Optimization of Nickel Ore Supply Network Amidst Declining Resources in the Sulawesi Region

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Abstract

The Indonesian government's nickel export ban, aimed at boosting domestic processing and adding value to exports, has led to a surge in the construction of smelters. This rapid development has created significant challenges in the nickel ore supply chain, posing a threat to the economic operation of smelters, particularly as resources are declining. To address these challenges, we developed a multi-periodic optimization model designed to ensure a stable supply of ore for smelters to operate economically throughout the planning horizon. Our model also identifies optimal smelter locations and capacities to minimize logistic and construction costs. We implemented two versions of the optimization model. The first model does not consider preferences of mines for specific smelters to supply. The second model introduces a preference mechanism for mines to supply ore to smelters with lower logistic costs. The second model proved difficult to solve due to its complexity. To overcome this, we employed a multi-step approach, which involved splitting the problem into manageable subproblems using a clustering technique. Our results indicate that while the second model allows individual mines to reduce their logistic costs, this preference mechanism leads to an overall increase in the total cost of the system.

Acknowledgments

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1 Introduction

1.1 Background

The Indonesian government has announced a ban on nickel ore exports which was effectively implemented in January 2020 [1]. This policy aimed at elevating the domestic processing industry and adding more value to its exports which was motivated by Indonesia's desire to become a global hub for nickel processing, especially given the increasing demand for nickel in the production of lithium-ion batteries, which are essential for electric vehicles. By enforcing this ban, Indonesia seeks to attract more investments in its nickel processing and refining sectors, thereby strengthening its economy.

As of 2023, Indonesia stands as the world's largest producer of refined nickel, contributing 49% to the global supply with a production volume of 1,800,000 metric tons in 2023 [2] [3]. This dominant position is highlighted by the country's rich reserves, which are estimated to be around 21 million metric tons, representing about 22% of the world's total nickel reserves. Before the export ban policy was implemented, a significant portion of Indonesian nickel ore was shipped to China, the world's largest consumer of nickel, where it was primarily used in stainless steel production and later in the burgeoning electric vehicle (EV) battery industry. Other destinations included Japan and South Korea, which also utilized the imported nickel ore for their extensive steel manufacturing industries.

Following the implementation of the export ban policy, the upstream nickel industry witnessed a significant surge in the development of nickel smelting facilities across the country. The aggressive response was shown predominantly by foreign investors aiming to capitalize on the domestic processing of nickel ore. The number of nickel smelters across the country increased dramatically from 15 in 2018 to 62 in 2023 with many more on the way [4]. However, the limited amount of mining ore resources and the aggressive expansion of nickel smelting facilities in Indonesia have led to concerns over a potential surplus of smelters indicated by the emerging issue of nickel ore understock, as domestic smelters' need for ore outpaces the supply (for example see [5] [6]). This situation is exacerbated by the imbalance between the overstocked refined products and the demand side [7]. The rapid expansion of smelting facilities, while bolstering Indonesia's position in the nickel processing industry, highlights the poor management of resource exploitation that led to an ineffective upstream nickel supply chain system and threatened the long-term sustainability of nickel reserves.

This study focuses on formulating the planning of mining production and processing capacity, taking into account the limited reserves at each site and their widespread geographical distribution. It examines Sulawesi Tengah and Sulawesi Tenggara province, a main nickel producer region in Indonesia, characterized by an extensive number of mining sites, each with varying production rates, reserves, and operational lifespans. The goal is to enhance effective management of resource exploitation by identifying an economically viable sequence of ore extraction while simultaneously optimizing the supply chain network between mining sites and processing facilities.

1.2 Nickel Mining Industry

Nickel mining starts with the extraction of nickel ore from the earth through open-pit or underground mining techniques. After extraction, the ore is crushed within the mining site and ground to separate the nickel-containing minerals from the waste rock. The nickel ore is then transported to the smelter to undergo various processes that extract pure nickel from the ore separating it from impurities. Two main types of processing facilities are pyrometallurgy (sometimes called a smelter) which uses high temperatures to extract metals and hydrometallurgy which involves an aqueous solution. They are selected based on the specific characteristics of the ore and the desired purity of the nickel product.

Nickel ore is categorized into three types: Saprolite, Limonite, and Nickel Sulfide, based on chemical composition. Indonesia's reserves predominantly consist of Saprolite [8], known for its high nickel content and lower moisture levels, making it simpler to process compared to other types of nickel ore. Consequently, Indonesia primarily employs pyrometallurgical processing facilities for its nickel extraction. Nickel smelters produce a variety of products, including pure nickel metal, nickel alloys, and ferronickel. These outputs are crucial for manufacturing stainless steel, batteries for electric vehicles, and various electronics.

1.2.1 Upstream Supply Chain System

The upstream segment of Indonesia's nickel industry, which encompass the activities from land acquisition to ore processing, is composed of mining companies, smelter companies, and the Indonesian government, which owns the land and grants mining rights. The government's role in providing rights is important, enabling a structured and regulated exploration and exploitation of nickel resources. Mining companies, upon being granted mining rights by the government, aim to maximize their profits by rapidly and efficiently exploiting the mining sites. This is because concession durations are limited, and often, the land is leased, imposing a time constraint on the operations of mining companies. Smelter companies focus on maximizing their profits by ensuring a consistent and sufficient supply of ore to maintain high and stable utilization rates of their smelting operations. This requires careful determination of the smelting plant capacities to align with the availability of ore, aiming to avoid underutilization, which can lead to inefficiencies. A form of strategic partnership with mining companies is often required to secure long-term ore supply.

The government's objectives in the nickel industry extend beyond regulatory function; they aim to maximize revenue through mining levies and taxes on the export of refined products. Additionally, the government focuses on the socio-economic impacts of the nickel industry, such as job creation and skill development, which contribute to the welfare and development of local communities. On the other hand, the government is also committed to maintaining a competitive and resilient upstream supply chain system ensuring that Indonesia remains an attractive and strategic player in the global nickel market.

1.2.2 Logistics in the Upstream Supply Chain System

Logistics plays a crucial role in the upstream nickel or mining industry in general. The process of extracting and transporting ore from mines to smelters or ports accounts for a substantial portion of the total operating costs of the smelting companies [9]. Therefore, companies that manage their logistic plan effectively improve operational efficiency and enhance competitiveness in the market. There are 134 mining sites spread over the Sulawesi Region (see Figure 1) where logistics primarily involve the use of trucks and ships for ore transportation between mining sites and processing facilities. There are no known railway networks used for ore transportation in this region. Conveyor belts are used within mining sites and in situ processing (such as crushing plants) but not for long-haul transportation. Figure 2 shows a typical logistic route from a mining site to a smelter. The ore is transported from the mining site to the nearest port by dump truck, and subsequently shipped to another port where the smelter is located.

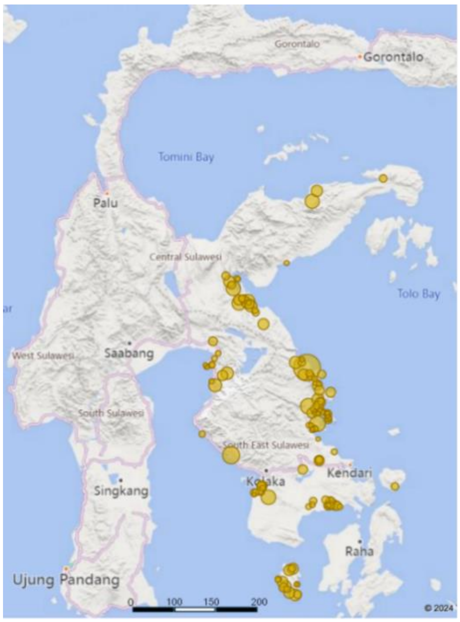

Figure 1 Nickel mining sites in Sulawesi region (bubble size represents amount of nickel reserve).

1.2.3 Mining Stages

A mining operation begins with prospecting and exploration activities to determine geological and economic assurance. Then it proceeds with development activities which include constructing facilities and securing access to the mining site. Once facilities are ready, exploitation starts and stops once the reserve is depleted or no longer economical. When exploitation stops mining companies are required to conduct post-mining reclamation to rehabilitate the environment. These activities are regulated by the Ministry of Energy and Mineral Resources Regulation number 7-2014. With this regulation and the fact that mining sites are leased with limited duration, mining companies are incentivized to maximize their production and continuously exploit until reserves are depleted and they are required to conduct post-mining reclamation.

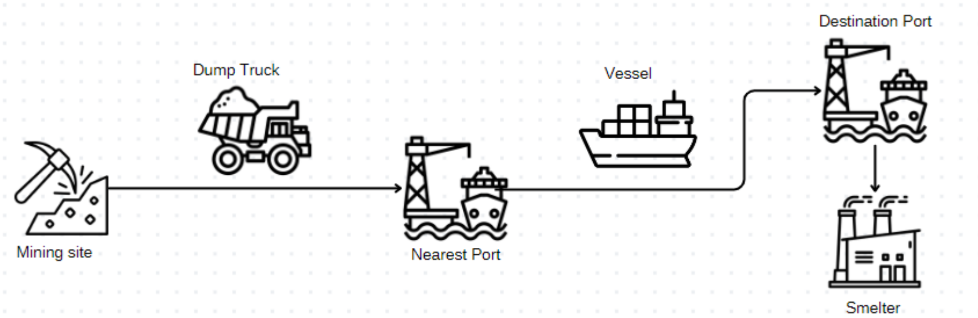

Figure 2 Typical nickel ore logistic route from a mining site to a smelter

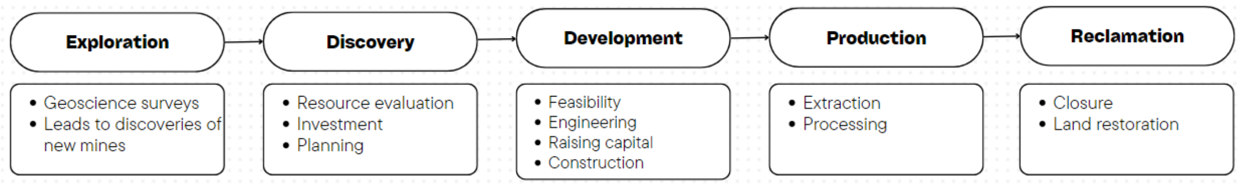

Figure 3 Overview of mining stages.

1.3 Mineral Resource and Reserve

As previously highlighted, mining resources are finite, and their availability continuously diminishes with ongoing exploitation. This reality makes the knowledge of available metal resources a crucial parameter in formulating an economically sustainable production and capacity planning, particularly in regions hosting multiple mining sites with different reserves and thus different production lifespan. The difference in production lifespan makes it challenging to plan the capacities of smelters that must be built in that region.

Indonesian Reporting Standard of Mining Resources and Reserves (SNI 4726:2011) defines resources as the occurrence of material that holds economic values in or on the earth's crust with certain manifestation, quality, and quantity that possesses reasonable prospect which can be economically extracted [10]. The reserve is defined as a deposit whose size, form, spread, quality, and quantity are known and can be extracted in a manner that is economically, technically, legally, environmentally, and socially feasible. Further terms are used to indicate the probability of these measures: inferred, indicated, and measured that respectively represent low, medium, and high geological assurance. In most economic feasibility calculations measured resource is used. However certain prospective calculations might include the inferred quantity with lower geological assurance. Generally, the reserves and resources of a mining area are subject to change. They can decrease as exploitation progresses or increase with new evidence obtained from exploration activities, however, in areas where extensive exploration has been done over a long period, the probability of an increase of reserve might be low. The Indonesian Ministry of Mineral Resources maintains and periodically updates a database of nickel mining reserves across the country which will be the valuable source of this study.

1.4 The Decline of Mining Reserve

The replenishment of certain minerals or any type of non-renewable resource consistently emerges as a recurring issue within the field of resource management and sustainability. There is only one widely recognized instance of mineral depletion when the rare mineral source, cryolite, known to exist only in Ivigtût, Greenland was completely exhausted [11]. Despite historical issues of resource depletion, most non-renewable resources continue to exist and remain accessible for extraction and use. This can be attributed to new technologies that enable lower mineral content to be processed.

However, in a regional context, there are many instances where an area has been completely depleted of its mining resources, leading to significant negative consequences for the local communities. For example, the coal mining regions in parts of Appalachia, USA, have experienced severe economic decline and environmental issues after the coal reserves were exhausted. The absence of sustainable planning and reliance on a single resource for economic prosperity led to widespread unemployment, poverty, and a host of social problems [12]. By avoiding overly aggressive extraction and adopting wise resource management strategies, we can extend the period of benefit and facilitate a smoother transition to post-mining conditions.

1.3 Objectives and Report Organization

From the previous discussion on Indonesia nickel supply chain situation, we know that: (1) there is an indication of nickel product surplus relative to the demand, (2) nickel reserves are limited, (3) there is an indication of ore understock, (4) sustainable exploitation is beneficial for the local community, (5) optimization of the supply chain network leads to efficient logistics that eventually support a competitive upstream nickel industry. With those conditions in mind, our study proposes the following questions:

- Can we propose a resource extraction policy that helps avoid ore understock and nickel product supply and demand imbalance?
- How does this policy impact the design of supply chain network?
- Can we reflect that policy in quantitative formulation to achieve an optimized supply chain network?
- How to solve that formulation?

The rest of this document is organized as follows. Chapter 2 covers supply chain mechanisms, stakeholder roles, and essential data collection. Chapter 3 reviews relevant studies and methodologies. Chapter 4 presents the mathematical models and optimization techniques used in the study. Chapter 5 analyzes the results, discussing implications and potential benefits. The final chapter summarizes key findings, offers recommendations for resource management and supply chain efficiency, and identifies future research areas in the related areas.

2 Supply Chain Mechanism and Data Gathering

This chapter examines the supply chain mechanisms and data gathering processes. It identifies key supply chain stakeholders, their respective goals, and their interactions, which are important for establishing the foundation of the formulation. We then discuss the data which are gathered from various sources, followed by the processing of these data to be used as input parameters for the model.

2.1 Mine Extraction Policy

Indonesia's policy in regulating mining activities has been transitioning into a more decentralized framework [13]. This allows for better benefits for local communities. However, it created some problems such as the overlap of mining areas and conflict of controls between government agencies. Furthermore, it prevents the government from controlling sustainable extraction, especially for commodities that are critical and rapidly declining. After the nickel export ban policy was implemented, demand for local smelters has been dramatically increasing. We identify the current supply chain stakeholders and their respective goals as follows:

Table 1Supply Chain Stakeholders and Objectives

Players	Objectives
Mining Companies	Maximize profit by maximizing production during their limited leasing period
Smelters	Maximize profit by keeping utilization as close as possible to the maximum capacity
Government	Maximize profit via mining levies and land leasing fees and intervene in the supply chain system to maintain a competitive nickel ecosystem.

