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# DEVELOPMENT A PREDICTIVE OPTIMIZATION MODEL TO MINIMIZE DELAYS AND INEFFICIENCIES AT SPECIAL PORTS

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***The object of this study is the transportation system of rock aggregates in an archipelagic logistics context, focusing on the integration of sea and land transportation modes at Terminals for Own Use (TOU) in Indonesia. In many island-based countries like Indonesia, maritime logistics efficiency plays a critical role in supporting economic competitiveness. However, challenges such as limited infrastructure, high logistics costs, and low accessibility persist, especially at Terminals for Own Use, where the loading and unloading of bulk commodities like rock aggregates can take 2–5 days due to equipment limitations. These inefficiencies increase mooring times and operational costs, weakening supply chain performance and industrial competitiveness. As demand for construction materials grows, optimizing port infrastructure and transportation connectivity becomes urgent. This study utilizes a Long Short-Term Memory (LSTM) model optimized with Particle Swarm Optimization (PSO) to improve the accuracy of rock aggregate demand forecasting. The model achieves a Mean Absolute Percentage Error (MAPE) of 0.46 % on training data and 5.26 % on test data, indicating high forecast reliability. Time series analysis identifies a downward trend in demand in 2022, indicating the importance of accurate forecasting in reducing inefficiencies. Better forecasting enables better port scheduling and inventory management, leading to a responsive logistics system. The results show that an efficient and demand-responsive transportation system significantly reduces loading time and overall logistics costs. The study highlights that a well-integrated forecasting approach can support better decision-making in port management and transportation planning. By optimizing transportation efficiency and connectivity, the proposed model offers insights for stakeholders, ensuring that future infrastructure planning is aligned with sustainability goals***

***Keywords:** demand, connectivity, loading time, long short term memory, optimization, rock aggregates, transportation cost*

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## 1. Introduction

In many parts of the world, the efficiency of maritime logistics plays a crucial role in ensuring the smooth distribution of goods. Especially in archipelagic or island-based countries, transportation infrastructure becomes a determining factor for economic competitiveness. Issues such as limited infrastructure, high logistics costs, and unbalanced accessibility are prevalent globally. These problems are particularly visible in bulk commodity transport, such as construction materials including rock aggregates. Indonesia as a maritime country has a high dependence on sea transportation in distributing production from various sectors, especially in logistics services at ports. Ports act as the main node in the supply chain that connects sea and land transportation. However, the development of the sea transportation sector, especially in the transportation of logistics products, still faces limited infrastructure constraints, especially in special ports or Terminals for Own Use. This limitation has an impact on low connectivity and accessibility, as well as increasing logistics costs which hamper the competitiveness of the national industrial sector.

Along with the strategic issues of transportation which emphasize on improving logistics connectivity and equitable accessibility, port infrastructure optimization is an urgent need. The efficiency of transportation systems and connectivity is crucial in facilitating the flow of distribution of goods and services, especially for regions that have great natural resource potential. In the context of global trade, improving port connectivity has proven to play an important role in reducing logistics costs, increasing supply chain efficiency, and strengthening a country's economic competitiveness.

The main problem faced by Terminals for Own Use in the process of loading and unloading rock aggregates is low productivity due to limited facilities and equipment. The process of loading rock aggregates onto ships takes 2 to 5 days, far from the efficiency standards of modern ports. This implies an increase in mooring time at the port which directly increases operational costs, both on land and at sea. These costs include loading and unloading, stacking, transportation, port services, and administrative costs that can be reduced through optimization of the transportation system and port connectivity (Fig. 1).



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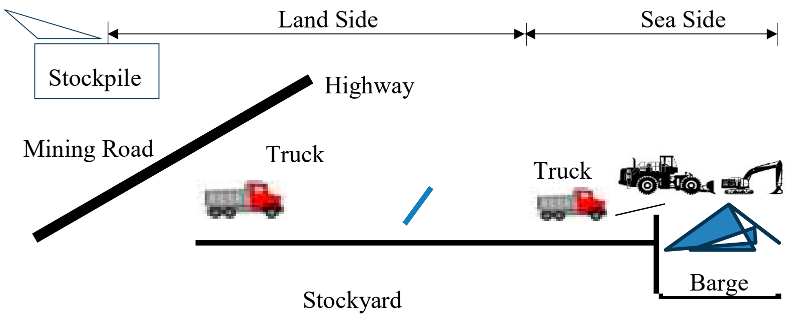


Fig. 1. Operational scheme at terminal for own use

Scientific research in this field is increasingly important due to the rising demand for as rock aggregates, which are essential in supporting urban development, public infrastructure projects, and industrial expansion. Delays or inefficiencies in their transportation can lead to significant cost overruns, project delays, and economic losses. Furthermore, with the growing emphasis on sustainable development and the optimization of resource use, there is a pressing need to enhance the productivity of existing port infrastructure without relying solely on large-scale physical expansion. This calls for intelligent systems that can predict demand, allocate resources efficiently, and streamline operations using integrated sea-land logistics approaches.

