf "%6d", l;
printf "\n";

for {a in AGE} {
    printf "%6d", a;
    for {l in LIFE} {
```

```
        printf "%6.0f",
            sum {c in LOC} uSH[l,a,c];
    }
    printf "\n";
}
printf "\n\n";

printf "Matrix: NEW IDLE by Age and Year\n";
printf "%6s", "Age";
for {l in LIFE} printf "%6d", l;
printf "\n";

for {a in AGE} {
    printf "%6d", a;
    for {l in LIFE} {
        printf "%6.0f",
            idleN[l,a];
    }
    printf "\n";
}
printf "\n\n";

printf "Matrix: SH IDLE by Age and Year\n";
printf "%6s", "Age";
for {l in LIFE} printf "%6d", l;
printf "\n";

for {a in AGE} {
    printf "%6d", a;
    for {l in LIFE} {
        printf "%6.0f",
            idleSH[l,a];
    }
    printf "\n";
}
printf "\n\n";

printf "Matrix: NEW RETIRE by Age and Year\n";
printf "%6s", "Age";
for {l in LIFE} printf "%6d", l;
printf "\n";

for {a in AGE} {
    printf "%6d", a;
    for {l in LIFE} {
        printf "%6.0f",
            rtrN[l,a];
    }
    printf "\n";
}
printf "\n\n";

printf "Matrix: SH RETIRE by Age and Year\n";
printf "%6s", "Age";
for {l in LIFE} printf "%6d", l;
printf "\n";

for {a in AGE} {
    printf "%6d", a;
    for {l in LIFE} {
        printf "%6.0f",
            rtrSH[l,a];
    }
    printf "\n";
}
printf "\n\n";
```

```
for {c in LOC} {
    printf "Matrix: NEW USE by Age and Year, Loc = %d\n", c;
    printf "%6s", "Age";
    for {l in LIFE} printf "%6d", l;
    printf "\n";

    for {a in AGE} {
        printf "%6d", a;
        for {l in LIFE} {
            printf "%6.0f",
                uN[l,a,c];
        }
        printf "\n";
    }
    printf "\n\n";
}

for {c in LOC} {
    printf "Matrix: SH USE by Age and Year, Loc = %d\n", c;
    printf "%6s", "Age";
    for {l in LIFE} printf "%6d", l;
    printf "\n";

    for {a in AGE} {
        printf "%6d", a;
        for {l in LIFE} {
            printf "%6.0f",
                uSH[l,a,c];
        }
        printf "\n";
    }
    printf "\n\n";
}
```

D. Mathematical Model: AMPL Output Data File

```
ampl: include model_final.run
CPLEX 22.1.1:   lim:time = 900
  mip:gap = 0.01
  tech:mipdisplay = 4
CPLEX 22.1.1: optimal solution within tolerance; objective 27.95991674
259791 simplex iterations
41923 branching nodes
absmipgap=0.247122, relmipgap=0.00883846

========================================
Optimal solution found
Total_NPV = 27.959917
========================================
```

Yearly Aggregated Fleet Events

Year	buyN	buySH	useN	useSH	retN	retSH	idleN	idleSH
1	12	0	12	0	0	0	0	0
2	3	0	13	0	0	0	2	0
3	0	1	14	1	0	0	1	0
4	2	0	17	0	0	0	0	1
5	2	1	17	2	1	0	1	0
6	10	0	19	0	9	0	0	2
7	6	0	20	0	4	0	1	2
8	5	0	20	2	0	0	6	0
9	3	0	23	0	4	2	2	0
10	6	0	24	0	5	0	2	0
11	8	0	25	0	8	0	1	0
12	8	0	26	0	7	0	1	0
13	11	0	27	0	4	0	7	0
14	2	0	29	0	6	0	1	0
15	5	1	30	1	5	0	0	0

Matrix: NEW USED by Age and Year

Age	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	12	3	0	2	2	10	6	5	3	6	8	8	11	2	5
2	0	10	4	1	1	3	10	4	7	3	6	7	9	11	2
3	0	0	10	4	1	1	3	6	7	7	3	7	1	14	11
4	0	0	0	10	4	1	1	3	5	7	8	3	6	2	12
5	0	0	0	0	9	4	0	2	1	1	0	1	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Matrix: SH USED by Age and Year

Age	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Matrix: NEW IDLE by Age and Year

Age	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	2	1	0	1	0	0	2	0	0	0	1	0	0	0
3	0	0	0	0	0	0	0	4	1	1	1	0	6	1	0
4	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0
5	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Matrix: SH IDLE by Age and Year

Age	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0