Since the implementation of the nickel ore export ban, the mining companies must rely on local smelting capacities within Indonesia. On the other hand, smelters are relying in their needs of ore stock on the mining companies to economically operate their plants. Driven by the huge demand, particularly in the EV industry, all stakeholders are incentivized for maximum resource extraction and hence a boom of smelter constructions. However, smelters need to carefully set their capacities to ensure that there are enough stocks of ore throughout their operational life. In the context of supply that is expected to decline over time, this could be more challenging. To illustrate that situation, Figure 4 shows how ore supply declines over time due to limited reserve and exploitation. In response to the export ban, the number of smelters needs to be increased dramatically to achieve full locally processed nickel ore. However, in the fifth year after 2022, the total ore supply is expected to decrease by more than 20%. With a minimum break-even period of 6 years (which will be shown in the next sub-chapter), smelters will be underfed with ore supply before they get the chance to break even. This highlights challenges associated with the ore understock issue previously discussed. Smelters have the option to import ore from abroad, but it incurs higher logistic costs and more importantly does not solve the demand issue.

Given the situation described above, we believe it is important for the government to intervene in the supply chain system in some form of control of ore production so that it stabilizes the overall ore supply. This will spur a potentially lower number of smelter constructions but with economically sustainable operations that balance both supply and demand sides. However, it is also critical to devise a policy that is not only helping for sustainable resource extraction but also preserving the investment climate, where mining rights holders can maximally produce ore without restrictions within the leasing periods. In the supply chain and economic context, the new mechanism must guarantee the individual profits, including mining levies for local governments, to be at least equal to the profit in the current supply chain system. The government cannot directly control how each of the mining sites should produce each year, because we have assumed that mining companies are only incentivized to produce as much as each of the mining sites (geologically and technologically) can allow (i.e. it will continuously produce once mining rights are acquired until the reserve is depleted).

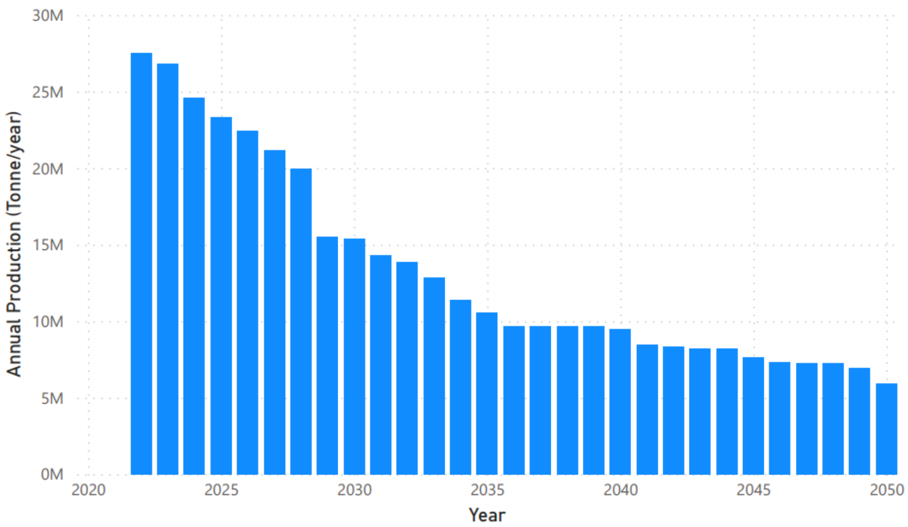

Figure 4 Time vs Expected Ore Annual Production Starting from 2022

Therefore, we propose a coordinated supply chain system where the government chooses when a mining site should be open for lease (hence starting the ore production) within the planning horizon. In this coordinated supply chain system, mining companies are guided on which smelters they should supply with ores at any given period throughout their lifespan. On the other hand, the government determines the necessary number of smelters and their locations. This mechanism helps in addressing two critical issues: economically sustainable extraction and optimal logistics. To facilitate optimal decision-making, factors such as the annual production, location, reserves, and lifespan of each mining site are considered.

Evidently, optimizing this coordinated supply chain network can be formulated generally as a Facility Location Problem (FLP) [14]. However, it extends the basic logistical optimization in FLP by incorporating economically sustainable extraction constraint. We consider this constraint is satisfied if all the smelters can operate with ore supplies that are relatively close to the smelters' capacities considering available ore supply for each period within the planning horizon. This constraint adds complexity as it requires us to strategically choose the right sequence of extraction commencements. Other characteristics that extend the problem beyond basic FLP are the capacity planning and multi-periodic model.

In addition to the fully coordinated supply chain model, we propose a second model that adds some level of preference of the mining and smelting companies in terms of supply assignment. Naturally, mining companies will try to supply the ores to the smelter with the lowest logistic cost. We can incorporate this behavior into the model, thus effectively extending it to reflect a more realistic and natural mechanism, thus increasing the stability of the supply chain. In the initial model, there is no guarantee the solution will be a supply chain network where mining sites are assigned to the closest smelters, especially when the economically sustainable constraints are in place. These constraints will generate supply assignments between smelters and groups of mining sites of which combination of life span ensures minimum capacity use within the planning horizon. This can prevent assignments of mining sites to the closest smelter. Therefore, to accommodate this formulation we add additional constraints to the formulation. We will evaluate how much this modification affects the main objective value, which is very useful for decision-makers in designing the supply chain network.

Reflecting on the smelters that are currently available, it is assumed that the candidates for these smelter locations are the existing ports in the region. This assumption is based on several justifications: firstly, many mining sites are located close to the seaside of the island (see Figure 1). Secondly, ports typically possess an established transportation network, which is crucial for the efficient movement of materials in the smelting operations. Thirdly, ports are already equipped with basic infrastructure, including a power grid, which supports the smelting operations. Lastly, the nickel product can be directly transported outside the region directly from the port by ship.

2.2 Data Gathering

We obtain the mining site data from the publicly accessible Minerba One Map Indonesia (MOMI) database[1]. This database includes the locations of all mineral resources throughout Indonesia. The ArcGIS-based map displays the proven reserves and the area for each mining site, from which crucial

[1] https://momi.minerba.esdm.go.id/

parameters such as ore supply rate and mining lifespan will be derived from. The database also contains information on existing ports that will be considered as potential candidates for smelter locations. There are 134 mining sites and 68 ports across the region. Additionally, we looked at studies to determine other critical parameters such as smelter construction cost and unit logistic cost. The following sections discuss how we calculate those parameters along with the underlying assumptions.

2.2.1 Ore Supply Rate and Production Lifespan

As previously mentioned, mining companies are incentivized to maximize ore production during their mining lifespan. Consequently, the supply capacity is primarily determined by the physical characteristics of the mining sites. Key factors include the geological conditions and the unique attributes of the ore deposits [15]. However, our database lacks this specific information. Given that nickel mining in Indonesia is predominantly conducted through open-pit mines, and considering we only possess data on the size of the mining area, we have assumed a linear correlation between the size of the mining site and production, drawing upon samples from mining sites with known actual ore production. In practice, the government holds detailed production data for each mining site, as mining companies are required by regulation to report their output. Then we define production lifespan as reserve divided by supply rate. For simplicity, we round it to have an integer lifespan value.

2.2.2 Construction Costs

The construction costs of smelters typically comprise both fixed and variable costs, which depend on the facility's capacity. However, within the context of mining smelters, there appears to be a lack of studies that separately show these two types of costs. A report published by USAID in 2013 indicates that economies of scale play a minimal role in the nickel processing business due to the substantial investment required per unit of capacity [16]. Therefore, we only account for the costs related to capacity. Nevertheless, to prevent the model from producing smelters with unrealistically low capacities, we have established a minimum smelter capacity of 1 metric ton of ore per annum, which reflects the minimum capacity of existing smelters in the region. As a reference, we use a feasibility study conducted by Haryadi in 2017 to estimate the unit capacity cost [17] for Indonesia market.

2.2.3 Distance-related Data and Unit Logistic Cost Data

Given the multiple islands and the nature of the region, the mining supply chain involves both land and sea transportation. As previously highlighted, no railway network exists for ore mining logistics within the region. Therefore, we only consider two forms of transportation: trucks and vessels. We gather distance data to ultimately create logistic cost table (in USD/tonnes) as parameters that are used in the optimization model. However, determining these parameters is not as straightforward as determining the construction cost and ore supply rates. Figure 11 reflects the processes for determining the logistic cost table. We first obtain the coordinates of the ports and mining sites and unit logistic costs (in

USD/tonnes/distance unit) for both truck and vessel. Then we conduct a preprocessing step to ultimately determine the cheapest route from any mining site to the any port, which form the logistic cost table. The preprocessing step will be discussed in more detail in Chapter 4. We obtain the coordinates for ports and mining sites from MOMI database. For the unit logistic cost of vessel, we refer to Indonesian Ministry of Energy and Mineral Resource decree number 18.K/HK.02/MEM.B/2022. This regulation states shipping cost per ton (in USD) is calculated as 0.0184 times the nautical distance (nautical mile) plus 3.1172 (assuming the Vessel size is 270 – 330 ft long). To estimate the truck transportation costs, we look at reports such as [18] and [19]. We assume 10-ton trucks are used for land which costs 0.16/tonnes/km.

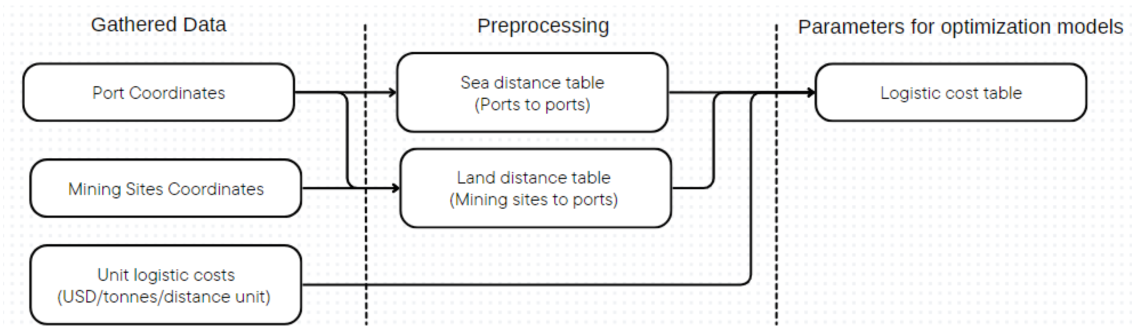

Figure 5 Workflow to obtain logistic cost from mining sites to ports.

3 Literature Review

This chapter explores the optimization problems prevalent in the mining industry, focusing on the unique challenges and solutions that have been developed over the years. It provides an examination of Facility Location Problems (FLP) and its various types, highlighting their relevance to supply chain optimization. Furthermore, the chapter identifies optimization problems similar to those faced in our study. The review also covers the solving techniques employed in these problems, including both exact and heuristic methods. Additionally, it discusses the shortest path algorithms used to produce the logistic cost table, which is crucial for optimizing the supply chain network.

3.1 Optimization in the Mining Industry

Optimization techniques have been extensively used in many areas of the mining industry, from planning and operation to rehabilitation. Since 1960, mining aspects such as mine planning and design, production scheduling, and equipment selection have benefited from Operations Research applications [20]. Algorithms are used to determine the optimal pit shape and size that maximizes the economic value of the mine, considering the orebody geometry, ore grades, and market prices of minerals [21]. Optimization also helps in designing the layout of underground mines, including the placement of shafts and tunnels, ensuring efficient access to orebodies while minimizing costs [22]. Nowadays, mine planning and design rely heavily on software such as *Surpac* and *Hexagon,* which employ optimization techniques.

Determining the cut-off grade for ore processing is one of the critical decisions in the upstream mining process. The cut-off grade is the minimum mineral content a parcel of ore must have to be considered economically feasible to process by looking at market prices and operational costs. Due to the heterogeneity of the mining deposit, the cut-off grade is needed to clearly distinguish valuable material from waste in the produced ores to ensure a smooth processing stream [23]. The chosen cut-off grade influences other areas, such as extraction techniques, equipment, and methods used for processing.

Optimization techniques have also been applied in mining production scheduling. In long-term production planning of a mining site where the orebody is represented as three-dimensional array of blocks, optimization models define the sequence and timing of block extraction over a number of periods within its mining lifespan [24]. The optimized production planning maximizes cash flow constrained by physical properties such as slope, equipment capacity, and processing plant minimum and maximum capacity. Some approaches include mixed integer formulation [25] and dynamic programming [26]. Many heuristics methods have been applied to this problem include Genetic Algorithm [24], Simulated Annealing [27], and Ant Colony Optimization [28].

Supply chain optimization in the mining industry includes capacity planning, green supply chain, network design, and inventory control. Issues such as capacity expansion, network design, and facility location are popular research topics in mining supply chain optimization [29]. Multi-criteria decision-making (MCDM) is used to score the sustainability performance of coal suppliers in the power sector [30]. Various mixed integer programming (MIP) models are proposed to solve issues related to storage location selection [31], production scheduling [32], and equipment selection [33]. In addition, heuristic methods are employed to solve complex and large-scale mining supply chain related problems [34] [35].

Very few research papers discussed optimization related to the interaction between mining and processing or storing facilities in a regional context. Most of the works consider optimization of the processes within the same mining complex. Some papers discussed optimization in a larger context, employing coordination between players in a large supply chain system. Liu (2021) explored the use of metaheuristics and big data analytics to help optimize mine supply chain planning [36]. In this research, he discussed how to coordinate production for each of a group of mining sites in order to minimize total cost considering the interaction of logistical centers shared by the processing facilities in delivering products to end users. Fadol (2002) employed simple MCDM ranking techniques to prioritize smelter location candidates around a region with high copper deposits. He considered factors such as established road network, vicinity to shipping yards and reserve size of the deposits [37]. In their study, Qaeze et al. (2015) consider a supply chain system consisting of multiple mining locations and a smelter facility [38]. In a collaborative setting between smelter and mining companies, the whole supply chain system maximizes value creation by adjusting the sequence of block extraction in the mining sites and adjusting the processing policy in the smelter, such as the addition of certain chemicals for the extracted ore. In this research, coordination and information sharing between a smelter and a set of mines with regard to the property of the extracted ore are important for cost minimization, which leads to maximum profitability.

There is a general similarity of problems this study has with the research discussed previously, such as capacity planning, network design, and facility location problems. However, our study is distinctive in some ways. Mainly, it considers ore-producing regions with hundreds of mining sites and smelters of which locations and capacities to be determined, encompassing a higher-level supply chain scope rather than an operational and tactical scope. In our study, the resource extraction policy reflects the periods in the planning horizon where each of the mining sites can start producing or allowed to be extracted. This differs from the ore extraction policy, which governs the sequence of blocks that are extracted at a mining site. Hence, we will look at other studies from different types of industries that exhibit similar problems in our studies. Our resource extraction policy can be thought of as a combinatorial problem that can be found in many contexts, such as logistics, transportation, and plant scheduling. On the other hand, facility location problems are relatively old problems in Operations Research with various approaches and solving techniques.