The results of such studies can be directly translated into practical applications, such as the formulation of policy recommendations for port management, the design of intelligent scheduling systems, and the improvement of terminal operating procedures. They can also support investment planning by identifying priority areas for infrastructure upgrades and help logistics providers reduce turnaround times and operational costs. In the broader context, enhancing the efficiency of transport systems contributes to national competitiveness, economic resilience, and the realization of long-term development goals.

## 2. Literature review and problem statement

In the context of port efficiency and multimodal transportation systems, numerous studies have highlighted the critical role of maritime connectivity in enhancing overall logistics performance. Some research focuses on improving port efficiency through enhanced maritime routes [1], while others emphasize the development of port infrastructure to improve regional connectivity. However, these studies are often partial and lack integration with data-driven planning approaches essential for holistic optimization. Paper [2] illustrates multi-objective optimization of rock aggregate product logistics in Eastern Indonesia, showing that multi-objective optimization results in a cost reduction of 11 %, but this study has a drawback in that it does not estimate future demand in transportation mode optimization to make it more integrated in operational planning. This is due to the fact that Big Data Analytics has a wide range of applications in Supply Chain Management, including customer behavior analysis, trend analysis, and demand prediction. In this paper, let's investigate the predictive Big Data Analytics applications in supply chain demand forecasting [3]. The survey also pointed out the fact that the existing literature is still severely lacking in the application of Big Data Analytics for demand forecasting in the case of supply chains, and hence highlighted the modes of transportation for future research. The imbalance between demand and the availability of rock aggregates, along with delays in loading services at the special port, and limitations in the number and capacity of heavy equipment, such as dump trucks and excavators used in the loading process, present significant challenges by the paper [4], these conditions can lead to delayed distribution and longer waiting times, ultimately impacting customer satisfaction and operational efficiency. To overcome the challenge of demand uncertainty in the supply chain, the Long Short-Term Memory (LSTM) method has been shown to have the lowest error rate in demand forecasting [5] this study shows that the LSTM method is suitable for handling complex demand forecasting in supply chain management. Cost calculation in transportation optimization does not have a significant impact on the overall total logistics costs [6], because optimization based on sea transportation does not take into account land transportation modes.

Decision-making in supply chains under uncertainty necessitates robust forecasting models to improve planning accuracy [7]. While some studies explore the optimization of rock aggregate transport [8], they often ignore key variables such as loading/unloading time. Furthermore, most rely on conventional time-series techniques like ARIMA or linear regression, which are limited in capturing non-linear and fluctuating demand patterns [9].

Recent advancements propose the integration of LSTM with Particle Swarm Optimization (PSO) to improve forecasting accuracy by optimizing neural network parameters [10]. This hybrid approach allows the model to adapt to dynamic demand conditions more precisely. Additionally, gaps remain in route optimization for multimodal transportation, particularly in integrating future demand forecasts into route selection and cost modelling [11]. Multimodal systems, when properly integrated, have been shown to mitigate cost increases during infrastructure failures or service delays [12].

In summary, while many studies have addressed individual aspects of maritime logistics and supply chain optimization, there remains a significant unresolved problem: the lack of a comprehensive, data-driven, and demand-responsive model that integrates LSTM-based forecasting with multimodal transportation optimization (both land and sea), specifically tailored for rock aggregates. This gap highlights the urgent need for research that not only forecasts demand accurately but also applies it directly to optimize logistics planning and operations in a geographically fragmented and infrastructure-limited context such as Indonesia.

## 3. The aim and objectives of the study

The aim of this study is to develop a predictive optimization model that integrates demand forecasting using LSTM-PSO with multimodal transportation planning for rock aggregate logistics. Practically, the results of this study are expected to support decision-makers in improving distribution planning, reducing logistics costs, and increasing the operational efficiency of rock aggregate.

To achieve the above aim, this study sets the following research objectives:

– to analyze historical patterns and trends in rock aggregate demand;

– to develop a forecasting model for rock aggregate demand using the LSTM-PSO method;

– to determine optimal transportation and inventory strategies based on forecasted demand.

