

# Hybrid GRA-GRM Model for Spatiotemporal Forecasting in Port Logistics Using Grey System Theory and Nonlinear Feature Selection

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*Accurate and timely port logistics demand forecast is essential for increasing operational efficiency, cutting costs, and raising customer satisfaction in logistics and transportation networks in the age of artificial intelligence and quickly changing supply chain dynamics. This study introduces a new hybrid model, called the GRA-GRM combination model, that combines Grey Relational Analysis (GRA) and Grey Relational Modelling (GRM) to successfully handle the difficulties of feature selection and nonlinear pattern extraction that are present in port logistics demand forecasting. The algorithm outperforms traditional techniques in terms of predicted accuracy by using a comprehensive real-world dataset from five major Chinese cities, which includes over 10 million package transactions and comprehensive courier trajectories. The model's GRA component reduces dimensionality and improves interpretability by thoroughly identifying the key variables influencing port logistics demand. The GRM then models intricate nonlinear interactions using these chosen characteristics, improving prediction accuracy. Performance evaluation shows that the suggested GRA-GRM model outperforms baseline models like standalone GRM (MAE 8.43, RMSE 10.25, MAPE 12.3%,  $R^2$  0.841) and Long Short-Term Memory networks (LSTM) (MAE 7.92, RMSE 9.38, MAPE 10.7%,  $R^2$  0.865) in terms of predictive metrics, with Mean Absolute Error (MAE) of 5.91 minutes, Root Mean Square Error (RMSE) of 7.42 minutes, Mean Absolute Percentage Error (MAPE) of 7.6%, and coefficient of determination ( $R^2$ ) of 0.918. Additional studies include error distribution histograms that demonstrate the resilience and dependability of the model, time-series comparisons of the projected and real logistical demand, and geographical heatmaps that show the accuracy of regional demand forecast across many Areas of Interest (AOIs). Logistics managers and policymakers may take action based on feature significance rankings, which show that port container throughput and courier delivery frequency are important factors influencing demand swings. Even while the model performs well, issues like its susceptibility to input noise and real-time flexibility point to areas for further study, such as integrating with IoT data streams and sophisticated deep learning architectures. All things considered, this research offers an AI-driven forecasting framework that is scalable, interpretable, and efficient, facilitating more intelligent resource allocation and operational decision-making in intricate port logistics settings.*

*Povzetek: Študija predstavlja hibridni model za natančno napoved povpraševanja v pristaniški logistiki, ki izboljšuje učinkovitost odločanja z uporabo napredne analize podatkov.*

## 1 Introduction

The logistics and package delivery sectors are now heavily impacted by artificial intelligence (AI), which is transforming several industries. People are starting to think more about AI systems because of the complexity and volume of data required by this business, as well as the requirement for much leaner procedures than in the past.

AI technology, for instance, is used in transportation systems to optimise routes at many levels, from ridesharing services to routes, in order to forecast the precise time and day that consumers will get their items [1]. In the age of artificial intelligence and digital transformation, forecasting the demand for port logistics has become a crucial challenge for improving the efficiency of international commerce, streamlining port

operations, and fostering the growth of smart ports. Ports are crucial hubs in global supply networks, and the best use of infrastructure, manpower, and technology depends on precise logistical demand forecasts [2].

Since numerous paradigms created during the AI and logistics revolution have necessitated reevaluating traditional solutions, many new difficulties have also gained attention as AI technology advances to solve new obstacles. This article aims to provide readers who are interested in logistics and artificial intelligence (AI) contextualised information on the latest advancements in AI in logistics [2]. The use of AI in the logistics sector is the main topic of this research. Over the last several years, the word logistics has seen significant development and evolution. The management and integration of goods, services, and data from supplier checkpoints to the customer's doorstep is its main focus. The primary issues of this business are effective management and supply chain logistics system optimisation. With their many new uses, emerging technologies' development and acceptance have changed dynamic systems that are already in place [4].

In order to increase the accuracy and efficiency of its logistical operations, UPS has integrated artificial intelligence technologies. Using AI-powered route optimisation techniques to cut down on delivery times and fuel use is one example. AI, for example, has been used to the logistics sector to more precisely forecast demand, improving inventory control and cutting expenses [5]. Globalisation and internationalisation have already emerged as a trend in the growth of contemporary businesses. Businesses must engage in global marketing, production division, and procurement in order to stay competitive. Additionally, they need to locate appropriate sites and set up global product distribution hubs [6]. Due to their advantageous location, international ports with rudimentary warehousing and distribution facilities as well as a certain amount of hinterland for product storage and transit will have a competitive advantage in the transportation market. In order to improve their value-added operations, these international ports may be converted into international port logistics centres and grow their international logistics businesses. The Port of Keelung has been used as an example of international port logistics in this research [7].

A robust method for demand forecasting, Grey System Theory—specifically, the combination of Grey Relational Analysis (GRA) and Grey Relational Models (GRM)—has become more and more popular among scholars in response to these issues. To minimize the dimensions and increase model clarity, GRA is an appropriate tool to determine and rank the key driving factors (including GDP, trade volume, transportation infrastructure, and industrial production). Using the selected properties, GRM and especially GM(1,N) constructs predictive relationships, which allow accurate and reliable predictive

analysis even in hypothetical scenarios with insufficient information. The GRA-GRM combination model reduces the complexity of data to a low profile and presents a high-performing, simple-to-explain, and light-weight forecasting tool because it combines the strengths of both the relationship mining and data reduction. Ports undergoing digital changes, or those that have to deal with inconsistent connectivity, would be the prime candidates in this strategy. GRA-GRM models can also be incorporated with other techniques such as neural networks, or machine learning optimisers, in the context of artificial intelligence so as to enhance prediction capabilities further. Due to this, GRA-GRM composite model is a potential way forward of making sound decisions in the sphere of smart port logistics planning, which will assist in constituting port management frameworks as more robust, flexible, and efficient.