3.2 Facility Location Problems

Facility location problems (FLP) focus on selecting a set of locations that minimizes the cost of meeting a certain set of demands while adhering to various constraints. There are many variations of FLP based on the nature of the problem, objective, constraint, and approach. Facility location problems are generally solved three types of spaces: continuous, discrete, and network spaces [39]. In continuous spaces, there are an infinite number of possible optimal locations inside feasible one, two, or three dimensional space. In discrete spaces, the candidates for the best locations are predetermined, where a subset of these locations are selected. For network spaces, we optimize problems represented as nodes and edges of a graph. Continuous space problems often involve calculus-based optimization to find optimal locations. On the other hand, discrete space problems are formulated with integer programming.

In the early development of facility location problems formulation, Hakimi (1964) investigated a problem of determining location of switching centers that interconnect a network of telephone line represented as a graph. He proposed a method that later is called *p-median* with the purpose of choosing *p* locations that minimize the total wire length from each of the vertex to its switching centers [40]. Unlike the *p-median* problems, the set covering problems aims to cover all demand points by opening a minimum or constrained number of facilities. One of the early works on covering problem is the study by Church and ReVelle (1974), where they modeled the maximization of covered demand, which is highly applicable in public service related to facilities such as ambulance bases and fire stations [41].

Recently, FLP has evolved into various types of problems that address a diverse range of objectives, constraints, and practical applications. This evolution reflects the growing intricacies of modern problems, especially in the field of logistics and supply chain management in general. One of the variations of FLP is the location routing problem (LRP), which combines FLP and vehicle routing problem (VRP). As the name suggests, it aims to optimize the routing of vehicles delivering the goods in addition to selecting the best facility location. There are various methods to formulate LRP, which include direct tree search, dynamic programming, integer programming, and nonlinear programming [42] with integer programming being the main approach [43]. LRP formulations have been applied for problems that involve the distribution and collection of materials, such as waste collection and disposal planning.

Another variation of FLP that is popular in supply chain management is the location-allocation problem (LAP). It extends the traditional FLP by also optimizing the allocation of resources from facilities to demand points which increases the combinatorial complexity. This type of problem was first formalized by Cooper in 1963 [43]. In addition to exact solving methods, Cooper proposed an approximate method due to combinatorial complexity. In the approximate method, we first generate p subsets of fixed points and then solve the location-allocation problem using the exact method to obtain a single optimal location. Then, each fixed point was reallocated to the nearest facility. After all points have been completely reallocated, we apply the exact method again to improve the facility location with changes in the customer assignment. These processes are repeated until no further improvement can be found. Since this only leads to a local minimum, we can repeat many times with different starting points to get close to optimality. Examples of LAP can be found in the selection of warehouses, distribution centers, and production facilities.

One more variation of FLP relevant to our study is the facility location with capacity planning problems (FLCPP) [44]. This model is suitable for scenarios where opening a facility incurs relatively high costs and correlates linearly with the capacity of that facility. In addition to determining locations and number of facilities, it aims to optimize the capacity of the facilities considering the variety of demand levels across the area. It increases the complexity in the original FLP by adding decision variables and constraints related to capacity, which influence the cost function of the objective. In this formulation we can allow different fixed and capacity costs of certain locations to better reflect actual condition.

There are a few more variations of FLP that have previously been studied but might not be strongly related to our study. This includes the dynamic facility location problem (DFLP), where a facility can be opened and closed within the planning horizon in response to the dynamics of demand, and the competitive location problem (CLP), which is closely related to spatial economics. In this model, interactions between facilities are usually related to market share competition [45].

The nature of our study exhibits some properties of the models discussed above, most notably the FLCPP. In our study, we must decide on the locations and capacities of the facilities in addition to demand assignments. The multi-periodicity of our problem is also a feature that differs itself from the original FLP. Employing a multi-periodic model in our problem is inevitable as demand (in this case, ore supplies to be processed) varies over time due to differences in mining lifespan.

3.3 Combinatorial Complexity

One critical feature of our problem has not been extensively discussed in the context of facility location problems. That is the economically sustainable extraction constraint, which restricts the number of active mining production at any given time so the smelters can operate economically within the planning horizon. This presents a more combinatorial complexity in the problem to optimize. Although, to the best of our knowledge, no studies yet combine this with FLP, we can find studies that present similar features that add combinatorial complexity to original optimization problem. Related examples include problems with compatibility constraints, such as equipment selection problems. In a study by Burt et al. (2016) on equipment selection problems in surface mining, these constraints require the right combination fleet of trucks and loaders to be selected as a feasible solution [33]. To reduce complexity, they employed branch and cut, relaxing the compatibility constraint first, then solving and checking for feasibility iteratively. Similarly, the facility location problem with incompatibility also increases the combinatorial complexity. In this type of problem, some customers cannot be assigned to the same facility or vice versa, thus requiring the formulation to have additional binary variables and constraints [46] [47]. Possible solving approaches include the use of kernel search (KS), which showed better outcomes than the result from Gurobi, a commercial integer programming solver, with a setting of one-hour time limit.

The additional complexity previously discussed only extends to one dimension, i.e. it is coupled with one type of the decision variable set. On the other hand, the economically sustainable constraints in our problem involve periodic variables due to the assumption of continuous production: a mining site will not stop producing once it has started until its mining lifespan is reached. The type of problem that might closely resemble our problem is the resource leveling problem (RLP), typically found in project/construction management. In this type of problem, the objective is not directly minimizing the cost but rather minimizing the peak of required resources due to task variations in the planning horizon [48]. Unstable resource requirements are indeed costly and impractical for construction companies. The decision variables in this problem represent job sequencing, allocations, and resource assignments. Nonetheless, due to the complexity generated in RLP formulation, studies usually consider ten to twenty activities [49]. Additionally, many of these studies employ metaheuristics, guaranteeing no global optimality [48] [49] [50]. Since our problem involves hundreds of demand nodes and location candidates with a multi-periodic model, it is important to simplify the formulation in terms of the number of variables, constraints, and linearity so the problem can be solved with global optimality within a reasonable timeframe.

3.4 Computational Complexity and Solving Techniques

In addition to the number of variables and constraints, one way to identify the complexity of an optimization model is by assessing the NP-hardness of the formulation. NP-hard problem is defined as a problem that is at least as hard as any problem in NP class. In general, both continuous and discrete space FLP in its basic form are known to be NP-hard [43]. There are cases of FLP, especially those with continuous space, that can be solved in polynomial time where specific requirements are satisfied. Our problem, despite has not been theoretically proven to be NP-hard in this study, is quite complex as it involves multiple sets of binary and integer variables with relatively intricate constraints.

Due to its NP-Hardness, many FLP problems and their variations utilize heuristic solving techniques. The NP-Hardness implies computation time increases drastically as the scale of the problem increases, making it impractical to find exact solutions for large-scale cases. Heuristics are algorithmic processes that obtain optimal solutions by iteratively improving candidate solutions with respect to certain quality measurements [51]. Metaheuristic algorithms are higher-level heuristics that help escape local optima that often found in heuristics, which applicable to a wide range of problems [52]. Current widely used metaheuristics include *Genetic Algorithm (GA), Tabu Search (TS), Simulated Annealing (SA), Ant Colony (ACO),* and *Particle Swarm Optimization (PSO).* Generally, metaheuristics can be categorized into two main types: population-based and neighborhood-based. Population-based algorithms are inspired by biological evolution as their improvement process involves modifying some elements that represent the solution. GA, PSO, and ACO are examples of population-based algorithms. On the other hand, neighborhood-based algorithms explore solution space by moving from a current solution to a solution in its neighborhood according to a predefined neighborhood scheme. These algorithms include SA and TA.

The capability to solve MILP models using exact methods has significantly advanced in the last decades. A study by Koch et. al. (2022) shows that solving MILP with current technology is about 1000 times faster than using solvers in 2001 [53]. This improvement is attributed to enhancements in computer hardware, computational environment, and the development of sophisticated algorithms within optimization software. Most optimization software employs common algorithms such as branch-and-bound and cutting planes in order to reach global optimality. The branch-and-bound is the core algorithm in optimization software that systematically explores the decision tree that represents integer value assignment to integer variables. Generally, there are two approaches in executing the exploration: bread-first search (BFS) and depth-first search (DFS). BFS explores the tree nodes level by level, exploring the nodes at the same level first before continuing with deeper nodes. On the other hand, DFS explores as deep as possible first before continuing with other nodes at the same level. Optimization software combines both approaches with some search strategies to effectively explore the solution space. In addition to branch-and-bound, cutting plane techniques are other common techniques used by optimization software. The cutting plane techniques improve the bounds in the branch-and-bound tree by adding linear constraints that exclude infeasible parts of the solution space without excluding the feasible solutions.

Even though optimization software are considered as an exact method, they do employ heuristics algorithms in order to help in exploring the solution space and improve the efficiency of the branch-and-bound process. This includes Relaxation Induced Neighborhood Search (RINS) [54] and local branching [55]. The RINS identifies a subproblem by combining integer variables from the best feasible solution (incumbent) and the solution to a linear relaxation. By combining solutions from continuous relaxation and the incumbent, we expect a good solution space to explore. Local branching is used in the branch-and-bound process by adding specific constraints to ensure exploration is done in solution space around a good feasible solution. This strategy is aimed at the early updating of the incumbent solution, where the gap between the lower bound (best possible solution) and the incumbent is still high.

3.5 Shortest Path Algorithms

Shortest path algorithms are critical in supply chain optimization that involves logistics. We use the road network and routing engine provided by the GIS software OpenStreetMap (OSM) to construct a logistic cost matrix for the model's parameters. OSM utilizes multiple shortest path algorithms, such as Dijkstra's and A* algorithms, for route optimization.

Dijkstra's algorithm calculates the shortest path in a network by starting at the initial node, assigning it a cost of zero, and assigning all other nodes an infinite cost. It then explores connected nodes, updating their costs based on the shortest discovered path, and continues this process until reaching the destination node. This method is used indirectly in OpenStreetMap (OSM) for land distance matrix and directly for logistic cost matrix from mining sites to ports. The A* algorithm enhances Dijkstra's approach by incorporating heuristics to prioritize nodes that likely lead to the shortest path, balancing actual travel cost and an estimated cost to the destination. This heuristic, often a straight-line distance, makes A* faster and more efficient for larger-scale geographic problems where we have some knowledge of the potential shortest path [56] [57]. We use A* to construct port-to-port sea route distance matrices.

4 Mathematical Formulation and Optimization

In this chapter, we discuss the mathematical formulation and optimization processes used in this study. First, we perform a preprocessing step to generate the logistic cost table, which involves calculating the distances and associated costs for transporting ore between mining sites and smelters. This logistic cost table serves as a critical input for our optimization models. We then formulate the optimization models, starting with the first model that minimizes total costs by determining the optimal locations and capacities for smelters and assigning ore supplies. Following this, we introduce the second model that incorporates additional constraints to reflect the preferences of mining sites, aiming to create a more stable and realistic supply chain network.

4.1 Logistic Cost Calculation

Using the distance data and unit logistic cost previously gathered, we will create a logistic cost table to be used as parameters in the optimization models. Figure 6 shows the steps that were done to determine the logistic cost matrix (also outlined in following sections). It is important to note that the ore transportation from the mining site to the smelter, even when located on the same island, might require both truck and vessel transportation, (i.e., from the mining site to the closest port first, then to the destination port). This is because of the significantly higher cost per unit distance associated with truck transportation compared to the vessel, as mentioned in Chapter 2. Given the many possibilities of routes from each mining site to the ports (as smelter location candidates), we do an optimization step to identify the route that minimizes the logistic cost. The following sections will discuss how we derive the land and sea distance table and eventually the logistic cost table.

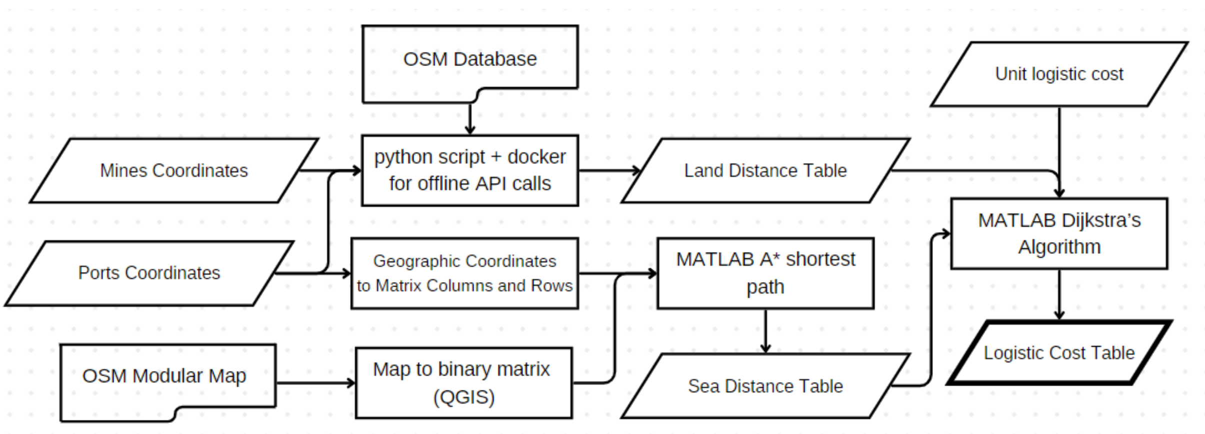

Figure 6 Flowchart in preprocessing step for determining the logistic cost table.

4.1.2 Land and Sea Distance Table

Using the OpenStreetMap (OSM) database, we can obtain distance between any pair of points in the database. The challenge is generating distances between 134 mines and 68 ports within a reasonable timeframe. For faster distance calculation we download the OSM database and use Docker (a containerization software) to set up a local server that holds the downloaded map database. We then create a python script that does API calls to that server to get the distances, creating the land distance table between mining sites and ports.

To calculate sea distances between ports, there are numerous commercial sea route distance calculation software options available. However, for academic uses, these options are limited to only a few calculations per day, which is inconvenient as we need to calculate distances for more than 68 ports (resulting in $\frac{68!}{(2!(68-2)!)} = 2278$ distance calculations). Consequently, we decided to develop a script using QGIS and a MATLAB package, based on the A* shortest path algorithm, for calculating these distances.

With QGIS we process the OSM modular map (*geofabrik*) of the region. Then we create a grid of 1000 x 2000 each representing 0.18 nautical miles (0.33 km) overlaying the area. This grid is then converted into the binary matrix where 0(white) represents sea and 1(black) represents land which reflects an occupancy map in the pathfinding procedure, shown in Figure 7A. We map the location coordinates of the ports into the matrix columns and rows. MATLAB is used as it offers an A* pathfinding package (plannerAStar) that we found sufficiently fast. This algorithm uses 8 degrees of freedom, 4 for vertical and horizontal movements and 4 for diagonal movements. One vertical and horizontal movement represent 0.18 nautical miles. The distance represented by the diagonal movements is roughly 1.41 times the distance represented by the vertical and horizontal movements. Figure 7B shows a result of a pathfinding process. The blue square represents the starting point, while the blue star represents the destination. The orange line reflects the shortest route, and the orange area represents the explored space.