## 4. Materials and methods

### 4. 1. The object and hypothesis of the study

The object of this study is the transportation system of rock aggregates in an archipelagic logistics context, focusing on the integration of sea and land transportation modes at Terminals for Own Use (TOU) in Indonesia. The main hypothesis posits that integrating demand forecasting with operational variables, such as historical demand data (X1), loading time at the port (Z1), and transportation load capacity (Z2), into a multimodal transportation model can significantly enhance distribution efficiency in terms of delivery time and total logistics costs. To support the modeling, the study assumes that demand can be forecasted accurately from historical data, port and land transport operations are coordinated under a unified system, transport resources are consistently available, and cost structures are stable. For simplification, the study excludes the influence of external macroeconomic factors, variability due to port congestion, stochastic demand behavior, and environmental or social impacts, allowing the research to focus on developing an effective, data-driven distribution strategy. The optimization process is shown below (Fig. 2).

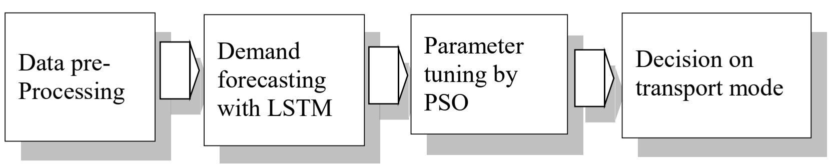


Fig. 2. Optimization decision-making process

The optimization process represents a structured approach to solving the problem of transportation efficiency of rock aggregates. This stage involves identifying the key issues in rock aggregate transportation, such as high loading times, increased logistics costs, and limited equipment capacity at Terminals for Own Use. To improve future demand forecasting, a Long Short-Term Memory (LSTM) model is built. The model's hyperparameters are optimized using particle swarm optimization (PSO), which raises prediction accuracy. The model uses loading times, transportation capacity, and historical demand data as inputs. Decision-making is grounded in realistic and predictable data behavior thanks to this modelling step.

To find the ideal transportation modes, optimization is done using the modelled system and the predicted demand. The objective is to reduce loading/unloading time and overall logistics expenses.

Applying the optimized strategy to actual planning is the last stage. Data pre-processing, forecasting, and optimization are done with Python, and the results are visualized using Microsoft Excel. By helping port managers and logistics planners with scheduling, resource allocation, and infrastructure development, the findings improve the responsiveness and dependability of the transportation system.

### 4. 2. LSTM model

The figure above illustrates the architecture of the Long Short-Term Memory (LSTM) model used in this study to forecast rock aggregate demand. LSTM is a type of recurrent neural network (RNN) specifically designed to overcome the limitations of traditional RNNs in capturing long-term dependencies in sequential data (as shown in Fig. 3).

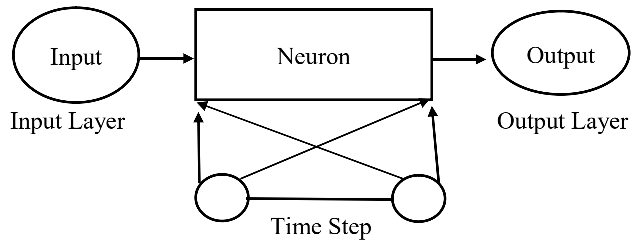


Fig. 3. LSTM MODEL

The image shown is the architecture of the Long Short-Term Memory (LSTM) model used in this study to forecast rock aggregate demand. This model consists of several main components, Input is used to receive time-series input in the form of historical data on rock aggregate demand, after that to the neuron section it functions to capture long-term patterns (long-term dependencies) from historical data. After that, it goes to the output to produce predictions of rock aggregate demand in the next period. The loss function used is MAPE, this function measures how much model error is in the form of a percentage of the actual value [10].

## 5. Results of research of the long short term memory model and optimization

### 5. 1. Demand history

Analyzing patterns and trends of a demand of rock aggregate, it is very important to identify factors that influence changes over time. This graph shows the development of demand from 2017 to 2021 (Fig. 4).

The demand graph from 2017 to 2021 shows that although there are some early-year increases, the demand trend seems to be declining overall. Demand climbed fairly quickly between 2017 and 2018, with many high peaks, most likely due to either greater economic growth or increasing use of rock aggregates in infrastructure and construction projects. This encouraging trend, however, was short-lived since there was a sharp drop at the close of 2018 and the start of 2019, as seen by the total lack of exports of rock aggregate. One of the primary causes of this was the earthquake, which caused a brief halt in aggregate demand by interfering with delivery and construction project activity. As 2019 got underway, demand once more displayed a cyclical pattern, albeit one that was less pronounced than in prior years. Even with the significant increase in demand, overall demand has not been able to reach its 2018 peak. This could be the result of both the fragile state of the construction industry and macroeconomic reasons. Due to the effects of the COVID-19 pandemic, since March 2020, there has been a more evident decrease in demand. Among the numerous economic sectors that have been greatly impacted by the pandemic are the construction and logistics sectors. Lockdowns and limitations on economic activity implemented in various regions delayed construction projects, hampered supply chains, and reduced infrastructure investment. As a result, the overall demand for rocks decreased even further, exhibiting a more erratic trend between 2020 and 2021.