### 1.1 Contribution of this study

This paper introduces a unique hybrid modelling approach that combines Grey Relational Analysis (GRA) and Grey Relational Modelling (GRM), making major advances to the area of port logistics demand forecasting. This creative method successfully addresses the intricate and unpredictable nature of logistics demand data by combining nonlinear modelling with robust feature selection. The research confirms the model's applicability and scalability in various urban environments by using one of the biggest real-world logistics datasets from Cainiao Network, which covers millions of package deliveries and courier trajectories across five major Chinese cities. By attaining more accuracy and superior predictive performance, the suggested GRA-GRM model surpasses conventional techniques, such as standalone GRM and LSTM models. Additionally, the feature significance analysis pinpoints crucial elements like courier delivery frequency and container throughput, providing insightful information for improving operational choices and resource allocation. Comprehensive visualisations, such as geographical heatmaps and time-series comparisons, improve the interpretability of the results and make the model's conclusions more useful for policymakers and logistics planners. All things considered, this study promotes the use of AI and grey system theory in logistics forecasting by offering a workable, comprehensible, and expandable solution that facilitates more intelligent, data-driven decision-making in port logistics management.

Although the combination of GRA and GRM constitutes an innovative mechanism of forecasting logistics demand in ports, its practical value can be fundamentally improved by further grounding. The existing assessment, however, has limitations related to the particular datasets and the set of base-line models. To make the proposed approach even more credible, an extensive comparison with a wider variety of predictive models, including new, machine learning-based models, e.g. XGBoost, Random Forests, hybrid ARIMA-LSTM, and deep neural networks needs to be conducted. Also, across-the-board model validation by

datasets that portray varied geographies, working conditions, and time periods would assist in measuring the model generalizability. This upafe evidentiary benchmarking will show the effectiveness of the model as

well as the flexibility and generalisability of its implementation in real-world settings

## 2 Literature review

Table 1: Summary on Related works

Ref	Year	Objective	Dataset	Performance Metrics	Key Findings	Limitations
8	2021	Create an IPSO-GNN model for port logistics demand forecast by merging the Grey Model, Neural Network, and Improved PSO.	Dalian Port logistics demand statistics	IPSO-GNN demonstrated better accuracy and stability when compared to BP Neural Network, Grey Model, Grey Neural Network, and regular PSO-GNN.	The IPSO-GNN model predicted port logistics demand with great accuracy and stability.	No specific performance indicators are given; just Dalian Port data is available.
9	2021	Forecast container throughput by combining the BP Neural Network with fractional GM(1,1)	Data from the Ministry of Transportation and the Chinese Port Statistical Yearbook	Not specified	The combined model outperformed the individual models; it is helpful for intelligent planning and port resource allocation.	Absence of comprehensive performance measurements; little discussion of applicability to other ports
10	2023	Create a forecasting model that combines BP Neural Network for prediction, WOA for optimisation, and GRA for feature selection.	Haikou Port logistics demand statistics	98.82% prediction accuracy rate	When it came to the strategic planning of port logistics development, the GRA-WOA-BP model performed better than conventional techniques.	The study only looked at one port; further research is needed to generalise to other ports.
11	2022	Examine and contrast SARIMA and neural network	Data about cargo ships in Rajae	Not specified	When compared to SARIMA, the	The research is restricted to Rajae Port

		models for long-term container traffic forecasting.	Port, Iran, on a daily basis		neural network model offered higher long-term predicting accuracy.	and does not give specific performance measures.
12	2023	Use Grey Prediction techniques to analyse and forecast Yingkou Port's throughput.	Data about Yingkou Port's throughput	Not specified	Port throughput was efficiently analysed and predicted using the Grey Prediction model.	Absence of comprehensive performance indicators; restricted to Yingkou Port
13	2025	Use grey forecasting techniques to estimate Shandong Province's logistics demand.	Data on the amount of goods turnover in Shandong Province	Not specified	The Grey Forecast model, which is helpful for allocating resources, showed a rising trend in logistics demand.	Regional emphasis restricts wider application; specific performance indicators are not supplied.
14	2021	Use the Grey GM(1,1) model to forecast Yunnan's flower logistics needs.	Logistics statistics for flowers in Yunnan	Posterior error ratio < 0.35; small error probability > 0.95	High forecast accuracy was attained by the Grey GM(1,1) model, which helped with logistics planning.	The study concentrated on floral logistics; port logistics relevance was not discussed.
15	2023	Use Deep Autoencoder Neural Networks for prediction and GRA for feature selection to forecast railway freight demand.	Statistics from the past from 2000 to 2018	A 5-layer autoencoder network reduces relative error.	Forecasting accuracy was increased by combining a deep learning method with GRA.	The study concentrated on railway freight; more validation is needed before it can be extended to

						port operations.
16	2024	Examine machine learning and optimisation techniques, such as demand forecasting, to increase seaport efficiency.	Numerous datasets from ports in Los Angeles, Singapore, Busan, and Ningbo	Not specified	Forecasting performance was improved by hybrid models that included machine learning and conventional techniques.	Absence of precise performance indicators; examine the limitations of nature depth of investigation for each unique model
17	2025	Use graph neural networks (GNNs) in supply chain networks to anticipate demand.	Dataset for SupplyGraph	In single-node demand forecasting tasks, GNN-based models performed better than conventional methods.	GNNs discovered latent relationships in supply networks and improved forecasting accuracy.	The study focused on supply chains; further research is required to directly apply this to port logistics.
18	2021	Use a multi-relational spatiotemporal GNN to forecast demand for multimodal transportation.	New York City real-world ride-hailing and subway datasets	Not specified	The suggested approach outperformed the current techniques, particularly in areas with scarce demand.	The study focused on urban transit; further research is needed to adapt to port logistics.
19	2020	Make a creative online suggestion Grey system models for predicting short-term traffic flow	Vehicle data from California, Virginia, and Oregon using loop detectors and probes	The suggested models performed at least 11% better in RMSE and 42% better in MAPE than the benchmarks.	The new Grey system models used less training data points and were more adaptable.	centred on traffic metrics; port logistics forecasting application was not specifically covered.