The resulting routes may not be as accurate as those generated by commercial software, as they do not consider factors such as vessel draft and sea depth. After conducting five random distance calculations, our results were always lower than those from the commercial software but consistently within 90% of their values. Nevertheless, it is nearly accurate, and we deem it sufficient for our purposes. The whole process produces a distance Table between all ports in the region.

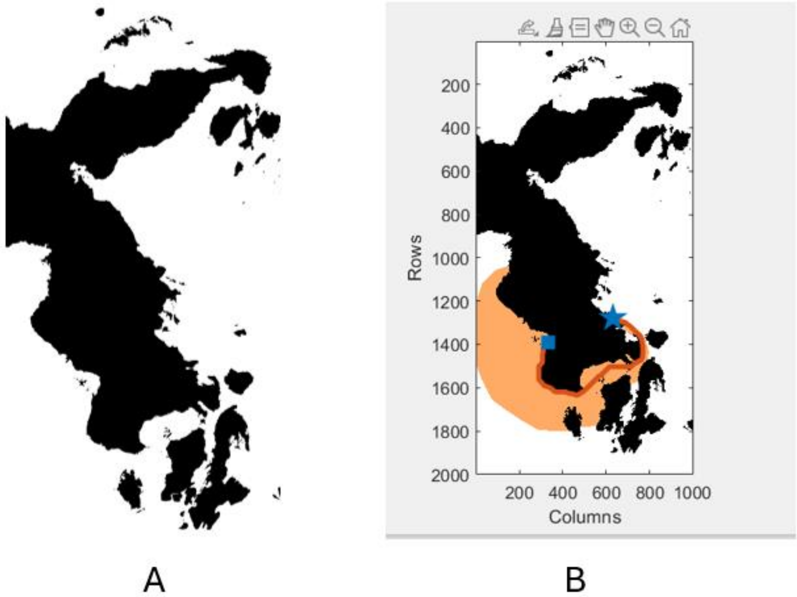

Figure 7 (A)Visual representation of the binary matrix of the region from QGIS and (B) Result visualization from pathfinding process using A.*

4.1.2 Optimized Mine-to-port Routes

There are many possibilities of routes to get ore supply to a port from a mining site and we want to obtain the routes that minimize the unit logistic cost from mining sites to ports using the land and sea distance tables and the following equations from collected data previously mentioned:

$$CL_{m,p}^{truck}\ (\$/ton) = 0.19 \times \text{distance (in km)} \quad (1)$$

$$CL_{m,p}^{vesel}\ (\$/ton) = 3.1172 + 0.0184 \times \text{distance (in nautical-mile)} \quad (2)$$

We only allow one transit location along each route to avoid the cost incurred from additional ore handling. This means that the route will either be a truck mode straight to the destination port or from the mining site to the transit port then to the destination port. For cases where the port and mining sites are located on different islands, the route can only be the latter. To obtain the optimized multi-modal route, first, we create a weighted graph where the edges represent the cost between all combinations of mines and ports and all pairs of ports. Then we use the Dijkstra algorithm to get the cheapest routes. The output of this process is a table that contains unit logistic costs from all mining sites to all ports and their associated routes. We will use this table as logistic cost parameters used in the main supply chain optimization model. Figure 8 illustrates a graph of a sample set of mining sites (green nodes) and ports (blue nodes) where, for example, the cheapest route from site 3 to port 4 are through port 6 costing 0.18+0.1= 0.28 unit cost. We assume that the material handling cost for transportation is calculated per unit of weight and is already incorporated into the unit logistic cost, thereby eliminating any fixed cost.

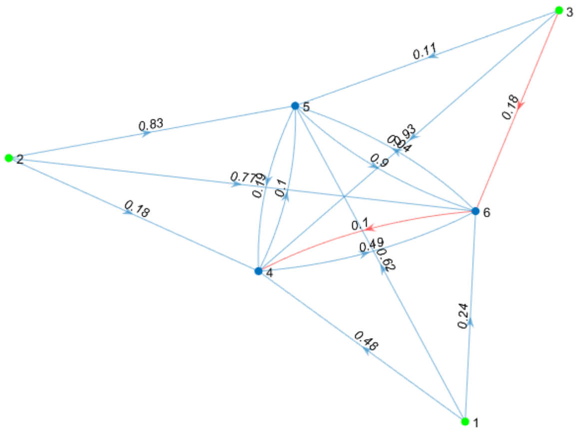

Figure 8 Weighted graph that illustrates multi-modal routes.

As a consequence of equations (1) and (2) mining sites located close to a port will have generally low unit logistic cost to all ports in the region. Mining sites with no surrounding port will have higher unit logistic costs dominated by truck costs. Figure 9 visualizes a mining site (orange) that is located near (left) and far from the shoreline (right) and ports (blue) with their associated logistic costs. As can be seen the mining site on the left has relatively lower logistic costs compared to the mining site on the right.

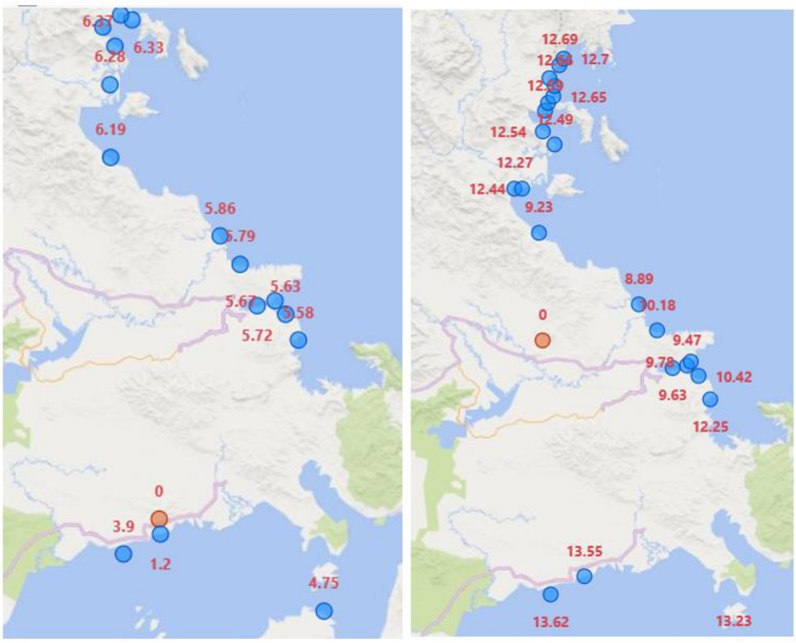

Figure 9 Unit logistic costs for a mining site(orange) to ports as potential smelter locations(blue) where the mining site is located near (left) and far (right) from the shoreline.

4.2 Supply Chain Mathematical Formulation

We aim to establish a nickel ore supply chain system that helps avoid ore understock in response to the surge in new smelters due to the nickel ore export ban policy, while at the same time design a network of smelters that can efficiently process the ore supplies in Sulawesi region by lowering the logistic and construction cost. This requires a strategic resource extraction policy that ensures a stable supply of ore, allowing smelters to operate economically. The government as the mining rights approver is responsible in shaping the ore supply chain system by implementing the extraction policy as well as designing the network of smelters and mines. The mining companies are incentivized to maximize their ore production during their concession period. Our formulation is developed to capture the complexities and constraints in achieving the above objective.

The objective function of the formulation is to minimize construction and logistic costs, deciding on where to open the smelter and how supplies of ore are distributed. The extraction policy dictates during which period a mine can start extracting, so all smelters have a minimum amount of supply relative to their capacities to operate economically within the planning horizon. This requires introducing a critical constraint that distinguishes our formulation from typical FLP. We define this constraint as the economically sustainable constraint. Once a mine starts the extraction, we assume it continues extracting until the resource is depleted. If the mining rights expire before the resource is depleted, it is more beneficial for the mining companies to extend their rights at an additional cost rather than abandoning the remaining resources and conducting land rehabilitation. Additionally, as the consequence of the nickel ore export ban, we assume that all ore produced in the region must be processed by the generated smelters during the same period it is produced. Hereafter, we will refer to this model as the first model.

The mathematical formulation can be written as follows.

Sets:

Mining sites $\boldsymbol{M} = \{1, 2, 3, m, \ldots, M\}$

Ports (potential smelter locations) $\boldsymbol{P} = \{1, 2, 3, p, \ldots, P\}$

Periods (represent quarters) $\boldsymbol{T} = \{1, 2, 3, t, \ldots, T\}$

Parameters:

Ore production at site m (tonnes/period): $\mathrm{Prod}_m, m \in \boldsymbol{M}$

Logistic cost per unit weight of ore ($/tonnes): $\mathrm{CL}_{m,p},\ m \in \boldsymbol{M},\ p \in \boldsymbol{P}$

Smelter Construction cost per capacity ($/ton): CC

Minimum installed smelter capacity (ton/period): $MinCap$

Minimum use of smelter processing capacity (%):$MinCapUse$

Number of periods site m can produce: $Life_m$

Sufficiently big number: B_1

Variables:

Smelter selection: $S_p \in \{0,1\}, p \in \boldsymbol{P}$, $S_p = 1$ if a smelter is opened at port p ,else $S_p = 0$

Capacity of smelter p (tonnes/quarter): $Cap_p \geq 0, p \in \boldsymbol{P}$

Ore supplied from site m to smelter p in tonnes at period t: $Sup_{m,p}^t \geq 0, p \in \boldsymbol{P},\ m \in \boldsymbol{M}, t \in \boldsymbol{T}$

Production start for mining site m:

$q_m^t \in \{0,1\}$, $q_m^t = 1$ if site m starts production at period t, else $q_m^t = 0$

Production state for mining site m:

$y_m^t \in \{0,1\}$, $y_m^t = 1$ if site m is producing at period t, else $y_m^t = 0$

Objective function:

$$min \sum_{m=1}^{M} \sum_{p=1}^{P} \sum_{t=1}^{T} Sup_{m,p}^t \times \mathrm{CL}_{m,p} + \sum_{p=1}^{P} CC \times Cap_p \qquad \forall\, m, p, t \qquad (2)$$

Subject to:

$$\sum_{p=1}^{P} Sup_{m,p}^t = Prod_m^t\,, \qquad \forall\, m, t \qquad (3)$$

$$\sum_{m=1}^{M} Sup_{m,p}^t \leq Cap_p, \qquad \forall\, p, t \qquad (4)$$

$$\sum_{m=1}^{M} Sup_{m,p}^t \geq MinCapUse \times Cap_p \qquad \forall\, p, t \qquad (5)$$

$$MinCap \times S_p \leq Cap_p \qquad \forall\, p \qquad (6)$$

$$B_1 \times S_p \geq Cap_p \qquad \forall\, p \qquad (7)$$

$$\sum_{t=1}^{T} q_m^t = 1 \qquad \forall\, m, t \qquad (8)$$

$$q_m^t \leq y_m^{t+i}\ , i \in \{0,1,2,\ldots, Life_m\}, \qquad \forall\, m, t \qquad (9)$$

$$\sum_{m=1}^{M} y_m^t = Life_m \qquad \forall\ m, t \qquad (10)$$

Equation (2) minimizes the total logistic cost and construction cost for smelters. Equation (3) ensures the total supply from a mining site to all smelters equals the ore production of that mining site to ensure ore balance within the system. Equation (4) limits the total ore supply to smelter p to its processing capacity in each time period t. Equation (5) requires a minimum supply to all smelters so they can operate economically (economically sustainable constraint). Equations (6) and (7) dictate that the minimum installed smelter capacity is satisfied if a smelter is opened (i.e. $S_p = 1$). Equation (8) ensure that the mines start the production only once while equations (9) and (10) ensure that once a mining site start producing it will be continuously producing until it is depleted.

In the second model we allow some level of assignment preference to the mining sites. As the mining companies want to have low logistic costs, they are only willing to supply N smelters with the lowest unit logistic cost out of available (opened) smelters decided by the whole system. In our case we use $N = 2$, but for generality we keep the notation N in the formulation. For that purpose, we add the following variables and equations to the equations (2) to (10) in the original model. Hereafter, we will refer to this model simply as the second model.

Sets:

Set $\boldsymbol{PO^m}$ that contains a list of ports ordered from the closest from mining site m, with index j:

$\{PO_1^m, PO_2^m, PO_j^m, \dots\}$, where $j \in \{1,2,3,\dots,P\}$, $m \in \boldsymbol{M}$, $PO_j^m \in \boldsymbol{P}$

Parameters:

Sufficiently big number: B_2

Number of allowed smelters to be supplied by a mining site: N

Variables:

Indicate smelter selection of PO_j^m:

$\rho_j^m \in \{0,1\}$, where $\rho_j^m = 1\ if\ \ S_p = 1$, else $\rho_j^m = 0$, where $p = PO_j^m$

Indicate allowed supply assignment (due to preference) from site m to port PO_j^m:

$K_j^m \in \{0,1\}$, $m \in \boldsymbol{M}, j \in \{1,2,3,\dots,\boldsymbol{P}\}$

Auxiliary variables 1: $g_j^m\ \ m \in M$

Auxiliary variables 2: $w^m\ \ m \in M$

Constraints:

$$K_j^m - g_j^m \leq 0 \qquad \forall\, m, j \qquad (11)$$

$$K_j^m - \rho_j^m - g_j^m + 1 \geq 0 \qquad \forall\, m, j \qquad (12)$$

$$\sum_{i=1}^{j-1} K_j^m + B_2 \times g_j^m \geq N \qquad \forall\, m, j \qquad (13)$$

$$K_j^m \leq \rho_j^m \qquad \forall\, m, j \qquad (14)$$

$$\sum_{i=1}^{j-1} K_j^m + g_j^m \leq N \qquad \forall\, m, j \qquad (15)$$

$$\sum_{j=1}^{P} K_j^m - \sum_{j=1}^{P} \rho_j^m \leq 0 \qquad \forall\, m \qquad (16)$$

$$\sum_{j=1}^{P} K_j^m \leq N \qquad \forall\, m \qquad (17)$$

$$\sum_{j=1}^{P} K_j^m - \sum_{j=1}^{P} \rho_j^m + B_2(1 - \mathrm{w^m}) \ \geq 0 \qquad \forall\, m \qquad (18)$$

$$\sum_{j=1}^{P} K_j^m + B_2 \times \mathrm{w^m} \ \geq \mathrm{N} \qquad \forall\, m \qquad (19)$$

$$K_j^m \times Prod_m^t \geq Sup_{m,p}^t \ , \text{ where } p = PO_j^m \qquad \forall\, m, j, t \qquad (20)$$

To clarify, we refer to ports as potential locations for smelters and the selected locations as smelters. Both are represented by the same index p. In this model, we first create a set $\boldsymbol{PO}$ for each of the mining sites, containing all ports ordered from the lowest logistic cost. Then we introduce new variables ρ_j^m which capture smelter location selection of the main optimization system with index j associated with $\boldsymbol{PO}$**.** The variables K_j^m represent the allowed supply target of mining site m due to the preference of the mining companies. Equation (11) to (14) dictates that $K_j^m = 1$ only if $\rho_j^m = 1$ (equivalently, port PO_j^m is selected as smelter location) and smelter PO_j^m is one of the N smelters with the lowest logistic cost from mining site m. Equation (16) to (19) ensure that in case there are only less than Nselected smelter locations, then the mining sites will allow any selected smelter location to be supplied rather than N smelters. The equation (20) connects the supply arrangements in the smelter location selection equations with the equations related to the preference of the mining companies.