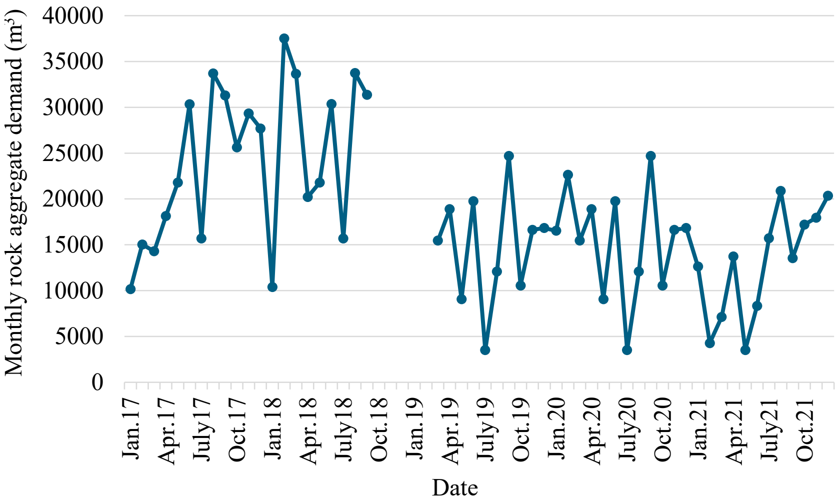


Fig. 4. Time series demand

Between 2020 and 2021, demand fluctuated, but the pattern of movement was more unpredictable than before. There were notable increases in demand, most likely brought on by specific infrastructure projects that required a large volume of overall supply in a short period of time. Overall, though, the demand trend remains lower than it was prior to the epidemic. This implies that the demand for rock aggregates is highly uncertain, which could be brought on by modifications to logistical regulations, interruptions in the supply chain, and delays in building projects because of unstable economic conditions.

This fluctuating demand pattern makes it difficult for businesses to manage their rock aggregate supply chain and inventory from a business planning standpoint. Demand instability can cause problems with distribution, scheduling deliveries, and managing resources. Businesses must develop a more adaptable and data-driven demand forecasting strategy to more accurately anticipate demand peaks and troughs. By understanding historical trends and external factors that affect demand, businesses may reduce any delays in the distribution of rock aggregates and optimize inventories. If the downward trend continues, the company may also need to re-evaluate its marketing strategy and diversify its market share to reduce dependence on specific customer categories. More proactive and data-driven approach, the company may improve operational efficiency in meeting the demand for rock aggregate and better prepare for future market uncertainty.

**5. 2. Forecasting rock aggregate**

Forecasting the demand for rock aggregates using the Long Short Term Memory-Particle Swarm Optimization (LSTM-PSO) method with parameter optimization performed at each time step. Time step is a certain interval or period in the data, such as daily, weekly, monthly, quarterly, or yearly, depending on the context of the data used. The data used in this forecasting model originates from historical records of stone aggregate demand collected by a mining and construction material supplier over several years. The model was designed to predict future demand trends based on these past observations, helping companies anticipate resource needs, improve logistics planning, and reduce operational inefficiencies. In this research, let's use time steps in quarters, semesters, and years (Table 2).

Based on the evaluation results of the LSTM-PSO model, it can be concluded that the model with the best configuration in forecasting rock aggregate demand is a model with a time step of 12, a batch size of 10, a neurons of 177, an epoch of 200, and a learning rate of 0.0085. The superiority of this model can be seen from the lowest Mean Absolute Percentage Error (MAPE) value compared to other models, which is 0.46 % for training data and 5.26 % for testing data. A low MAPE number shows that the model can forecast with little error and has a high degree of accuracy in identifying patterns in past data. In the context of forecasting, a longer selection time step of 12 months, have means that the model forecasts demand for the upcoming month using data from the previous year. This offers a benefit in identifying potential yearly or seasonal trends in the demand for rock aggregate. For instance, the season of the construction project, the weather, and government regulations pertaining to infrastructure all have an impact on the demand for specific resources in the mining and construction sectors. The model can determine whether there is a recurring trend of rising or falling demand by taking into account data from the preceding 12 months. For instance, the model with a longer time step is better able to identify this pattern than models that only use shorter time steps, like three or four months, if the demand for rocks rises during a particular season as a result of construction projects that typically begin at the beginning of the year or end of the season. Additionally, the model with a time step of 12 is more stable in reducing mistakes in data testing when compared to other models. The MAPE Testing of 41.19 % for the model with a time step of 3 in contrast shows that the model is less able to generalize to new data, resulting in forecast results that often have a high error rate. Though they still have a greater error rate than time step 12, models with time steps 4 and 6 do demonstrate improvements over time step 3. This suggests that taking into account longer historical trends improves prediction accuracy in the context of rock aggregate demand forecasting.