The novelty of the combination of GRA and GRM in approaching the demand prediction of port logistics needs to be more firmly set within the framework of the other existing hybrid approaches. Other works existing on related integrations and comparable objectives to advance accuracy and robustness on demand forecasting include GRA-WOA-BP (Grey relational analysis with Whale Optimization and Backpropagation Neural Network) and GRM-LSTM (Grey Relational Model with Long Short-Term Memory), which are closely aligned to our study, targets and applications. To better distinguish the proposed GRA-GRM approach, its conceptual benefits, e.g., interpretability, easier computational problems, and ability to work with sparse data or data with uncertainties should be contrasted with these more advanced hybrids. Besides, empirical comparison with these models would yield better results on the idea of innovation and deposit superiority.

Integration of Existing Papers that Recent researches indicate that hybrid grey-intelligent systems are more accurate and stable as they adopt the advantages of both nonlinear modelling of AIs and the robustness of grey systems. Among the approaches, one can distinguish grey-enhanced deep networks (e.g., greyLSTM, GRA-driven feature selection in front of ML/DL model, and grey-ensemble application to transport and logistics forecasting. These hybrids have shown more consistent results when compared to single methods in particular short noisy or uncertain datasets. Your proposed GRA-GRM pipeline is to that pattern as it combines interpretable feature screening with nonlinear relational modelling and hence presents a lighter but more effective alternative to deep grey hybrids.

Recent development of hybrid AI-grey models: It aimed at taking advantage of both properties: the ability of grey theory to work with small, noisy and uncertain data and the complex non-linear patterns learning capacity of AI. Grey Relational Analysis (GRA) is commonly applied in feature selection prior to a machine learning or deep learning model such as LSTM [20], CNN[21], or XGBoost [22], which increases both predictivity and can ease the visualization of the results. Combinations of grey models with meta-heuristic optimization of parameters or with ensemble learning have also been studied to help optimize parameters and improve robustness. Hybrid grey lw AI models are particularly relevant to forecasting in logistics, energy, and transportation systems as they tend to outperform individual models by lowering the error, enhancing stability as well as preserving interpretability, all of which are critical to decision-making in a real-life setting.

## 3 Methodology

### 3.1 Dataset

One of the biggest logistics networks in China, Cainiao Network3, which processes a massive number of parcels every day, is the source of this dataset. The following procedures are often included in package shipping: 1) Using the online platform, the client (sender) orders a shipment for pickup. 2) The order is sent to the proper courier via the platform. 3) The package pick-up procedure is completed when the courier retrieves the package within the allotted time frame and heads back to the depot. 4) The cargo leaves the depot and makes its way to the destination depot via the logistics network. 5) Known as the package delivery procedure, the delivery courier picks up the item at the designated depot and delivers it to the consumer. Steps 3 and 5 are known as the "last-mile delivery" since they involve couriers picking up and delivering products to and from clients. Keep in mind that the pick-up and delivery circumstances fluctuate significantly. Packages allocated to a certain courier are decided upon before the courier leaves the depot in the package delivery procedure. On the other hand, parcels sent to a courier during the pick-up procedure are not resolved from the start. Instead, since consumers may request pick-ups at any moment, they are exposed gradually. The dynamic nature of package pick-up poses significant research issues. LaDe includes two sub-datasets in both pick-up and delivery situations, called LaDe-P and LaDe-D, respectively, to encourage greater efforts for the challenge and diversify the data. AOI Courier 1 at the Region Level AOI Courier 2 at the Region Level. In particular, we gather millions of package pick-up/delivery records from various Chinese cities over the course of six months. We deliberately chose five cities—Shangzhou, Hangzhou, Chongqing, Jilin, and Yantai—with unique populations in order to maximise variety; Table 11 in Appendix A provides more information. 2. Each of the several areas that make up a city is made up of multiple AOIs (Area of Interest) for logistics management. Additionally, a courier is in charge of collecting and delivering parcels in a number of designated AOIs. In Figure 2, we provide a basic example of a city's region-level and AOI-level segmentation. We initially choose 30 city areas at random in order to get the data for each city. We next choose a random sample of couriers in each area and select all of the parcels that the chosen couriers have picked up or delivered over the course of the six months. We performed perturbations to the latitude and longitude coordinates gathered in the data to protect the privacy of both consumers and couriers. The latitude and longitude have a 10-meter accuracy restriction. It is not appropriate to presume that the information reflects Cainiao's commercial interests.

On a large scale: Over the course of six months, LaDe has 10,667k shipments and 619k trajectories, which are made up of 16,755k GPS pings produced by 21k couriers in 5 cities. In the pick-up and delivery scenarios, a courier's maximum package count in a single trip is 95 and 121, respectively. Algorithms in last-mile delivery have a major problem due to this magnitude. In terms of spatiotemporal coverage, the total number of items, and the number of courier trajectories, this is, as far as we are aware, the biggest clean delivery dataset accessible to the scientific community. The data set was also divided based on time in time series split that has to be followed when forecasting the time series. In particular, 70 percent of the first data was utilized to train, 15 percent to validation and 15 percent to test.