4.3 Reducing Computational Complexity

Due to the multitude of the number of variables, constraints, and complexity of the formulation, solving the second problem is highly challenging. In the initial attempt, the solver did not produce a feasible solution even after 6 hours of runtime. Therefore, it might be necessary to find ways that help simplify the model so that it can be solved within a reasonable duration. There are some options which include reducing the time resolution of the period variables. Currently, we are using quarterly resolution, hence for ten years of planning horizon, the total number of periods is forty. Modifying the time resolution to annual will reduce the number of variables and constraints that are looped over the time periods to a quarter. Nevertheless, given the combinatorial complexity of the problem, this reduction may not sufficiently simplify the formulation to ensure that it is solvable within a reasonable duration. Moreover, by significantly reducing the periodic variables, we suppress allocation flexibility throughout the planning horizon.

We can apply more variable reduction by not declaring assignment variables that we believe will end up assigned as zeros. For example, since the model will generally generate the assignment of smelters and mining sites with close or low logistic costs, we can avoid creating variables with relatively high logistic costs (this can equally be achieved by setting the upper bound of those variables to zero). A simple way to apply this is first by ordering the ports by the logistic cost for each mining site and setting the assignment variables for the fourth or both the third and fourth quantiles of that ordered list of ports to be zeros. However, by doing this we can expect lower solution quality as we effectively apply more constraints to the model. Furthermore, similar to reducing time resolution, this strategy might not sufficiently reduce computation complexity.

4.3.1 Splitting into Clusters

For more significant computation complexity reduction, we can divide the problems into k sub-problems and solve them separately. By applying this, the number of assignment variables which are indexed by port and mining site is reduced to k^{-2} of the original numbers for each subproblem. To minimize the solution's quality degradation, we can start with the minimum number of clusters, *k=2,* and see if it improves computation time sufficiently. In addition to creating sub-problems with a fairly equal number of ports and mining sites, the clustering was intended to create clusters where, for each cluster, the aggregated logistic costs between its members are minimized. For this purpose, we cannot use Euclidean distance-based clustering algorithms as the Euclidean distances do not necessarily reflect logistic costs. Instead, we will implement a graph-based clustering technique. We can consider the network of ports and mining sites as bipartite graphs, where one set of nodes represents mining sites, and the other set represents ports. Each of the mining nodes is connected to all port nodes, with edges reflecting the logistic costs (see Figure 10).

For simplicity in the formulation, we will use clusters 0 and 1, making it easier to incorporate the cluster number into the equation. The clustering algorithm can be represented as a simple MILP formulation with the following descriptions.

Parameters:

Average logistic cost from mining site m to all ports: $\overline{\mathrm{CL}_m}$

Clusters: $c = 0$ for cluster 0 and $c = 1$ for cluster 1

Variables:

Indicate mining site m is included in cluster c:

$U_m^c \in \{0,1\}, U_m^c = 1$ if mining site m is included in cluster c, else $U_m^c = 0$

Indicate port p is included in cluster *c:*

$V_p^c \in \{0,1\},\ V_p^c = 1$ if port p is included in cluster c, else $V_p^c = 0$

Indicate mining site m and port p are in the same cluster:

$Z_{m,p} \in \{0,1\}, Z_{m,p} = 1$ if mining site m and port p are in the same cluster, else $Z_{m,p} = 0$

Objective function and constraints:

$$min \sum_{m=0}^{M} \sum_{p=1}^{P} (\mathrm{CL}_{m,p} - \overline{\mathrm{CL}_m}) \times \mathrm{Z}_{m,p} \qquad \forall\, m, p \qquad (21)$$

$$\mathrm{Z}_{m,p} - U_m^c - V_p^c + 1 \geq 0 \qquad \forall\, m, p, c \qquad (22)$$

$$\mathrm{Z}_{m,p} + U_m^c + V_p^c - 1 \geq 0 \qquad \forall\, m, p, c \qquad (23)$$

$Z_{m,p} - U_m^c + V_p^c - 1 \le 0$	$\forall\, m, p, c$	(24)
$Z_{m,p} + U_m^c - V_p^c - 1 \le 0$	$\forall\, m, p, c$	(25)
$\sum_{p=1}^{P} V_p^1 \le P \times 0.5 \times\ 1.25$	$\forall\, p$	(26)
$\sum_{p=1}^{P} V_p^1 \ge P \times 0.5 \times\ 0.75$	$\forall\, p$	(27)

The objective function in equation (21) reflects the summation of values that reflect logistic cost for pairs of port and mine that are located in the same cluster. Notice that instead of minimizing the logistic cost directly, we use ($\mathrm{CL}_{m,p} - \overline{\mathrm{CL}_m}$) to reflect how low the logistic cost is from m to p in comparison with the average logistic cost of all ports to m. This creates more polarized sets of ports; thus, the model can easily divide between 'distant' and 'close' ports. Equations (22) and (23) ensure $Z_{m,p} = 1$ when m and p are in the same cluster. Conversely, equations (24) and (25) ensure $Z_{m,p} = 0$, when they are not in the same cluster. Equations (26) and (27) ensure two important conditions are met: 1) ports and mines are not exclusively included in separate clusters, and 2) there are comparable number of ports in both clusters. Without equations (26) and (27), the model will produce one cluster composed entirely of ports and another composed entirely of mining sites. As seen in equations (26) and (27), instead of exactly divide the ports equally for each cluster, we allow one cluster to have more ports than the other (by using the factors 1.25 and 0.75) so the model can have more flexibility in determining the cluster that minimize ($\mathrm{CL}_{m,p} - \overline{\mathrm{CL}_m}$) for each port. Without these factors, we will have the same number of ports for each cluster, but we will find ports that belong to a cluster with mining sites that have higher logistic cost compared to the mining sites in the other cluster. With Gurobi, the computation time for solving this formulation is 12 seconds. The result is shown in Figure 11.

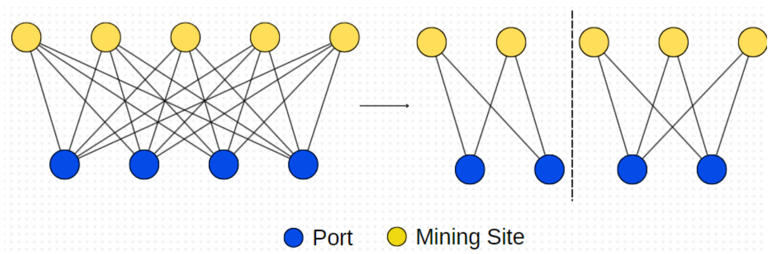

Figure 10 Graph representation of ports and mining sites before and after clustering

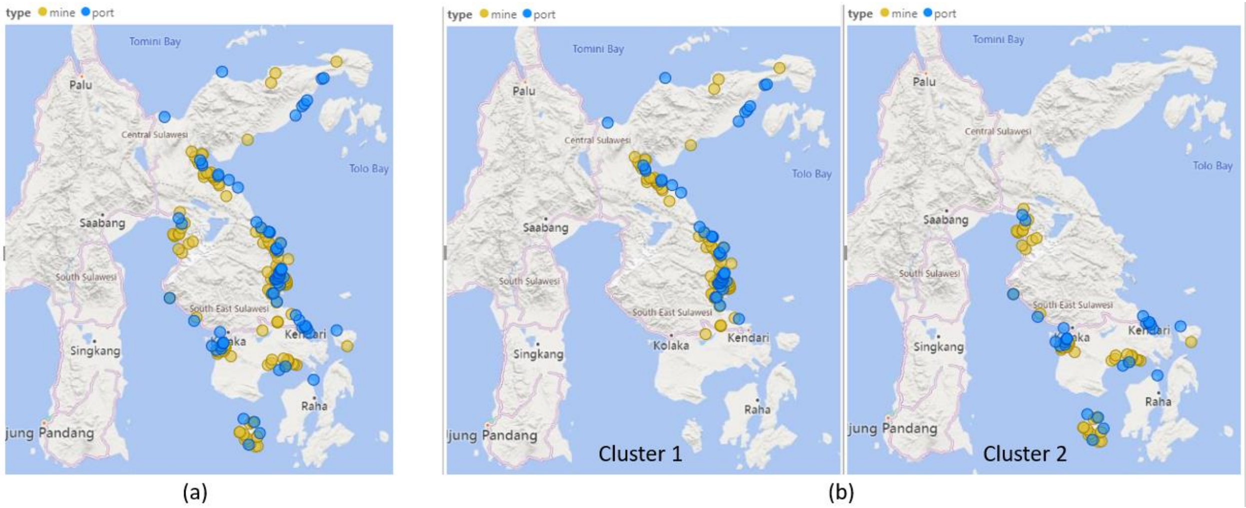

Figure 11 Ports and mining sites in the original problem (a) and the clustered sub-problems (b).

4.3.2 Resolving Suboptimality

The optimization problems for clusters produced from previous splitting (section 4.3.1) can now be solved with significantly lower computation time, as each cluster has a reduced number of ports and mine nodes compared to the original problem. We will refer to the process of optimizing the clustered sub problems as Step 1 process. Solutions from Step 1 are only a subset of the original full problem's solutions. Consequently, the combined solution from Step 1 is potentially suboptimal. To improve this situation, we can look for possible partial solutions that were not considered in the clustered problems and modify the existing solution if those solutions have better objective value.

As seen from the result of Step 1, the second model creates more localized solutions, i.e. all mining sites are assigned to relatively ‘closer’ (according to lower logistic cost) ports. This contrasts to the result from the first model, where we can find mining sites assigned to distant ports. Given these facts, it is safe to assume that assignments in the parts that are located far away from the splitting point are relatively more optimal; with the splitting point defined as the shoreline position dividing the two clusters. It is less likely to get improvement from exploring partial solutions around the parts that are far from the splitting point than from the parts that are close to the splitting point because some possible supply assignments around the splitting point were not previously considered as they belong to different clusters. Hence, we first focus the exploration on the locations close to the splitting point.

Figure 12 illustrates explorations of solutions around the splitting point. By looking at the solutions from both clusters we can decide how much further from the splitting point we can consider for the new solution space to explore. We create the new partial solution exploration space as large as possible to allow new possible partial solutions but as small as possible to not include solutions that are less likely to improve. Moreover, the new problem should be smaller than the previous clusters so it can be solved within a reasonable computation time. In this case, we include two ports that are selected as smelter locations from both sides of the clusters in addition to surrounding unselected ports and mining sites, by visually inspecting the solution of Step 1.

To ensure that the new partial solutions do not clash with the preserved solution, we add constraints to nodes that are involved in both the new and preserved solutions. Hence, the overall solution from this exploration is at least as good as the solution from Step 1. For example, if, from Step 1, smelter is opened at port p (hence, smelter p) and it is included in the new partial solution exploration but one of the mining sites the smelter p is supplied from, e.g. mining site m, is not included in the new partial solution exploration, then the constraints related to the capacity of smelter p in the new partial solution exploration must accommodate supply from mining site m, in addition to supply from mining sites in the new partial solution exploration. Similarly, if smelter p is not included in the new partial solution exploration and mining site m which supply the smelter p is included in the new partial solution, then the constraints related to supply assignments of mining site m in the new partial solution exploration must accommodate supply assignment from mining site m to the smelter p. These constraints are reflected in the dash lines and circles shown in Figure 12. The dashed line represents the supply assignment value, while the dashed circle represents the capacity value that must be enforced in the new partial solutions to ensure the preserved solution is feasible. The partial solution from this exploration will be used to modify the solution from Step 1 resulting in complete solution. We will refer to this process as Step 2 process.

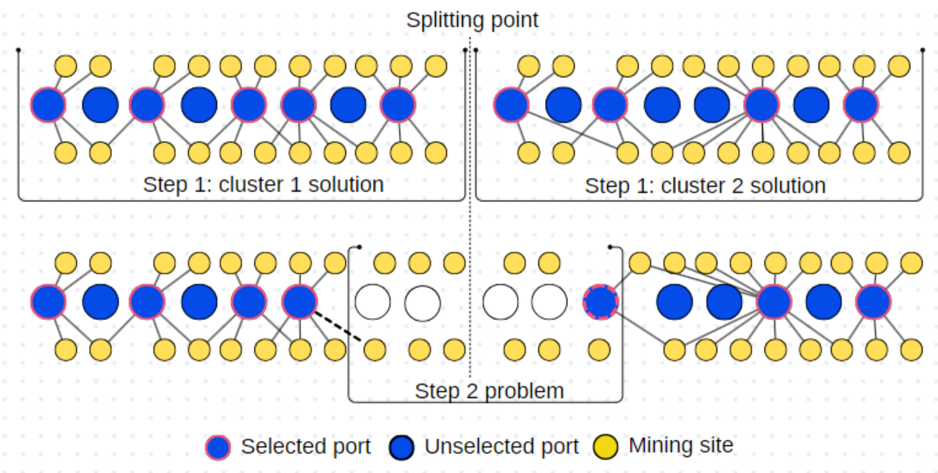

Figure 12 Solution exploration around the splitting point.

The Step 2 solution might result in a change of cluster and supply assignments for mining sites that are very close to the splitting point. In that case, these mining sites are likely to be assigned to the 'closer' smelters, which were previously located in different clusters. The change of assignments can influence the optimal assignment of the neighboring locations, which eventually propagate to locations further from the splitting point, especially when supply assignments are interconnected. In other words, the current solution for each cluster (that is now may have slightly different members) is potentially not optimal. To improve the quality of our current solution (produced from Step 2) we can do an optimization process for each cluster as done in Step 1 once again, which is Step 3. In Step 3 we can use the values of the variables from the Step 2 solutions as a starting point for exploring improved solutions.

5 Result and Discussion

5.1 Optimization Result

In this study, computational works for optimization were conducted using Gurobi Optimizer (version 11.0), a widely used software for solving mixed-integer linear problems. The calculations were performed on a portable computer equipped with an Intel Core i7-9750H CPU containing 6 cores and 12 threads running at a base clock speed of 2.6GHz. The system was supported by 16 GB of DDR3 RAM and 1 TB NVMe SSD. Python programming language was used as a scripting interface.

Our formulations are intended to find the minimum total logistic and smelter construction costs by determining (1) the smelter locations, (2) supply assignments between mining sites and selected smelter locations, and (3) extraction commencement for each of the mining sites within the planning horizon. It is important to note that a mining site can supply multiple smelters and a smelter can be supplied from multiple mining sites. Also, the supply assignments are dynamic; they may change from one period to another. We use a quarter to represent a time period within a 10-year planning horizon, resulting in a total of 40 periods.