Table 2

Long short term memory-particle swarm optimization model

| Time step | Batch size | Neuron | Epoch | Learning rate | MAPE training | MAPE testing |
|---|---|---|---|---|---|---|
| 3 | 8 | 140 | 200 | 0.0087 | 15.19 % | 41.19 % |
| 4 | 4 | 123 | 200 | 0.0082 | 3.69 % | 12.19 % |
| 6 | 5 | 116 | 197 | 0.0069 | 6.70 % | 12.38 % |
| 12 | 10 | 177 | 200 | 0.0085 | 0.46 % | 5.26 % |

The selected LSTM-PSO model uses a time step of 12, meaning it analyzes data from the past year to capture seasonal and long-term trends in rock aggregate demand. A batch size of 10 ensures efficient and stable learning by updating model parameters every 10 samples. With 177 neurons, the model has enough capacity to learn complex patterns without overfitting, and training over 200 epochs allows it to fully learn from the data. The learning rate of 0.0085 strikes a balance between speed and stability in weight updates, enabling the model to converge effectively without overshooting or getting stuck.

In this study, a hybrid approach that combines Particle Swarm Optimization (PSO) and Long Short-Term Memory (LSTM) networks is used to estimate the demand for rock aggregate. This strategy makes use of both approaches advantages to improve prediction accuracy in a dynamic and complicated setting, such as rock aggregate material and logistics. A particular kind of recurrent neural network (RNN) called an LSTM was created especially to model time-series data and identify long-term dependencies in sequential data. Because LSTM networks have memory cells and gate mechanisms (input, forget, and output gates), they can effectively handle the vanishing gradient problem and retain information for longer than typical RNNs. However, the performance of an LSTM model heavily depends on the choice of hyperparameters, such as the number of hidden layers, learning rate, batch size, and the number of epochs. To address this, the model is optimized using Particle Swarm Optimization (PSO). PSO is used to fine-tune the hyperparameters of the LSTM model. Each "particle" in the swarm represents a potential set of LSTM parameters, and particles iteratively update their positions based on personal and global best performance, measured using the Mean Absolute Percentage Error (MAPE) as the fitness function industries and the result of forecasting (Fig. 5).

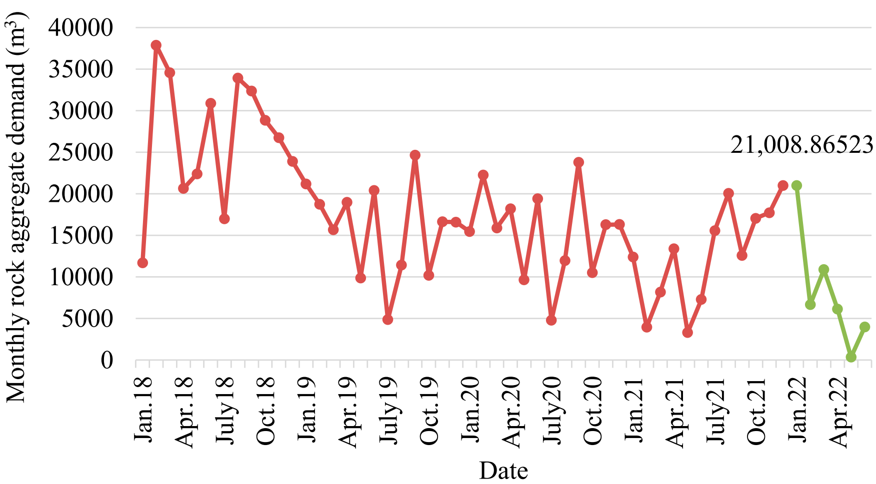


Fig. 5. Future demand (6 period)

The results of forecasting rock aggregate demand using the LSTM model which include demand estimates for the January–June 2022 timeframe. It is clear from these predictive results that there will likely be a sharp drop in rock demand after January 2022. Rock aggregate demand was predicted to reach 21,008.87 $m^3$ in early January 2022, but it then gradually declined to about 352.14 $m^3$ in May 2022, before slightly increasing to 3,986.75 $m^3$ in June 2022.

This drop in demand can be linked to a number of historical occurrences that have influenced Indonesian building operations, particularly in regions impacted by the 2020–2021 COVID-19 pandemic and the Palu and Donggala earthquakes. The trend of diminishing demand in 2020–2021 is expected to have an impact on the 2022 projection findings because LSTM is a historical data-based model that makes use of prior data patterns to generate forecasts. Given that prior data continues to demonstrate the pandemic's effects on the construction industry and allied sectors, the model thus forecasts that this downward trend will continue.