```
      6     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      7     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      8     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0


Matrix: NEW RETIRE by Age and Year
    Age     1     2     3     4     5     6     7     8     9    10    11    12    13    14    15
      1     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      2     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      3     0     0     0     0     0     0     0     0     0     0     0     0     0     0     1
      4     0     0     0     0     0     0     0     0     0     0     0     0     0     0     2
      5     0     0     0     0     1     0     0     0     2     4     7     7     3     6     2
      6     0     0     0     0     0     9     4     0     2     1     1     0     1     0     0
      7     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      8     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0


Matrix: SH RETIRE by Age and Year
    Age     1     2     3     4     5     6     7     8     9    10    11    12    13    14    15
      1     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      2     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      3     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      4     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      5     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      6     0     0     0     0     0     0     0     0     2     0     0     0     0     0     0
      7     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      8     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0


Matrix: NEW USE by Age and Year, Loc = 1
    Age     1     2     3     4     5     6     7     8     9    10    11    12    13    14    15
      1     3     0     0     1     2     0     0     0     0     0     0     0     2     2     4
      2     0     3     0     0     0     0     0     0     0     0     0     1     0     1     0
      3     0     0     3     1     1     0     3     0     0     0     1     1     1     1     0
      4     0     0     0     1     0     0     1     1     3     3     3     2     1     0     0
      5     0     0     0     0     0     4     0     1     1     1     0     0     0     0     0
      6     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      7     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      8     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0


Matrix: NEW USE by Age and Year, Loc = 2
    Age     1     2     3     4     5     6     7     8     9    10    11    12    13    14    15
      1     9     3     0     1     0    10     6     5     3     6     8     8     9     0     1
      2     0     7     4     1     1     3    10     4     7     3     6     6     9    10     2
      3     0     0     7     3     0     1     0     6     7     7     2     6     0    13    11
      4     0     0     0     9     4     1     0     2     2     4     5     1     5     2    12
      5     0     0     0     0     9     0     0     1     0     0     0     1     0     0     0
      6     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      7     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      8     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0


Matrix: SH USE by Age and Year, Loc = 1
    Age     1     2     3     4     5     6     7     8     9    10    11    12    13    14    15
      1     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      2     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      3     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      4     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      5     0     0     0     0     0     0     0     2     0     0     0     0     0     0     0
      6     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      7     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      8     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0


Matrix: SH USE by Age and Year, Loc = 2
    Age     1     2     3     4     5     6     7     8     9    10    11    12    13    14    15
      1     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      2     0     0     0     0     0     0     0     0     0     0     0     0     0     0     1
      3     0     0     1     0     0     0     0     0     0     0     0     0     0     0     0
      4     0     0     0     0     2     0     0     0     0     0     0     0     0     0     0
      5     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      6     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      7     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
      8     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0

ampl:
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CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Serbest, İnanç Taha

EDUCATION

Degree	Institution	Year of Graduation
MSc	METU Mining Engineering	2021
MEM	METU Industrial Engineering	2019
BSc	METU Mining Engineering	2017
High School	Ankara (Anadolu) High School, Ankara	2011

WORK EXPERIENCE

Year	Place	Enrollment
2025-Present	OYAK Çimento	Senior Project Engineer
2024-2025	OYAK Çimento	Project Engineer
2020-2024	OYAK Çimento	Sales Planning Specialist
2018-2020	OYAK Beton	Performance Controller

FOREIGN LANGUAGES

Advanced English

HOBBIES

Tennis, Gourmet, Computer Technologies, Movies, Motor Sports.