We consider two main scenarios of supply chain mechanisms. The first model does not consider the preferences of the mining companies. In the second model, the mining sites can only supply N closest smelters because the mining companies prefer to have low logistics costs. The first model was solved directly with one step of calculation. The second model, due to its scale and complexity, went through four stages of calculation. First, splitting the original problem into subproblems using graph-based clustering. Second, optimizing the subproblems separately. Third, by exploring new partial solutions at the ports and mining sites around the splitting point and use it to modify the combined solutions from the previous stage creating a new complete solution. And finally, we use that complete solution as starting point to explore solutions that can produce lower objective value. To easily review the result, especially for the resource extraction sequence and supply assignments, we setup an online web-based visualizations both the first[2] and second[3] model. In these interactive visualizations, we gain a clear understanding of what the solutions mean in the context of ore supply assignments in multi-period settings. There are four visualization pages for each model. The first page shows the general information about the solution such as the total costs and the locations of the smelters. The second page shows information related to the mining sites. This includes the ore production lifespan, the starting period of

[2] https://app.powerbi.com/view?r=eyJrIjoiYWE2ZTEwMGEtOTcyYi00ZmQ4LWIyZDYtYzQ1MDk2Njg3MTdiIiwidCI6ImRjOGI2M2Y2LWE1NmUtNDliMS04ZGU3LWQ2ODQyMjlhYTkwYyJ9

[3] https://app.powerbi.com/view?r=eyJrIjoiYzg0MTczODItNDAwNC00MTk3LTkyNWQtNmY0MzU1MmJjODRiIiwidCI6ImRjOGI2M2Y2LWE1NmUtNDliMS04ZGU3LWQ2ODQyMjlhYTkwYyJ9

production, and the supplied smelters for each period in the planning horizon. The third page shows information related to the smelters such as the smelters capacities and the mining sites that are served for each of the smelters throughout the planning horizon. The final page presents a Gantt chart illustrating the sequence of mine extraction activities in the region.

5.1.1 First Model

Within the first model, we consider two types of formulations. In the first formulation, all possible combinations of supply assignments were included. The second formulation aims to obtain a solution more quickly, potentially with lower quality, by excluding a combination of mining sites and ports that are located far apart (with high logistic cost). This can be done by simply ordering ports (as potential smelter locations) by logistic cost (from the lowest) for each of the mining sites and including only the first and second quantiles. Later, we can evaluate how solutions are degraded from this method. The first formulation has 364548 continuous and 2198 binary variables (after *Gurobi* pre-solve). The minimum gap is set to 1% with an 18000-second time limit. The maximum time limit is reached with a gap of 1.25%. The result is summarized in Table 2. In that table, the total capacity refers to the sum of capacity of all the smelters. The utilization rate is defined as the amount of ore processed by a smelter in a time period divided by the smelter capacity. The average utilization rate is the utilization rate averaged over the smelters and the periods.

There are 16 selected smelters costing 1,455,833k USD in total. The total logistic cost is 949,457k USD, making the overall cost 2,405,291k USD. Both types of cost are comparable, reflecting how the model needs to balance the number of smelters to add that can minimize the logistic cost with the total construction cost. Despite no fixed cost incurred for building a smelter, generating numerous smelters with lower capacities to minimize logistic cost is not allowed due to the minimum smelter capacity constraint (equation (6)). Additionally, the economically sustainable constraint, which requires smelters to operate at least 80% utilization rate (equation (5)) during the planning horizon, makes it even less likely.

Table 2 Result from the first model.

Total Cost (usd)	Construction Cost (usd)	Logistic Cost (usd)	Number of Smelters	Total Capacity (tonnes/quarter)	Average Utilization Rate
2,405,291 k	1,455,833 k	949,457 k	16	5,514,520	0.9558

Figure 13 (left) shows how smelters are spread in the region. The size of the bubbles reflects the size of the ore resource and the processing capacity of the smelters. In general, the selected smelters tend to be located at locations where surrounding mining sites can provide sustainable supply. We can find some areas where numerous mining sites exist with various sizes of ore resource, but no nearby smelter is selected because the combined supply is still below the required minimum capacity for building a smelter or the extraction rate is too fast that it cannot sustainably supply a smelter along the planning horizon. Figure 13 (right) shows samples of smelters and their assigned mining sites, illustrating that some smelters have more localized supply assignments while others have mining sites spread across the region.

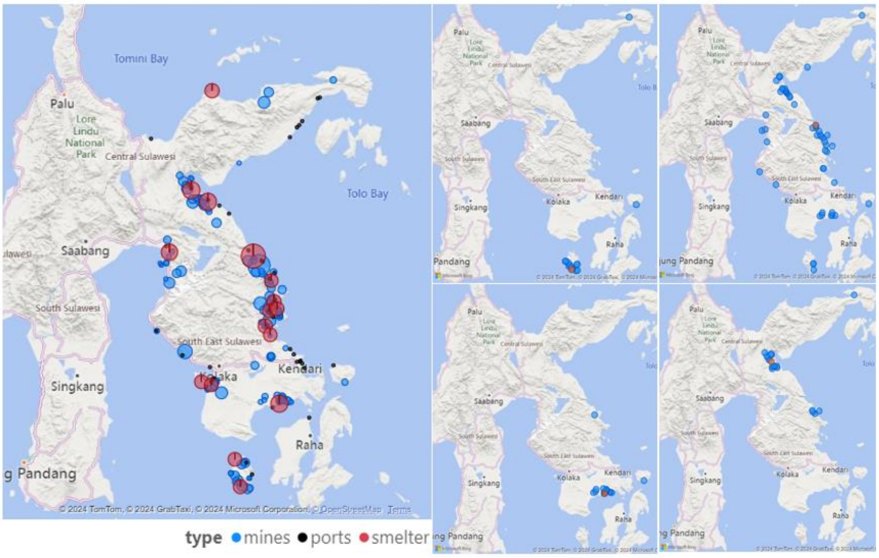

Figure 13 Smelter locations and samples of smelters and mining sites assignments in first model.

It is also interesting to see that some mining sites are assigned to smelters with high logistic costs, though smelters with lower logistic costs do exist. In this case, we can assume that the model chooses to assign the mining sites to other smelters that need more supplies for a stable input rather than increasing the capacity of the closer smelter to accommodate supply from that mining site, especially when those mining sites have only a limited number of extraction periods. To test this assumption, we set up multiple smaller cases, each using about a third of the mining sites and ports from the original problem and optimized them using the same formulation as the first model with modifications in the minimum capacity use, construction cost, and logistic cost. The result is the model generates more clustered/localized assignments, as we see in common FLP, only if the minimum capacity used is significantly decreased (allowing unstable input) in addition to increasing the logistic cost and decreasing the construction cost for a more dramatic effect. This signifies the distinction of our problem with common FLP as a result of variability in the mining site lifespan and the sustainability constraint.

Figure 14 shows the total amount of ore produced for each period in the region, represented as a bar chart. Different colors within a bar represent different mining sites, with the length of each color indicating the amount of ore produced by that site. Figure 15 shows a sample of smelters and the amount of ore supplied from different mining sites for each period. Despite the model assignment for some mining sites and smelters that are located far from each other, it offers the advantage of maintaining a high utilization rate. The average utilization rate is 0.9558, significantly higher than the minimum allowed of 0.8. Looking at individual smelters, we can see that some have a consistent 100% utilization rate, while others experience fluctuating inputs of ore. The smelter with a stable 100% utilization rate is in an area where most of the surrounding mining sites have a long lifespan (at least equal to the planning horizon). The dynamic assignments allow the model to flexibly assign ore supplies to underutilized smelters, leading to a high overall utilization rate. To provide more clarity and avoid an overcrowded chart, the mine extraction sequence can be viewed in the online visualizations (page 4) mentioned previously.

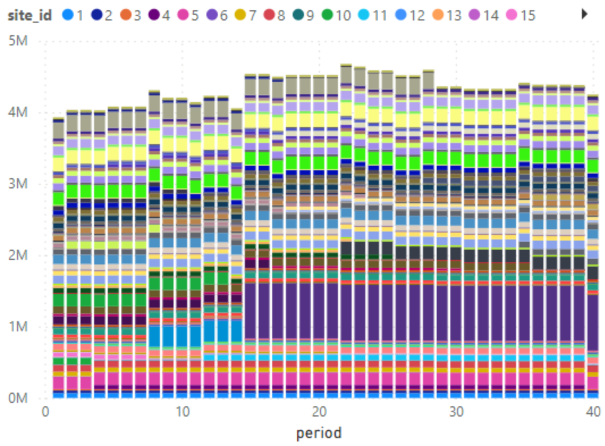

Figure 14 Total processed ore over the periods (first model). Different colors and bar length represent different smelters and amount of ore supply for each period.

Figure 15 Processed ore over the periods for a sample of smelters (first model). Shown above are smelters 63, 22, and 44 with their assigned mining sites over the periods indicated by the colors.

We apply variable reduction by using only the first and second quantiles of the ports for each mining site (as mentioned in subchapter 4.3) to see how computation time can be reduced. There are now 182146 continuous and 2198 binary variables. The computation time is also reduced to only 9277 seconds, with a 0.95% gap. The decrease in computation time is almost proportional to the variable reduction. As expected, this formulation produces a lower solution quality of 2,480,111k USD, 3% higher than the previous solution. The model generates precisely the same overall smelting capacity with the same average utilization rate but less in the number of locations. Despite the restrictions of assigning mining sites to smelters that are too far apart, it creates more mining sites not to be assigned to the closest smelters, leading to higher overall logistic costs. Table 3 shows the result from the second formulation.

Table 3 Result from the first model (second formulation).

Total Cost (usd)	Construction Cost (usd)	Logistic Cost (usd)	Number of Smelters	Total Capacity (tonnes /quarter)	Average Utilization Rate
2,480,111 k	1,455,833 k	1,024,277 k	15	5,514,520	0.9558

5.1.2 Second Model

Formulating the second model requires adding multiple equations, thereby significantly increasing the complexity of the model. Initially, we attempted to solve the problem directly without breaking it down into sub-problems. This formulation has 182,416 continuous and 11,167 binary variables. After 21,600 seconds (6 hours) of computation, the solver has not found any feasible solutions. Consequently, it is necessary to make the model more solvable, in this case, by breaking it into sub-problems.

5.1.2.1 Second Model: Step 1

The location of the ports and the mining sites along the shoreline creates a unique pattern of the logistical network. This pattern resembles a backbone, represented by Figure 12 in the previous chapter. In this configuration, the route from a mining site to any port must first go through the nearest port to the mining site, given the significantly lower cost of using sea routes compared to land routes. Having this type of pattern helps the clustering process to determine a sensible clustering and splitting point, which can be visually verified (Figure 11). The result of the clustering process is presented in Table 4 and Figure 11.

To further reduce the complexity, we apply the assignment variable reduction as applied in the second formulation of the first model. We only consider a possible assignment to the 75% percentile of ports based on the logistic cost for each of the mining sites. It is reasonable to assume that, since the mining sites are only willing to supply the first or second nearest smelters (based on logistic cost), the model will produce a localized assignment. Therefore, while it is possible that the quality of the solution may degrade with this reduction, it is unlikely. After the clustering process, we then solve each of the sub-problems separately, with the result shown in Table 5.

Table 4 Clustering Result

Cluster	Number of Mining Sites	Number of Ports
Cluster 1	58	26
Cluster 2	76	42
No Clustering	134	68

Table 5 Step 1 Result

Cluster	Total Cost (usd)	Construction Cost (usd)	Logistic Cost (usd)	Number of Smelters	Total Capacity (tonnes/quarter)	Average Utilization Rate
Cluster 1	837,797	509,638 k	328,158 k	5	1,930,448	0.9793
Cluster 2	1,736,629 k	1,001,664 k	734,965 k	9	3,794,185	0.8909
Combined	2,574,426 k	1,511,303 k	1,063,123 k	14	5,719,963	0.9207

The first cluster generated 44,106 continuous and 3,245 binary variables with a computation time of 4,351 seconds, reaching 0.87% gap. The second cluster generated 94,120 continuous and 5,602 binary variables, far greater than the first cluster. Due to the large number of variables, the solving process was too slow to reach the preset minimal gap of 1%. The maximum solving time of 66,000 seconds (18.3 hours) was reached, terminating the process at 2.68% gap.

As anticipated, the second model yields a higher objective value because it essentially imposes additional constraints on formulation of the first model. The model did create more localized assignments where the smelters are supplied by surrounding mining sites as seen in Figure 17 (right) compared to Figure 13 (right) from the first model. There are more mining sites with decreased logistic cost (43.28%) compared to those with constant (20.90%) or increased costs (35.82%), as shown in Figure 16. However, in terms of total logistic cost, this model produces 10.69% higher value. This is because of the decrease in the number of smelters selected from previously 16 to 14. The model results in fewer smelters due to the additional constraints. By allowing only the two closest smelters to be supplied by each of the mining sites, a lower number of smelters are preferable. This condition makes it more likely for a smelter to accommodate more mining sites and balance the supply of ore over the planning horizon, thereby satisfying the sustainability constraint. This model also produces higher processing capacity (and thus higher total construction costs) with a lower utilization rate. This localized solution prevents mining sites with suitable production lifetime, which are not in the vicinity, from balancing the underutilized smelters. Figure 18 shows the total ore production throughout the planning horizon, which appears slightly more variable, particularly at period 27, compared to Figure 14 of the first model.

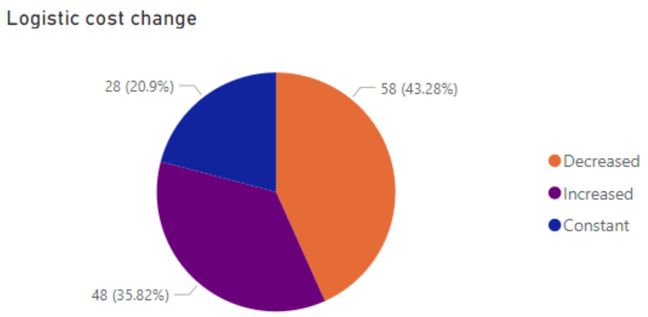

Figure 16 Proportion of mining sites' change in the logistic cost in the second model from the first model.

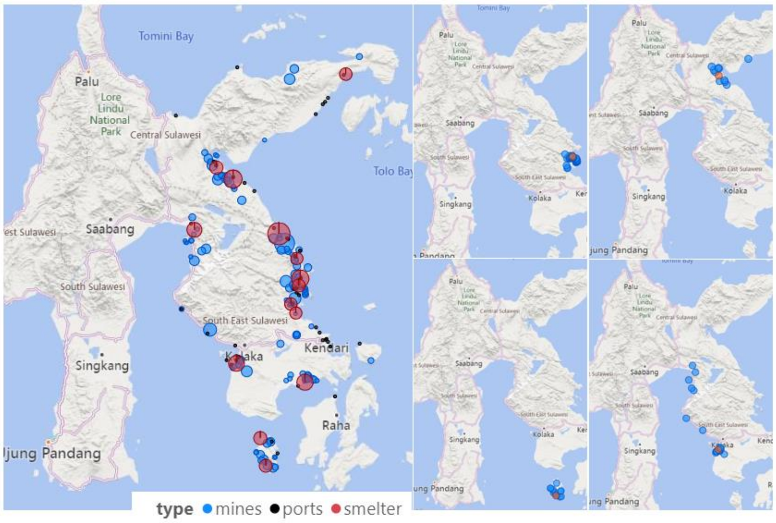

Figure 17 Smelter locations and samples of smelters and mining sites assignments in the second model (Step 1).