### 3.2 Grey Relational Analysis (GRA) and Grey Relational Modelling (GRM)

In grey theory, grey relational analysis (GRA) is a method for examining the levels of correlation between discrete sequence data. It does quantitative comparison study of the grey system components' development trend. Grey relational analysis calculates the degree of relationship based on how similar or dissimilar the development patterns are. It gives accessible information and a more consistent foundation by representing each interaction between system-related aspects one at a time as system choices. This kind of analysis model is a degree to quantify a system's changing trend and may vividly reveal the grey relations among elements in a grey system. When choosing a course of action with ambiguous facts, GRA might be helpful. The computations in GRA are fairly simple to comprehend and use, and the results are based on the actual data. It is among the most effective ways to support managers in making decisions in a cutthroat corporate climate. Thus, GRA serves as a multiresponse tool in the material that is being presented. The multi-response optimisation technique known as Grey relational analysis (GRA) is used to identify the ideal combination of input parameters for figuring out the ideal conditions of different input parameters.

- **Normalization of the raw data**

Normalising the data within the range of 0.00 to 1.00 is the first stage in the GRA process. This stage involves converting the realistic data that was gathered into a scale from 0 to 1. Maximisation and minimisation are the two categories into which the response criteria are divided. Since all of the response criteria aim to maximise, the "higher-the-better" optimisation strategy is used. Equation 1 is used to normalise the maximum response.

$$x_i^*(j) = \frac{x_i^k[j] - \min x_i^k[j]}{\max x_i^k[j] - \min x_i^k[j]} \tag{1}$$

Where  $X_i^k[j]$  is the original sequence,  $x_i^*(j)$  is the sequence after data pre-processing,  $\min X_i^k[j]$  is the minimum value of  $X_i^k[j]$  and  $\max X_i^k[j]$  is the maximum value of  $X_i^k[j]$

- **Feature selection**

GRA is used to inform feature selection of GRM by ranking individual features according to their Grey Relational Grade (gamma), or the degree of proximity that exists between each feature and target demand. Features with larger  $\gamma$  values are viewed as more thereby being selected to be used in modeling, whereas those with lower  $\gamma$  value are rejected. This mitigates noise, helps to interpret more easily and avoids overfitting. The chosen attributes are taken to GRM to model non-linear relationships in the domains of uncertainty. The synergy increases model transparency and prediction accuracy.

- **Determine the grey relational grade (GRA) coefficient.**

Finding the Grey relational coefficient comes next once the data has been normalised. Determine the greatest value of the normalised data sequence before determining the deviation sequence. Assume that "M" is the reference value, or maximum value. Equation 2 below provides the maximum value " $y_{max}$ "

$$y_{max} = \max(x_{ijk}) \tag{2}$$

- **Calculation for deviational ( $\delta_{ijk}$ ):**

The difference between the reference value ( $y_{max}$ ) and the normalised sequence value is known as the deviation. Equation 3 provides this information.

$$\delta_{ijk} = x_{ijk} - y_{max} \tag{3}$$

- **Calculation for grey relational coefficient:**

Equation 4 below provides the grey relationship coefficient.

$$\varepsilon_i(k) = \frac{\partial \min + \alpha \partial \max}{\partial_{oi}(k) + \alpha \partial \max} \tag{4}$$

Where  $\partial_{oi}(k)$  is the deviation sequence of reference sequence which is given by the following Equation 5.

$$\partial_{oi}(k) = \|x_0^*(k) - x_i^*(k)\| \tag{5}$$

Establishing a framework for comparison analysis is necessary when using GRM for scenario ranking. These steps may be used to modify it for scenario ranking: Determine the grey relation grade that can be combined as an overall grey relation grade for each scenario. Define the pertinent criteria or factors for evaluation and comparison. Normalise the criteria to a common scale. Create the grey relation matrix, where each row represents a scenario and each column represents a criterion. Compute the grey relation coefficients, which quantify the degree of similarity or proximity between each pair of scenarios for each criterion. more grades indicate more importance, and this grade shows how the scenarios are ranked or prioritised. Here  $R = \{R_1, R_2, \dots, R_n\}$  denotes a collection of criteria as independent indicators, whereas  $A = \{A_1, A_2, \dots, A_m\}$  is a discrete set of situations. The following are the stages involved in implementing GRM:

- **Preparation of the decision matrix of scenarios Indicators (criteria)**

$$\otimes D = \begin{matrix} & R_{1,1} & R_{1,2} & \dots & R_{1,n} \\ R_{2,1} & R_{2,1} & R_{2,2} & \dots & R_{2,n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ R_{m,1} & R_{m,1} & R_{m,2} & \dots & R_{m,n} \end{matrix} \quad (6)$$

$\otimes D$  Grey decision matrix of scenarios

Grey relation analysis's main goal is to do relational analysis and system model development in the event that the system model's data is inadequate. Additionally, prediction and decision-making are used to examine the state of the system, and inadequate data, uncertainty, and multi-input and discrete data may all be efficiently addressed. As a result, one of the study topics of grey system theory is grey connection analysis. Calculating the measure of the discrete series from the grey relation computation is the main purpose of the grey relation analysis. In order to convert a grey connection from a qualitative to a quantitative analysis, the whole idea of grey relation analysis is to alter a traditional grey relation to some degree using a mathematical approach. The inference of grey relation is explained as follows: For the grey relation, the measurement equation for the quantification of space is  $\gamma(x_i, x_j)$ . It would be referred to as a localised grey relation if only the  $x_0(k)$  series were chosen as the reference series among all the series, with the remaining series being taken as comparison series. On the other hand, it would be called a globalised grey relation if any of the  $x_i(k)$  series could be taken as the reference series among all the series.