Furthermore, the erratic pattern that is still evident during some times indicates that, despite the fact that demand generally tends to fall, there are occasionally notable surges in demand. A small number of current development projects may be the cause of these spikes, or project completion may have accelerated before plateauing. The fundamental trend, which has been declining since 2020, cannot be altered by the surges alone, though.

In addition, the fluctuating pattern still seen over the years shows that although demand is generally declining, there are certain times when demand spikes considerably. These spikes could be due to building projects continuing albeit in limited numbers, or because they have been accelerated to complete their work before stagnation. However, the spikes are not strong enough to change the main trend that seems to be stalling since 2020.

The lowest delivery volume, 352.14 cubic meters, occurred in May 2022, indicating that the construction rock aggregate supply chain will be highly vulnerable if this trend continues. Oversupply or an imbalance between production and demand could occur, and rock aggregate suppliers could suffer losses if construction activity does not increase significantly. However, the small increase in June 2022 to 3,986.75 $m^3$, well below the normal demand level before 2020, may show signs of recovery.

However, the forecast results will probably be better and more representative of the state of the economy now if the model incorporates data up to 2023 and beyond. Infrastructure projects have begun to be recommenced since the post-pandemic recovery era began, and as the construction industry expands, there will likely be a greater need for rock aggregates.

### 5. 3. Optimization

To improve efficiency and optimize the rock aggregate transportation process, analysis of the capacity and speed of transportation is a very important step. Based on the data obtained, currently the transportation process is carried out using five units of dump trucks, with a total daily transportation speed reaching 2596,406 $m^3$/day, or equivalent to 519,281 $m^3$/day per dump truck with a working day a month for 20 days. Meanwhile, the capacity of the Terminal for Own Use storage area is 20,250 $m^3$, which is the limit of storage capacity before the rock aggregate is sent to the final destination. Optimization with previous forecast results, for example, in the first month with a demand of 21,008.87 $m^3$ as the highest demand (Table 3).

Based on the results of the rock aggregate demand forecast and the largest demand was taken in the first month, reaching 21,008.87 $m^3$. Analysis of the dump truck transport capacity shows that the use of three dump trucks is sufficient to meet transportation needs. It is supported by the total transport capacity of three dump trucks, reaching 31,156.87 $m^3$ per month – well above the projected demand. Therefore, from a resource optimization perspective, using more than three dump trucks, such as five, would result in excess transportation capacity that is not efficiently utilized.

If operational efficiency and cost minimization are prioritized, deploying three dump trucks is the most appropriate option. This number allows the company to fulfill the demand for rock aggregates without surplus capacity, effectively reducing operational costs such as labor, fuel, and vehicle maintenance. Moreover, optimizing the fleet size helps improve delivery scheduling, potentially reducing waiting times and enhancing the overall efficiency of the rock aggregate supply chain.

Table 3

Monthly demand optimization

| Scenario | Initial stock in storage | No. of dump trucks | Capacity | Total load | Demand | Capable |
|---|---|---|---|---|---|---|
| A – with stock reserve | 20,250 $m^3$ | 1 | 10,385.62 | 30,635.67 | 21,008.87 | Yes |
| | | 2 | 20,771.25 | 41,021.25 | 21,008.87 | Yes |
| | | 3 | 31,156.87 | 51,406.87 | 21,008.87 | Yes |
| | | 4 | 41,542.49 | 61,792.49 | 21,008.87 | Yes |
| | | 5 | 51,928.12 | 72,178.12 | 21,008.87 | Yes |
| B – without stock reserve | 0 $m^3$ | 1 | 10,385.62 | 10,385.62 | 21,008.87 | Not |
| | | 2 | 20,771.25 | 20,771.25 | 21,008.87 | Not |
| | | 3 | 31,156.87 | 31,156.87 | 21,008.87 | Yes |
| | | 4 | 41,542.49 | 41,542.49 | 21,008.87 | Yes |
| | | 5 | 51,928.12 | 51,928.12 | 21,008.87 | Yes |

However, based on company data, the average daily demand for rock aggregate ranges between 3,000 and 4,500 $m^3$. In peak conditions, with daily demand reaching 4,500 $m^3$, renting three dump trucks is still optimal for handling the daily transportation needs without experiencing critical shortages or excessive unused capacity.

Nevertheless, deeper analysis based on scenario simulations shows that the optimal number of dump trucks can vary depending on whether stock is available at the storage terminal. If there is an initial stock of 20,250 $m^3$, then even a single dump truck is sufficient to meet monthly demand, as the combination of stored material and transported load exceeds the required volume. This condition supports a highly efficient operation, reducing the need for multiple trucks and associated operational costs.