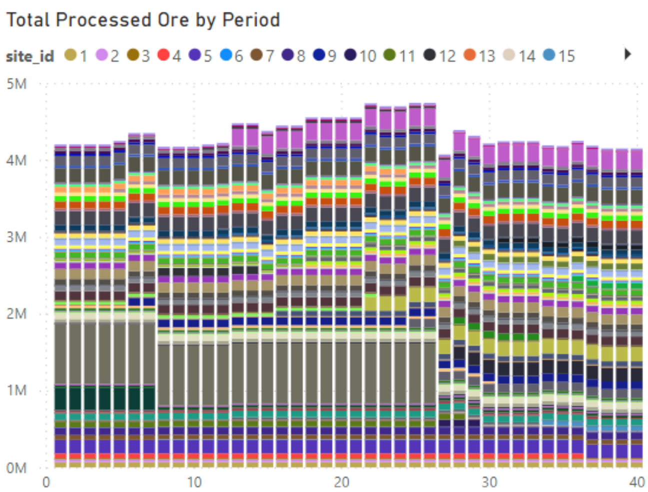

Figure 18 Total processed ore over the periods (second model). Different colors and bar length represent different smelters and amount of ore supply for each period.

5.1.2.2 Second Model: Step 2

At this stage, our objective is to improve suboptimality resulting from solving two subproblems separately (Step 1). To achieve this, we explore new partial solutions by considering a subset of mining sites and ports around the splitting point, covering some areas in both cluster 1 and cluster 2. The subset should include at least two selected locations from each cluster, along with the surrounding mining sites and unselected ports (see Figure 19 and Figure 11 for comparison). Then, we consider this subset as a new problem to optimize. Since there are mining sites outside of this subset assigned to one or more of the locations within this subset and vice versa, we need to add constraints to ensure assignments for locations outside this subset are still valid after solving Step 2. There are 68 mining sites and 25 ports in this subset. With 55,465 continuous and 3,586 binary variables, this step was solved in 1,444 seconds, reaching 0.82% gap. After the solving process is completed, we combine the solution for this subset with the previous solution from the last step. There is one additional smelter selected. Total processing capacities are slightly increased, and a small adjustment of supply assignment was made. It can also be observed that one mining site, which is located close to the splitting point, switched to smelters located in a different cluster throughout the entire planning horizon, lowering its logistic cost. The Step 2 optimization step generates an increase in construction cost by 7k USD and a 4,269k USD decrease in logistic cost. Thus, a total cost decrease of 4,262k USD (0.17%) was made compared to the first step. Hence, we can conclude that the second step improves the logistic costs by removing the partition, allowing assignments that were previously impossible.

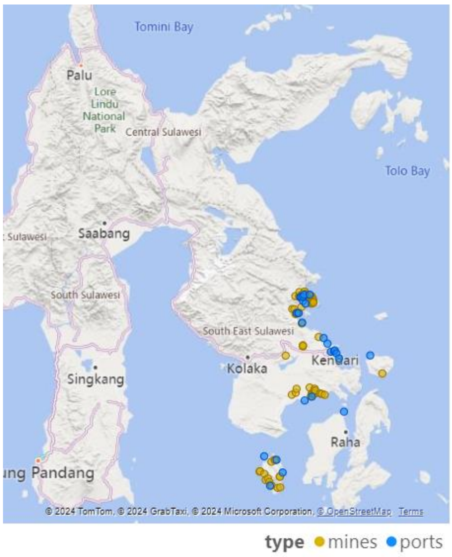

Figure 19 Mining sites and ports that are considered in the Step 2 subset.

5.1.2.3 Second Model: Step 3

The change in cluster structure due to the switching of one mining site in the second step creates further opportunities to explore improved solutions. Therefore, we do separate optimization processes for each cluster once again. To save time, we feed the model with the result from step 2 as a starting solution, facilitated by Gurobi via *mip.Start* function. However, we cannot directly use the continuous variables, as they trigger infeasibility due to possible decimal tolerance problems. Therefore, we provide the model with a partial solution of binary variables and let it calculate the complete solution as a starting point. We set the minimal gap of 1% and 21600 seconds (6 hours) maximum solving time. The first cluster was solved in 5062 seconds with 0.98 gap. Similar to Step 2, the second cluster could not reach a 1% gap within the maximum solving time, terminating the process at a 2% gap. After the solving processes, we combine again the solution, which is shown in Table 6. As can be observed, there is a slight improvement in both logistic cost and construction cost and consequently, the overall utilization rate. The improvement that can be achieved in Step 3 is also reflected in the decreased value of the combined lower bound, which dropped from 2,520,631,302 USD in the first step to 2,515,809,090 USD. However, further improvements seem unlikely because during the Step 3 solving process, the incumbent solution changed during the first few iterations, and the gap decreased mainly because the upper bound increased.

Table 6 Step 3 Result

Total Cost (usd)	Construction Cost (usd)	Logistic Cost (usd)	Number of Smelters	Total Capacity (tonnes/quarter)	Average Utilization Rate
2,563,392 k	1,510,070 k	1,053,322 k	15	5,719,962	0.9215

5.2 Sensitivity Analysis

In this section, we explore the impact of key parameters on the first model to understand their influence on the overall system with sensitivity analysis. For this analysis, we focus on two parameters: the mining production rate factor and the minimum capacity use (equation (5)). The mining production rate factor significantly impacts the optimization model, and it is an estimation with likely high variability. Understanding how variations in the mining production rate affect the model will help in assessing the robustness of the optimization results. On the other hand, the minimum capacity utilization is a crucial parameter for ensuring the smelters operate economically. It controls the amount of ore supply in each period which, in turn, helps shape the mine extraction sequence. The minimum capacity use is determined from an economic feasibility study as a result of various factors such as material costs, nickel product prices, and discount rate. Since these factors can also vary, it is important to assess their impact on the total cost.

We use a ±50% multiplying factor in the mine production rate factor to reflect the variability in the actual production rate factor at the mining sites. An increased factor of 50%, increased the amount of ore supply of the mines by 50% but also decrease their lifespan to $1/1.5 = 0.67$ of the original lifespan. Consequently, the model rearranges the extraction sequence in such a way that there is a stable (relative to total smelting capacity) overall ore supply throughout the planning horizon. In this way, the total ore supply for each period does not increase by 50%. The increase comes from mines with a lifespan greater than the planning horizon. Previously, some proportion of ore from these mines was to be produced beyond the planning horizon. Now, it is to be produced within the planning horizon due to a faster rate of extraction. The average increase of ore supply for each period is 27.82%. The average ore supply per period can be calculated by summing up the total ore produced divided by planning horizon or equivalently by multiplying the total capacity and the average utilization rate. As the consequence of the ore supply increase per period, the total capacity, number of smelters, construction cost, and logistic cost are also increased as shown in Table 7.

Decreasing the mine production rate factor by 50%, decreases the average total ore supply per period but not with the same proportion as the previous scenario (50% increase). This is because in addition to mines with lifespan greater than the planning horizon, other mines with enough lifespan value have a proportion of ore that is previously produced within the planning horizon, now produced beyond the planning horizon due to slower rate of extraction. With more mines having a greater lifespan than the planning horizon, more mines now start producing in the first period. The decrease of average total ore supply per period is 40.54%. Consequently, the total capacity, number of smelters, construction cost, and logistic cost are decreased significantly as shown in Table 7.

Table 7 Result of sensitivity analysis on mine production rate factor

Production Factor Change	Total Cost (usd)	Construction Cost (usd)	Logistic Cost (usd)	Number of Smelters	Total Capacity (tonnes/quarter)	Average Utilization Rate
+50%	3,081,985 k	1,837,852 k	1,244,133 k	18	6,961,561	0.9678
Baseline	2,405,291 k	1,455,833 k	949,457 k	16	5,514,520	0.9558
-50%	1,436,054 k	852,737 k	583,316 k	11	3,230,066	0.9702

We use ±10% change in minimum capacity use to reflect the range of this value to have as a constraint for the smelters to achieve economic operation. As seen in Table 8, there are only small changes, most notably in the logistic cost. A lower minimum capacity use allows smelters to have a wider range of ore supply which, in turn, allows the model to produce supply assignments with lower logistic cost. It is interesting to observe that, despite the reduced restriction on the ore supply for the smelters, the overall average utilization rate does not decrease. This is because, ultimately, the amount of ore supply to be processed is the same. This means that a lower utilization rate during certain periods in certain smelters is compensated with a higher utilization rate during other periods and/or smelters. From a system perspective, this may not pose a significant issue, but from the smelters' perspective, it can cause an imbalance in ore supply between different periods and smelters compared to the baseline model. In the scenario with 90% of minimum capacity use, we found that higher minimum capacity use makes the model less flexible in terms of assigning the ore supply with low logistic cost, resulting in higher total logistic cost. Despite implementing a more restricted (higher) value of minimum capacity use, the average utilization rate remains relatively unchanged. In contrast to the scenario with 70% minimum capacity use, we can expect a more balanced ore supply between different smelters and periods, but this comes with higher logistics cost.

Table 8 Result of sensitivity analysis on minimum capacity use

Min. Capacity Use	Total Cost (usd)	Construction Cost (usd)	Logistic Cost (usd)	Number of Smelters	Total Capacity (tonnes/quarter)	Average Utilization Rate
70%	2,400,584 k	1,455,833 k	944,751 k	16	5,514,520	0.9558
Baseline	2,405,291 k	1,455,833 k	949,457 k	16	5,514,520	0.9558
90%	2,417,082 k	1,456,233 k	960,849 k	16	5,516,036	0.9555

5.3 Managerial Insight

5.3.1 Optimized supply chain network

The optimization model results provide crucial details on how to better manage resource extraction in the region. Comparing Figure 4 with Figure 14 reveals how we have optimally arrange mine extraction sequence that helps ensure a stable supply of ore during the planning horizon. The mine extraction sequence (see page 4 in the online visualizations) can be used by the government as the mining license approval in finding the right period for each of the mining sites to be mined. As mentioned in the first chapter, the existing supply chain network faces issues in maintaining long-term sustainability due to unbalanced supply and demand leading to periods with over- and under-utilization of smelters. By optimizing the assignment of mining sites to smelters in multi-periodic formulations, the models ensure high utilization rates of processing facilities (>90% on average) as shown above. This leads to more efficient operations and better returns on investment. However, this benefit can only be achieved if there is coordination among stakeholders including the mining companies, smelter companies and most importantly the government as the mining license approver.

Based on the result of sensitivity analysis, the mining production rate impacts the overall system significantly, as shown by the difference of number of smelters and the total capacity compared to the baseline. This underlines the importance of obtaining an accurate production rate of the mining sites. If production rate of each mine is controlled (as opposed to the assumption in this study where mines are always producing to the maximum level), using a 50% lower rate of extraction results in higher utilization rate which can be an advantage in terms of return on investment. However, there is potential economic loss by not producing nickel products (as a consequence of lower extraction rate), especially when nickel product demand is high.

The changes in minimum capacity use do not significantly change the optimal number and capacity of smelters. However, lower minimum capacity use allows lower logistic cost but resulting in an unfairness between smelters as they can have different utilization rates. Higher minimum capacity use incurs higher logistic cost with the benefit of balance of utilization rates (hence, fairness) between the smelters.

5.3.2 First Model vs Second Model

The second model was proposed to ensure supply chain stability by allowing the mining sites some level of preference, decreasing the possibility of the mining sites to supply smelters other than their preassigned ones, particularly for those assigned to smelters that are located far apart as we found in the first model. We found that the first model achieves lower overall costs by optimizing facility locations and supply assignments purely based on cost minimization. The second model results in higher overall costs due to the additional constraints. The total cost was 6.58% higher in the second model compared to the first model. Thus, we can observe that by allowing the individual preference of the mining sites to minimize their logistic cost individually, the overall cost of the system is instead increased.

Nevertheless, in a more open market ecosystem, the second model is a more natural approach to mitigating the risk of supply chain disruption. It provides greater stability which is crucial in maintaining the long-term planning of economically sustainable resource exploitation. It also provides logistic cost fairness by establishing more localized supply assignments. In contrast to the second model as natural approach, there are several interventionist instruments that can be applied to ensure supply chain stability, such as:

1. Contractual agreements: establish contracts that specify supply assignments.
2. Control and audit: implement regular audits and control mechanisms to ensure that mining sites comply with their supply assignments.
3. Incentive mechanisms: offer incentives or compensation for mining sites to adhere to their preassigned smelters.

The comparison highlights the trade-offs between cost efficiency and supply chain stability that network designers and decision-makers must address.

6 Conclusion and Future Work

6.1 Conclusion

This study has developed an optimization model for the nickel ore supply chain in Indonesia specifically in Sulawesi region, focusing on resource extraction planning, smelter locations and capacity planning. The implementation of the nickel ore export ban by the Indonesian government has driven the need for a well-structured domestic processing industry. Our model aims to address the challenges posed by the rapid expansion of nickel smelting facilities and the limited nickel reserves.

We use a combination of Dijkstra's and A* shortest path algorithms for constructing land and sea route distance tables, and eventually the logistic cost table. The optimization model balances the logistics and construction costs of smelters in finding the lowest total cost. The introduction of an economically sustainable constraint ensures that smelters operate at an optimal capacity throughout the planning horizon. By comparing the model with (second model) and without (first model) preference to lower the logistic cost individually, we found that while the second model offers a more localized assignment, it incurs higher total costs due to additional constraints.

The formulation in the second model was designed to incorporate preferences of the mining companies, specifically allowing mining sites to select two smelters with lowest logistic costs, thus representing a more natural supply chain system. Initially, the complexity of the second model made it difficult to find feasible solutions. To address this, the problem was split into sub-problems using a clustering algorithm. Each sub-problem was then solved separately, significantly reducing computational complexity. Finally, the solutions from the sub-problems were combined and improved by exploring new partial solutions around the splitting points, further enhancing the overall solution's quality. This approach demonstrated that breaking down the problem into smaller, more manageable pieces could yield feasible and optimized solutions.

The sensitivity analysis revealed how the model's solution is affected by variations in selected key parameters: the mining production rate factor and minimum capacity use. It is important to accurately obtain the production rate factor, as it significantly influences the total cost and optimal extraction sequence. Additionally, changes in the minimum capacity utilization did not affect the number of smelters or their capacities but impacted the balance of ore supply between different periods and smelters.