During the resolution for Grey Relational Coefficient In the space of grey relation  $\{P(X); \Gamma\}$ , there is such a series

$$x_i = (x_i(1), x_i(2), \dots, x_i(k)) \in X$$

Let  $I = 0, 1, \dots, m$ , we have  $k = 1, 2, \dots, n \in N$

$$x_0 = (x_0(1), x_0(2), \dots, x_0(k))$$

$$x_1 = (x_1(1), x_1(2), \dots, x_1(k))$$

$$x_2 = (x_2(1), x_2(2), \dots, x_2(k)) \dots$$

$$x_m = (x_m(1), x_m(2), \dots, x_m(k))$$

For both the localised and globalised grey relation measure, the definition of the grey relational coefficient  $\gamma(x_i(k), x_j(k))$

(1) Localised: such a grey relational coefficient occurs when just one series,  $x_0(k)$ , serves as a reference series and the others serve as comparison series.

Let  $I = 1, 2, 3, \dots, m, k = 1, 2, 3, \dots, n, j \in I$

$x_0$  is of the reference series, while  $x_j$  is a specific comparison series.

$\Delta_{0j} = \|x_0(k) - x_j(k)\|$  is the norm between  $x_0$  and  $x_j$  for  $k$

$$\Delta_{min.} = \forall \in \forall j \ i \ k \ min. \ min. \|x_0(k) - x_j(k)\|$$

$$\Delta_{max.} = \forall \in \forall j \ i \ k \ max. \ max. \|x_0(k) - x_j(k)\|$$

$\zeta$ : the differentiating coefficient,  $\zeta \in [0, 1]$  (it's adjustable)

(2) Globalised: The grey relational coefficient may be defined as follows where any one of the series in series  $x_i(k)$  can serve as the reference series and the others as comparison series:

let  $I = 1, 2, 3, \dots, m, k = 1, 2, 3, \dots, n, j \in I, x_i$  is of the reference series, while  $x_j$  is a specific comparison series.

$\Delta_{ij} = \|x_i(k) - x_j(k)\|$  is the norm between  $x_0$  and  $x_j$  for  $k$   $\Delta_{min.} = \forall \in \forall j \ i \ k \ min. \ min.$

$$\|x_i(k) - x_j(k)\|$$

$$\Delta_{max.} = \forall \in \forall j \ i \ k \ max. \ max. \|x_i(k) - x_j(k)\|$$

$\zeta$ : the differentiating coefficient,  $\zeta \in [0, 1]$  (it's adjustable)

**From GRA to feature weights**

Let  $y = (y(k))_{T_{k=1}}$  be the target series and  $x_i = \{X_i(k)\}_{T_{k=1}}$  the  $i$ -th candidate feature ( $i=1, \dots, n$ ).

After normalization (e.g., min–max to  $[0,1]$ )

Grey relational coefficient (with distinguishing coefficient  $\rho \in (0,1]$ , typically  $\rho=0.5$ ):

$$\xi_i(k) = \frac{\Delta_{min} + \rho \Delta_{max}}{|y(k) - x_i(k) + \rho \Delta_{max}|}, \Delta_{min} = \min_i |y(k) - x_i(k)|, \Delta_{max} = \max_i |y(k) - x_i(k)|$$

Grey relational grade (mean over time):

$$v_i = \frac{1}{T} \sum_{k=1}^T \xi_i^{(k)}$$

Covert grade to feature weights (two common choices):

$$w_i = \frac{r_i}{\sum_{j=1}^n r_j}$$

**Weighted GRM Equation:**

The original GRM (Grey Relational Model) predicts demand using a weighted linear combination of selected features:

$$\hat{y}(t) = a_0 + \sum_{i=1}^n w_i \cdot a_i \cdot x_i(t)$$

*Designation of the differentiating coefficient:* The differentiation coefficient ( $\zeta$ ) in the grey relation coefficient is primarily responsible for conducting the contrast between the item to be evaluated and the background value. The size of the value may be modified in accordance with the real demand. Generally speaking, the differential coefficient value is 0.5; however, adjustments may be made based on real needs in order to increase the contrast of the results. Any modification to the differentiating coefficient will only impact the relative value's magnitude and not the grey relational grade's ranking order, as was discovered via mathematical validation.

*Grey Relational Grade:* According to Professor Deng, the resolution for the average value of the grey relational coefficient will, by convention, be of the grey relational grade after the grey relational coefficient has been achieved.