Conversely, in a no-stock scenario, where all material must be transported directly from the source, at least three dump trucks are required to meet the demand. Using fewer than three trucks would result in under-capacity and failure to fulfill monthly requirements. Therefore, the presence or absence of stock significantly affects transportation strategy, highlighting the importance of inventory planning.

On the other hand, information from the company shows that the demand for rock aggregate in a day ranges from 3,000 to 4,500 $m^3$. In the process of optimizing the daily transportation of rock aggregate, if the average daily demand is 4,500 $m^3$, the best option is to rent 3 dump trucks if no initial stock in storage (Table 4).

Table 4

Daily demand optimization

| Scenario | Dump truck capacity | Initial stock in storage | Total load | Capable |
|---|---|---|---|---|
| A – with stock reserve | 1557.84 $m^3$ | 20,250 $m^3$ | 21,807.84 $m^3$ | Yes |
| B – without stock reserve | 1557.84 $m^3$ | 0 $m^3$ | 1557.84 $m^3$ | Not |

It can be explained that if the storage capacity at the Terminal for Own Use has an initial stock of 20,250 $m^3$, then this stock can be directly loaded onto the ship (instant load) without having to wait for additional rock aggregate from the land transportation process. In this condition, with the addition of three dump trucks, each with a daily transport capacity of 519.281 $m^3$, then in one day the total rock aggregate available will reach 21,807.84 $m^3$. This amount is more than enough to meet the daily demand for rock aggregates of 4,500 $m^3$, so that the loading process onto the ship can run without constraints from the availability of rock aggregate.

However, if there is no rock aggregate stock available in the storage area, then the transportation process is entirely dependent on dump trucks that transport rock aggregate directly from the source to the ship. In this scenario, even by renting five dump trucks with a total daily transport capacity of 2,596.40 $m^3$, it still takes about two days to meet the daily demand of 4,500 $m^3$. This shows that without stock reserves in the storage area, there is a risk of delays in the provision of rock aggregate needs, which can affect operational efficiency and potentially disruptions to the supply chain.

Therefore, in strategic operations, it is very important to ensure that stock availability in the Terminal for Own Use is always maintained so that the loading process onto the ship can run optimally. This stock management can be done by implementing an inventory management system that considers demand patterns and the speed of transportation from the rock aggregate source to the storage location. The company can avoid situations where transportation must work at maximum capacity just to meet daily needs, which can ultimately increase operational costs due to the high frequency of dump truck use.

In addition, in a scenario without stock reserves, the company needs to consider alternative options to improve transportation efficiency, such as optimizing travel routes, better operational scheduling, or even increasing transportation capacity by increasing the number of dump trucks in a certain period. By implementing this tactic, without causing issues that can hinder distribution or overall operations, the company can ensure that the demand for rock aggregates is met. These findings demonstrate how important careful logistics planning is to ensuring the effective distribution of building rock aggregate, according to the study and industry application. Finding equilibrium between storage capacity operational needs, and transportation availability, businesses may increase supply chain efficiency and lower the risk of delays. This is particularly important in the construction sector, as the smooth operation of projects greatly depends on the availability of enough supplies.

## 6. Discussion of optimization of long short-term memory model forecasting results

The demand for rock aggregates from 2017 to 2021 shows a declining and unstable trend, influenced by events such as natural disasters and the COVID-19 pandemic. After peaking in 2018, demand dropped sharply due to an earthquake and continued to decline amid pandemic-related disruptions. Although there were temporary spikes driven by infrastructure projects, overall demand remained below pre-2019 levels. This volatility highlights the need for a more flexible, data-driven forecasting strategy to optimize inventory, reduce distribution delays, and enhance operational efficiency in a highly uncertain market environment (Fig. 4). The results of forecasting rock aggregate demand using the LSTM model, which include demand estimates for the January–June 2022 timeframe. It is clear from these predictive results that there will likely be a sharp drop in rock demand after January 2022, this drop in demand can be linked to a number of historical occurrences that have influenced Indonesian building operations, particularly in regions impacted by the 2020–2021 COVID-19 pandemic and the Palu and Donggala earthquakes (Fig. 5).

Based on the findings (Table 2), the LSTM-PSO model with a time step of 12, batch size of 10, 177 neurons, 200 epochs, and a learning rate of 0.0085 achieved the highest forecasting accuracy, with an MAPE of 0.46 % for training and 5.26 % for testing data. The longer time step enables the model to capture seasonal trends in rock aggregate demand, resulting in more stable and accurate predictions. The use of PSO effectively optimizes the LSTM hyperparameters, enhancing model performance in a complex, dynamic logistics environment.