6.2 Future Work

While this study provides a comprehensive framework for optimizing the nickel ore supply chain, several areas could be improved and expanded upon in future research:

1. Supply chain and mathematical formulation
    - Future models should adopt a more holistic approach by integrating financial calculations. This integration will help in combining the benefit of a high utilization rate into the objective function.
    - Incorporate environmental and social impact assessments, including carbon emissions and ecological footprints, to ensure sustainable mining practices.
    - Develop a multi-objective optimization framework that simultaneously considers economic, social, and environmental objectives that could provide a more balanced approach to supply chain optimization.
2. Solving technique and hardware
    - Exploring advanced heuristics and metaheuristics could improve the computational efficiency of solving large-scale optimization problems, especially for second model. We can try implementing metaheuristics for the second model without clustering and compare it with the current result.
    - Reduce computation time by using high-performance computers for complex optimization problems, especially for the second model.
3. Data gathering
    - Use accurate production rate by using data from mining companies and government agencies related to mining activities. Explore the use of machine learning techniques with geological and physical characteristics of the mining sites as predictors.
    - Obtain more accurate distance data, especially the sea distances, by using commercial software in sea routing to accurately calculate the logistic cost table.

References

[1] "https://www.iea.org/," 12 December 2023. [Online]. Available: https://www.iea.org/policies/16084-prohibition-of-the-export-of-nickel-ore. [Accessed 29 01 2024].

[2] "https://katadata.co.id/," 13 February 2024. [Online]. Available: https://databoks.katadata.co.id/datapublish/2024/02/13/indonesia-negara-penghasil-nikel-terbesar-di-dunia-pada-2023. [Accessed 15 February 2024].

[3] P. Adhiguna, "Indonesia's battery and EV developments are far out of step with its nickel exploitation promise," Energy Shift Institute, Jakarta, 2024.

[4] "https://.nikkei.com," 12 June 2023. [Online]. Available: https://asia.nikkei.com/Spotlight/Market-Spotlight/Nickel-surplus-seen-widening-in-2023-as-Indonesian-output-soars. [Accessed 18 02 2024].

[5] "https://usnews.com/," 30 August 2023. [Online]. Available: https://money.usnews.com/investing/news/articles/2023-08-30/indonesian-nickel-smelters-turn-to-philippines-for-ore-as-local-supply-tightens. [Accessed 18 February 2024].

[6] 28 October 2023. [Online]. Available: https://www.reuters.com/article/indonesia-nickel-idUSKBN31R19Z/. [Accessed 18 February 2024].

[7] "https://jakartaglobe.id/," 23 January 2024. [Online]. Available: https://jakartaglobe.id/business/indonesian-nickel-miners-face-plummeting-prices-and-oversupply-concerns. [Accessed 18 February 2024].

[8] J. IBP, "Indonesia Business Post," Indonesia Business Post, 22 January 2024. [Online]. Available: https://indonesiabusinesspost.com/risks-opportunities/indonesia-still-holds-vast-nickel-potential-with-1-2-million-hectares-untapped/.

[9] F. Dionori and M. Zehtabchi, "The Role of Transport-Related Innovation in the Mining Sector," in *Global Challenges for Innovation in Mining Industries*, Cambridge, Cambridge University Press, 2022, pp. 117-141.

[10] N. S. Body, *Reporting Standard of Mining Resources and Reserves,* Jakarta: National Standard of Indonesia, 2011.

[11] K. Goodenough, B. Upton and R. Ellam, "Geochemical evolution of the Ivigtut granite, South Greenland: a fluorine-rich "A-type" intrusion," *Lithos,* vol. 51, no. 3, pp. 205-221, 2000.

[12] T. Young, J. Baka, Z. He, S. Bhattacharyya and Z. Lei, "Mining, loss, and despair: Exploring energy transitions and opioid use in an Appalachian coal community," *Energy Research and Social Science,* vol. 99 (103046), 2023.

[13] B. Devi and D. Prayogo, "Mining and Development in Indonesia: An Overview of Regulatory Framework and Policies," International Mining for Development Center, Jakarta, 2013.

[14] M. Melo, S. Nickel and F. Saldanha-da-Gama, "Facility Location and Supply Chain Management : A Review," *European Journal of Operational Research,* vol. 196, no. 2, pp. 401-412, 2009.

[15] G. Gosson and L. B. Sminth, "Reasonable Prospects for Economic Extraction," *Canadian Institute of Mining Magazine Online,* pp. https://mrmr.cim.org/en/library/magazine-articles/reasonable-prospects-for-economic-extraction/, December 2007.

[16] Nathan Associates Inc, "Economic Effects of Indonesia’s Mineral-Processing Requirements for Export," United States Agency for International Development, 2013.

[17] H. Haryadi, "The Financial Feasibility Analysis for Construction Plan Of Ferro-Nickel Smelter Plant at South Konawe Regency, South East Sulawesi," *Indonesian Mining Journal,* vol. 20, no. 2, pp. 131-142, 2017.

[18] "https://www.titaninfra.com," 15 September 2022. [Online]. Available: https://www.titaninfra.com/perhitungan-biaya-angkut-batubara/. [Accessed 18 February 2024].

[19] Nurkhamim, H. R. Adha, T. H. Cahyadi, Kresno and Inmarlinianto, "Transportation Fuel Consumption Analysis UD Quester CWE 370 In Nickel Ore Transportation," *Indonesian Mining Professionals Journal,* vol. 5, no. 1, pp. 7-20, 2023.

[20] A. M. Newman, E. Rubio, R. Caro, A. Weintraub and K. Eurek, "A Review of Operations Research in Mining," *Interfaces,* vol. 40, no. 3, pp. 222-245, 2010.

[21] A. B. Jalloh and K. Sasaki, "Geo-statistical Simulation for Open Pit Design Optimization and Mine Economic Analysis in Decision-Making," in *Mine Planning and Equipment Selection*, Cham, Springer, 2014, pp. 93-103.

[22] Z. Gligoric, C. Beljic and V. Simeunovic, "Shaft location selection at deep multiple orebody deposit by using fuzzy TOPSIS method and network optimization," *Expert Systems with Applications,* vol. 37, no. 2, pp. 1408-1418, 2010.

[23] M. W. A. Asad, M. A. Qureshi and H. Jang, "A Review of Cut-off Grade Policy Models for Open Pit Mining Operations," *Resources Policy,* vol. 49, pp. 142-152, 2016.

[24] A. Paithankar and S. Chatterjee, "Open Pit Mine Production Schedule Optimization Using a Hybrid of Maximum-Flow and Genetic Algorithms," *Applied Soft Computing,* vol. 81(105507), 2019.

[25] A. Bley, N. Boland, C. Fricke and G. Froyland, "A Strengthened Formulation and Cutting Planes for the Open Pit Mine Production Scheduling Problem," *Computers & Operations Research,* vol. 37, no. 9, pp. 1641-1647, 2010.

[26] H. Sevim and D. D. Lei, "The Problem of Production Planning in Open Pit Mines," *INFOR,* vol. 36, no. 1-2, pp. 1-12, 1998.

[27] F. A. Consuegra and R. Dimitrakopoulos, "Stochastic Mine Design Optimisation Based on Simulated Annealing: Pit Limits, Production Schedules, Multiple Orebody Scenarios and Sensitivity Analysis," *Mining Technology: Transactions of the Institutions of Mining and Metallurgy,* vol. 118, no. 2, 2009.

[28] S.-O. Gilani and J. Sattarvand, "Integrating Geological Uncertainty in Long-Term Open Pit Mine Production Planning By Ant Colony Optimization," *Computers & Geosciences,* vol. 87, pp. 31-40, 2016.

[29] L. Zeng, S. Q. Liu, E. Kozan, P. Corry and M. Masoud, "A Comprehensive Interdisciplinary Review of Mine Supply," *Resources Policy ,* vol. 74(102274), 2021.

[30] P. Ghadimi, C. Wang, A. H. Azadnia, M. K. Lim and J. W. Sutherland, "Life Cycle-based Environmental Performance Indicator for the Coal-to-energy Supply Chain: A Chinese Case Application," *Resources, Conservation and Recycling,* vol. 147, pp. 29-38, 2019.

[31] P. Benalcazar, J. Kamiński and P. W. Saługa, "The storage location problem in a coal supply chain: Background and methodological approach," *Mineral Resource Management,* vol. 33, no. 1, pp. 5-14, 2017.

[32] H. A. Nasab, Y. Pourrahimian, E. Ben-Awuah and S. Kalantari, "Mixed integer linear programming formulations for open pit production scheduling," *Journal of Mining Science,* vol. 47, no. 3, pp. 338-359, 2011.

[33] C. Burt, L. Caccetta, L. G. Fouché and P. Welgama, "An MILP approach to Multi-location, Multi-Period," *Journal of Industrial and Management Optimization,* vol. 12, no. 2, pp. 403-430, 2015.

[34] J. Fung, G. Singh and Y. Zinder, "Capacity Planning in Supply Chains of Mineral Resources," *Information Sciences,* vol. 316, pp. 397-418, 2015.

[35] L. Canales-Bustos, E. Santibañez-González and A. Candia-Véjar, "A Multi-objective Optimization Model for the Design of an Effective Decarbonized Supply Chain in Mining," *International Journal of Production Economics,* vol. 193, pp. 449-464, 2017.

[36] W. Liu, "A Robust Optimization Modeling for Mine Supply Chain Planning under the Big Data," *Wireless Communications and Mobile Computing,* vol. 2021 (Special Issue), 2021.

[37] A. Fadol, "Optimal Location of a Copper Smelter in Saudi Arabia for Polymetallic Deposits Using a Computerized Numerical Approach," *Engineering Sciences Journal (JKAU: Engineering Science),* vol. 14, no. 2, pp. 119-140, 2002.

[38] F. Qaeze, R. Guillaume and C. Thierry, "A Collaborative Planning Model to Coordinate Mining and Smelting Furnace," in *16th Working Conference on Virtual Enterprises (PROVE)*, Albi, 2015.

[39] T. S. Hale and C. R. Moberg, "Location Science Research: A Review," *Annals of Operations Research,* vol. 123, pp. 21-35, 2003.

[40] S. L. Hakimi, "Optimum Locations of Switching Centers and the Absolute Centers and Medians of a Graph," *Operations Research,* vol. 12, no. 3, pp. 450-459, 1964.

[41] R. Church and C. ReVelle, "The Maximal Covering Location Problem," *Papers in Regional Science,* vol. 32, no. 1, pp. 101-118, 1974.

[42] H. Min, V. Jayaraman and R. Srivastava, "Combined Location-Routing Problems: A Synthesis and Future Research Directions," *European Journal of Operational Research,* vol. 108, no. 1, pp. 1-15, 1998.

[43] R. Z. Farahani and M. Hekmatfar, Facility Location: Concepts, Models, Algortihms and Case Studies, Berlin: Springer-Verlag, 2020.

[44] A. Baghestani, M. Abbasi, S. Rastegar, A. R. Mamdoohi, A. Afaghpoor and M. Saffarzadeh, "Logistics Village Location with Capacity Planning Problem, an MILP Model Approach," *Sustainability,* vol. 15, no. 5, 2023.

[45] T. Drezner, "Competitive Facility Location," in *Encyclopedia of Optimization* , Boston, Springer, 2019, pp. 396-401.

[46] R. Mansini and R. Zanotti, "Two-phase Kernel Search: An Application to Facility Location Problems with Incompatibilities," in *11th International Conference on Operations Research and Enterprise Systems*, Online Streaming, 2022.

[47] M. R. Maia, M. Reula, C. Parreno-Torres, P. P. Vuppuluri, A. Plastino, U. Souza, S. Ceschia, M. Pavone and A. Schaerf, "Metaheuristic techniques for the capacitated facility location problem with customer incompatibilities," *Optimization,* vol. 27, pp. 4685-4698, 2022.

[48] D. Prayogo, M.-Y. Cheng, F. T. Wong, D. Tjandra and D.-H. Trand, "Optimization Model for Construction Project Resource Leveling Using a Novel Modified Symbotic Organisms Search," *Asian Journal of Civil Engineering,* vol. 19, pp. 625-638, 2018.

[49] C. Kyriklidis and G. Dounias, "A Ship-construction Dataset for Resource Leveling Optimization in Large Project Management Problems," *Data in Brief,* vol. 49(109340), 2023.

[50] A. Duraiswamy and G. Selvam, "An Ant Colony-Based Optimization Model for Resource-Leveling Problem," in *Advances in Construction Management*, Singapore, Springer, 2022, pp. 333-342.

[51] F.-S. Wang and L.-H. Chen, "Heuristic Optimization," in *Encyclopedia of Systems Biology*, New York, Springer, 2013, p. 885.

[52] V. Kumar and S. Yadav, "A state-of-the-Art Review of Heuristic and Metaheuristic Optimization Techniques for the Management of Water Resources," *Water Supply,* vol. 22, no. 4, pp. 3702-3728, 2022.

[53] T. Koch, T. Bethold, J. Pedersen and V. Charlie, "Progress in mathematical programming solvers from 2001 to 2020," *EURO Journal on Computational Optimization,* vol. 10(100031), 2022.

[54] E. Danna, E. Rothberg and C. Le Pape, "Exploring relaxation induced neighborhoods to improve MIP solutions," *Mathematical Programming,* vol. 102, pp. 71-90, 2005.

[55] M. Fischetti and A. Lodi, "Local branching," *Mathematical Programming,* vol. 98, pp. 23-47, 2003.

[56] A. Candra, M. A. Budiman and K. Hartanto, "Dijkstra's and A-Star in Finding the Shortest Path: a Tutorial," in *International Conference on Data Science, Artificial Intelligence, and Business Analytics*, Medan, 2020.

[57] D. Rachmawati and L. Gustin, "Analysis of Dijkstra's Algorithm and A* Algorithm in Shortest Path Problem," in *4th International Conference on Computing and Applied Informatics 2019*, Medan, 2019.

[58] "https://www.cnbcindonesia.com/," 28 October 2023. [Online]. Available: https://www.cnbcindonesia.com/news/20211028122600-4-287205/drama-harga-bijih-nikel-ke-smelter-domestik-belum-berakhir. [Accessed 18 February 2024].

[59] K. N. S. Setiawan, T. Achmadi and S. D. Lazuardi, "Analisis Skala Penambangan Mineral dan Pengangkutan," *Jurnal Teknik ITS,* vol. 7, no. 1, 2018.

[60] Y. Marinakis, A. Migdalas and P. M. Pardalos, "A new bilevel formulation for the vehicle routing problem and a solution method using a genetic algorithm," *Journal of Global Optimization,* vol. 38, pp. 555-580, 2007.

[61] S. A. Curtis, "The Classification of Greedy Algorithms," *Science of Computer Programming,* vol. 49, pp. 125-157, 2003.

[62] J.-F. Camacho-Vallejo, Á. E. Cordero-Franco and R. G. González-Ramírez, "Solving the Bilevel Facility Location Problem under Preferences by a Stackerlberg-Evolutionary Algorithm," *Mathematical Problems in Engineering,* vol. 2014, 2014.

[63] J. Stepan, "An analysis of Nickel price variation and its impact on the global economy," in *AGH Faculty of Management-XVII International Scientific Conference*, Krakow, 2015.

[64] D. Fickling, "The Economic Times," India Times, 08 March 2022. [Online]. Available: https://economictimes.indiatimes.com/markets/commodities/news/five-things-to-know-about-nickels-90-price-surge/articleshow/90074055.cms. [Accessed 13 June 2024].