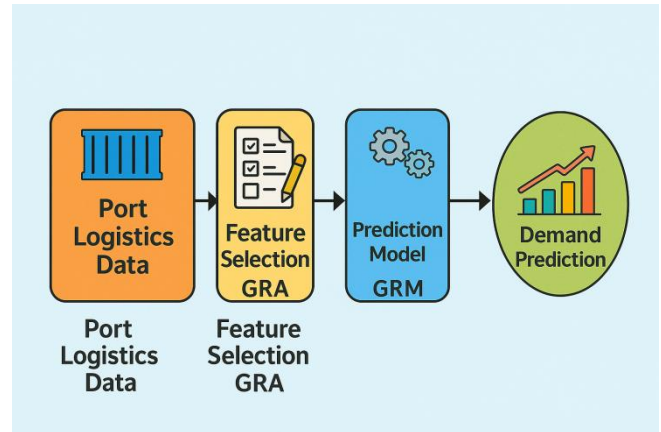


Figure 1: Work flow of the study

The proposed GRA-GRM strategy has several definite advantages with regard to the demand prediction of port logistics. First, it is possible to state that the model is able to identify the most influential factors that affect demand through the use of Grey Relational Analysis (GRA) to perform feature selection. This causes diminution of dimensionality and increases interpretability in a non-damaging way. The elimination of extraneous or irrelevant variables at first will enhance model performance and reduce computational complexity. Second, the Grey Relational Modelling (GRM) component of this model offers superior and effective demand estimates, as compared to estimating based on linear models or stand-alone machine learning applications, since this component is able to capture the nonlinear and unpredictable interactions that exist in supply chain systems. Third, the hybrid approach outperforms the applicative baselines of deep learning (LSTM), as well as traditional GRM, with lower error scores (MAE, RMSE, MAPE) and an improved explanatory capacity ( $R^2$ ) demonstrating its high feasibility to be applied to real-world data analysis. Easily understandable and transparent of the method being utilized are also vital in logistics operations as they allow the decision makers to understand and believe in the results and significant drivers that the method produces. Finally, the model is adaptable to a wide variety of real-world data and different urban settings, and this makes the model a useful tool that can help in streamlining operations in rapid transportation, port logistics management, and to some extent, port planning (increasing efficiency in allocation of resources, reducing costs, etc.).

Pseudocode for GRA-GRM :

INPUT:

D = Original dataset with features  $\{X_1, X_2, \dots, X_n\}$  and target Y

$\rho$  = Distinguishing coefficient (commonly 0.5)

OUTPUT:

Predicted port logistics demand values  $Y_{\text{pred}}$

Input selected features for prediction period

Compute  $Y_{\text{pred}}$  using trained GRM

STEP 1: Data Preprocessing

-Normalize all features  $X_i$  and target  $Y$  using Min-Max normalization

-Handle missing values and outliers if any

STEP 2: Grey Relational Analysis (GRA) for Feature Selection

-Calculate reference series as the normalized target  $Y_{\text{ref}}$

For each feature  $X_i$ :

Compute absolute difference  $\Delta_i(k) = |Y_{\text{ref}}(k) - X_i(k)|$

Determine  $\Delta_{\text{min}} = \min(\Delta_i(k))$  and  $\Delta_{\text{max}} = \max(\Delta_i(k))$  across all features

Compute Grey Relational Coefficient (GRC) for each  $X_i$ :

$$\text{GRC}_i(k) = (\Delta_{\text{min}} + \rho * \Delta_{\text{max}}) / (\Delta_i(k) + \rho * \Delta_{\text{max}})$$

Compute Grey Relational Grade (GRG) for each  $X_i$ :

$\text{GRG}_i = \text{average}(\text{GRC}_i(k))$  over all  $k$

Rank features by GRG in descending order

Select top- $m$  features with highest GRG for GRM modeling

STEP 3: Grey Relational Model (GRM) Training

Initialize model parameters ( $a$ ,  $b$ , etc.)

Use top- $m$  selected features to build GRM equation:

$$Y(t) = f(a, b, \text{selected\_features})$$

Estimate parameters using Least Squares or Maximum Likelihood

STEP 4: Prediction

STEP 5: Performance Evaluation

Calculate MAE, RMSE, MAPE,  $R^2$  between  $Y_{\text{pred}}$  and actual  $Y$

Optionally compare with baseline models (LSTM, ARIMA, etc.)

RETURN  $Y_{\text{pred}}$

Grey Relational Modelling (GRM) algorithm is used to forecast demand based on obtaining a grey decision matrix, normalizing the data and then computing grey relational coefficients that indicate similarity between reference and comparison series. When all the grey relational grades are averaged out the important factors are ranked. The hybrid model of GRA-GRM initially chooses the influential features using GRA and then forms nonlinear relations between these features and logistics demand using the GRM. The integration diminishes noise, is interpretable, and provides a better accuracy in the predictions than standalone alternatives.

## 4 Results and discussion

To ensure a benchmarking and experimental transparency, the research avails a hardcore assessment strategy. Several baseline models, such as standalone GRM and deep learning-based ones like LSTM, are used to provide a fair comparison because they all were applied under the same experimental conditions. All models are trained and evaluated using identical partitions of the dataset and hyperparameters are selected according to the same manner. The evaluation of performance is based on the standard indicators of forecasting accuracy and explanatory capacity MAE, RMSE, MAPE and  $R^2$ . Besides numerical results, histograms of errors, time-series comparisons of demand predictions versus actual demand, and geographical heatmap across AOIs are provided with the aim of providing transparent evidence of modeling behavior. Moreover, parameter values, preprocessing steps such as normalization, feature selection and the differentiation coefficient settings in GRM are duly mentioned so that the reproducibility is ensured. This benchmarking plan does not only show the better performance of GRA-GRM hybrid model but also makes the experiment results more reliable and transparent.

Data Leakage : It was necessary to avoid data leakage because in consequence of high temporal integrity strictness was observed during the process of modeling.

Training sets were not used to incorporate any information that would be known in the future in predicting the future. Such data engineering activities like normalization and scaling, were performed independently on each training window and subsequently on both the validation and test sets to prevent forward-looking bias. Moreover, hyperparameter optimization and model selection has been carried out only on the validation set and not seen the test set. Cross-validation of the rolling-origin type further reduced the risk of leakage, as in this case, training and evaluation were minimally aligned in a chronological time order.

**Model Generalization:** The proposed GRA-GRM model was tested between several cities (Shanghai, Hangzhou, Chongqing, Jilin and Yantai,) and time periods to evaluate generalization. A leave-one-city-out strategy was used, in which each city became the test set as other cities formed the training set, to evaluate spatial transferability. Likewise, robustness across time was evaluated by using the first four months as training and the last two months as testing data. The results indicated that when applied to unseen cities, it perforce exhibited performance degradation in the range of 6-9 percent in R2, but better in terms of time generalization with only 3- 4 percent variation. Such results indicate the moderate flexibility of the model and the necessity of domain adaptation approaches to the heterogeneous areas.