The optimal transportation optimization for monthly demand is to use only three dump trucks, because it can fulfill the needs of the rock aggregate transportation demand. The highest monthly demand projection of 21,008.87 $m^3$ from the forecast results shows a lower value than the total monthly transportation capacity of 31,156.87 $m^3$ if 5 dump trucks are used. As a result, it is inefficient because it creates extra capacity that is not optimally utilized. After all, the other 2 dump trucks will be idle. In terms of operations, the use of three dump trucks can also be saving costs because it is in accordance with needs (Table 3).

The average daily demand is between 3,000 $m^3$ to 4,500 $m^3$, take the case with the highest daily demand. Transportation optimization for daily demand is highly dependent on dump trucks that move supplies directly from their source to the ship if the initial stock at the Terminal for Own Use is not available, because if the stock in storage at the terminal is still available, an instant load can be carried out with a total storage capacity of 20,250 $m^3$. Take the case with the highest daily demand. It takes two days to meet the daily needs of 4,500 $m^3$ when using 5 dump trucks in conditions where storage stock is not available because the total capacity that can be transferred each day is only 2,596.40 $m^3$ (Table 4). If to use dump trucks according to the monthly demand strategy, it can be done by optimizing the use of stock storage, so that it can reduce loading time and demand fulfillment can be done in one day. This suggests that the supply chain may experience delays as a result of insufficient stock reserves. To guarantee that there is an adequate supply of rock aggregate at the terminal and that the loading procedure onto the ship can go without hiccups, an inventory management strategy is crucial.

The solution developed in this study has several advantages, including the fact that it is very important to ensure that stock availability in Terminal for Own Use is always maintained so that the loading process onto the ship can run optimally and reducing the loading time (Table 4). By using three dump trucks is more efficient than using five trucks because it can reduce operational costs. According to the optimization of the number of trucks. As long as the storage area is always full and free from emptiness, three dump trucks can fulfill the maximum daily demand of 4,500 $m^3$ without producing waste or delays, according to the monthly or daily demand and transportation capacity.

However, this study is limited. Unlike the research in [2] that considers various modes of transportation, this study relies entirely on dump trucks without exploring alternative logistics options that may be more economical. Additionally, data-driven stone aggregate distribution planning has not been optimally applied since the developed model does not incorporate external factors such as fuel prices, road conditions, and congestion levels, which could enhance the accuracy of logistics decisions. Furthermore, the data used in this study is restricted to 2017–2021, which may not fully reflect the latest demand trends post-pandemic. This contrasts with research [9], which uses more recent data to improve the accuracy of the prediction model. Therefore, applying a more accurate and representative LSTM model still requires a broader update of historical data so that the resulting demand patterns are more relevant to current conditions.

## 7. Conclusions

1. According to the study's findings, there is a seasonal pattern in the demand for stone aggregate, which is impacted by several outside variables like the climate, governmental regulations, and active building projects. By MAPE of 0.46 % for training data and 5.26 % for testing data, the LSTM-PSO model created in this study can accurately forecast demand. These findings demonstrate that the model outperforms models with shorter time steps in capturing past trends and forecasting shifts in demand. Furthermore, the downward trend shown since 2020 shows how the COVID-19 pandemic and other economic issues have affected the demand for stone aggregates. For distribution and inventory management tactics to be optimized, demand trends must be monitored using suitable prediction models.

2. The Terminal for Own Use serves as a vital conduit for the distribution of stone aggregates between land and sea transportation modes. The study discovered that the initial stock's availability has a significant impact on the terminal's performance. The delivery of rock aggregate to the vessels may encounter considerable delays if the initial stock at the terminal is inadequate. Even with five dump trucks, it can take up to two days to meet the daily requirement of 4,500 $m^3$ due to the maximum daily transit capacity of 2,596.40 $m^3$. This disparity points to the need for more effective inventory control techniques, including better-planned replenishment or more storage capacity. Furthermore, using three dump trucks is thought to be more efficient than using five because it avoids unused capacity, lowers operating expenses, and still meets the demand for immediate distribution of stone aggregate as long as the initial stock at the terminal is available.

3. Improving the effectiveness and efficiency of transportation modes in stone aggregate products. This study highlights that minimizing logistical bottlenecks requires balancing transportation capacity and optimizing distribution routes. Enhancing the transportation system's flexibility – for example, by implementing a truck leasing program based on seasonal demand – is one tactic that can be used to lower operating costs while maintaining efficient distribution. En-

hancing the logistical efficiency of stone aggregates can also be accomplished in the long run by multimodal integration of transportation modes, such as more effective use of railroads or maritime shipping. Increased connectivity can lead to fewer distribution delays, more efficient operations, and better fulfillment of the demand for stone aggregate.

## Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

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The study was performed without financial support.

## Data availability

The data will be made available on reasonable request.

## Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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