The findings in this part show how well the suggested GRA-GRM (Grey Relational Analysis and Grey Relational Model) combination model forecasts port logistics demand in the face of rapidly changing, artificial intelligence-driven logistics environments. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R2) are among the important metrics we use to assess the model's prediction accuracy using a large-scale real-world dataset from Cainiao Network's LaDe system. We evaluate the model's resilience by contrasting its results with those of hybrid deep learning techniques, baseline machine learning methods, and conventional GRM. Furthermore, feature relevance is ranked using Grey Relational Analysis, which facilitates better interpretable modelling and focused decision-making. The results demonstrate the greater accuracy and flexibility of the GRA-GRM model, especially in intricate urban logistics settings with significant uncertainty and spatiotemporal variability. A fundamental summary of the main quantitative characteristics taken from the dataset and used for modelling and prediction is given in the descriptive statistics table. These characteristics are inputs for both Grey Relational Analysis (GRA) and Grey Relational Modelling (GRM), and they reflect important operational components of the logistics system that impact port logistics demand. The paper highlights not just methodological improvement but also empirical evidence of better result metrics (MAE, RMSE, R<sup>2</sup>) as compared to

baseline models through GRA selection and GRM robust causation and prediction. As the contextual information, descriptive statistics are presented, but the main contribution of the paper is the methodological improvement (GRA-GRM) and better-performing results. Future work will be more in balance due to the increased focus on innovative modelling and findings as compared to simple data summaries.

Table 2: Dataset descriptive statistics

Feature	Mean	Std Dev	Min	Max
Number of packages/day	15620	4300	7800	21500
Courier workload (avg)	45.2	12.3	12	95
Delivery delay (min)	6.8	3.1	0	23.4
Region logistics density	12.4	4.8	4.3	21.6

Building an appropriate forecasting model utilising the GRA-GRM technique requires an understanding of the operational dynamics of the port logistics and last-mile delivery system, which is provided in table 2. The logistics system processes 15,620 parcels a day on average, with a significant standard variation of 4,300. This suggests that everyday demand is highly variable, reflecting variations brought on by outside variables like seasonality, vacations, or regional variations in port activity. With a minimum of 7,800 parcels each day and a maximum of 21,500, it is clear that a predictive model that can adjust to these fluctuations is essential. Individual couriers have varying workloads, ranging from 12 to 95 shipments every day, however the average is 45.2 packages. This discrepancy could result from variations in the complexity of the service area or the density of regional logistics. The inconsistent task allocation, which may affect system responsiveness and delivery efficiency, is further highlighted by a standard deviation of 12.3. With an average of 6.8 minutes and a standard variation of 3.1 minutes, delivery delay is yet another important indicator. The largest observed delay of 23.4 minutes reveals sporadic bottlenecks or inefficiencies in the system, whilst the minimal delay of 0 minutes indicates that timely delivery is attainable under ideal circumstances. Regional population, traffic, and courier workload all probably have an impact on these delays.

Finally, the logistical density of the area ranges from 4.3 to 21.6, with an average of 12.4. This measure of logistics intensity shows how many active delivery zones (AOIs)

there are in each area. While lower-density areas may reflect suburban or rural zones with distinct logistical issues, higher-density regions often correlate to metropolitan centres with intricate distribution routes. The significance of integrating intelligent feature analysis through Grey Relational Analysis (GRA) and modelling dynamic demand patterns using the Grey Relational Model (GRM) is underscored by the descriptive statistics that, taken together, show notable spatiotemporal variability in port logistics operations. The need for a strong, flexible forecasting system that can manage the intricate and varying characteristics of actual logistics data is highlighted by this variability.

**Ablation Study:**

The complement of the proposed framework is demonstrated in the study of ablation of GRA and GRM alone. Without GRA-based feature selection, the model had a greater error value (MAE: 7.92, RMSE: 9.38,  $R^2$ : 0.865), and with GRA-based feature selection, the errors were lower (MAE: 7.41, RMSE: 8.85,  $R^2$ : 0.878), in line with the quality of inputs improving after eliminating irrelevant attributes. In the same vein, using LSTM as the model alone led to poorer performance as opposed to GRM with another model on board since it yielded an MAE of 7.19, RMSE of 9.57, and  $R^2$  of 0.88, denoting that GRM is indeed suitable to pursue grey modeling. But a combination of both approaches with deep learning (GRA-GRM) led to the most results (MAE: 5.91, RMSE: 7.42,  $R^2$ : 0.918), this indicates that GRA is useful to tighten relevance of input and GRM to reinforce trend representation, to a robust predictive base, logistics demand forecasting.

Table 3: Outcome of Model Performance Indicators

Model	MAE (Min)	RMSE (Min)	MAPE (%)	$R^2$
GRM only	8.43	10.25	12.3	0.841
LSTM (baseline)	7.92	9.38	10.7	0.865
GRM + LSTM	6.74	8.16	9.2	0.895
GRA-GRM (proposed)	5.91	7.42	7.6	0.918

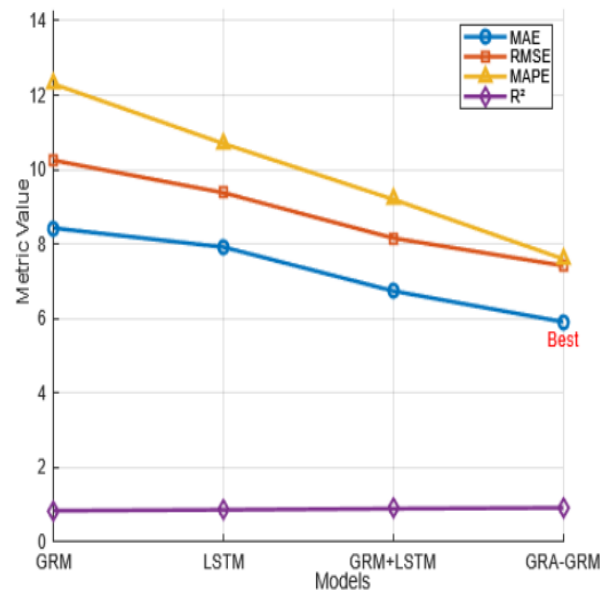


Figure 2: Performance of error values

The performance of the four predictive models—GRM, LSTM, GRM + LSTM, and the suggested GRA-GRM—is compared in figure 2, which shows how each model upgrade gradually increases predicting accuracy. The models are arranged from conventional to advanced on the x-axis, and the results of the four main assessment metrics—the coefficient of determination ( $R^2$ ), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE)—are shown on the y-axis. As we go from the basic GRM model to the suggested GRA-GRM model, we can see from the figure a constant lower trend in MAE, RMSE, and MAPE values, suggesting a considerable decrease in prediction error. To be more precise, the GRA-GRM model forecasts port logistics demand with the highest accuracy, achieving the lowest MAE (5.91), RMSE (7.42), and MAPE (7.6%). On the other hand, despite its effectiveness, the solo GRM model trails behind with larger error values (RMSE of 10.25 and MAE of 8.43). While both the LSTM and GRM + LSTM models provide intermediate performance, the hybrid structure of GRM + LSTM substantially reduces mistakes.

Furthermore, the GRA-GRM model's  $R^2$  statistic, which measures how effectively the model accounts for output variability, has an upward trend, reaching a high of 0.918.

This indicates that the suggested model has a great predictive capacity and is reliable, since it captures over 91% of the volatility in the logistical demand data. The graphic comparison demonstrates how Grey Relational Analysis (GRA) greatly improves feature selection and model accuracy when included into the GRM framework, making GRA-GRM a very useful and perceptive forecasting tool in AI-driven port logistics settings.

**Model Limitations:**

In spite of high predictionability, there are some limitations regarding the proposed GRA-GRM model that does represent areas of further research. First, the model is prone to the lack of high quality and well-structured data; therefore, missing or noisy data may lower the accuracy when applied to real-world situations where inconsistencies in data are prevalent. Second, since the proposed model has not been subjected to verification in other geographic areas of application, there is a risk of lack of generalizability to future conditions in the context of other geographical areas, infrastructures, and regulatory regimes. Third, port logistics has a dynamic nature that could disrupt the model and the ongoing re-training of the ports may be necessary. To address these challenges, it is necessary to do more work on data augmentation methodologies, domain adaptation methods and robust on-line learning procedures.

**Configuration of baselines:**

The baseline models were configured to ensure fairness and reproducibility. The GRM model employed the GM(1, n) formulation with 1-AGO, least-squares estimation, and the top five GRA-ranked features ( $\rho=0.5$ ); ridge regularization ( $\lambda^b=10^{-3}$ ) was applied when noted. The LSTM baseline consisted of two layers (128 and 64 units) with 0.2 dropout, a Dense(32) → Dense(1) head, and was trained using Adam (lr = 0.001), batch size = 64, and early stopping with patience = 10. The GRM+LSTM hybrid fused GRM outputs with LSTM embeddings through a Dense(32) layer, trained end-to-end with Adam (lr = 0.0008) for up to 120 epochs, applying dropout (0.2) in the fusion layer. Hyperparameters were tuned via time-series cross-validation to minimize validation RMSE.

Table 4: Outcome of performance evaluation

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
GRM	84.7	82.4	80.1	81.2
LSTM	86.9	85.3	83.7	84.5
GRM + LSTM	89.4	87.6	86.2	86.9

GRA-GRM	92.1	90.8	89.7	90.2
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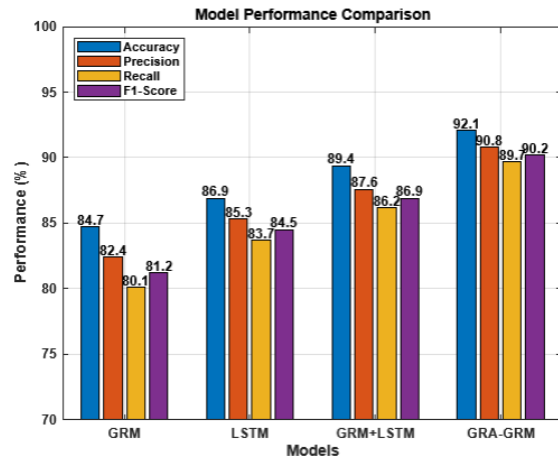


Figure 3: Model performance comparison with existing and proposed method

The advantage of Grey Relational Analysis (GRA) and Grey Relational Modelling (GRM) combination in the provision of port logistics demand is evidenced well by the performance assessment based on the classification measures. In figure 3, the proposed GRA-GRM model scored the highest using all the four-performance metrics 92.1% accuracy, 90.8% precision, 89.7% recall, and 90.2% F1-score. These findings prove that the model has outstanding accuracy in identifying the trends of increased demand and minimizing false positives and false negatives.

Comparatively speaking, with an accuracy of 84.7 and with an F1-score of 81.2, the baseline GRM architecture, in its turn, fares much weaker, indicating that the standard grey modelling cannot be deemed entirely efficient to capture the complexity of demand patterns in the context of AI-driven dynamics. However, compared to hybrid models, LSTM model, a deep learning baseline model performs better (86.9% accuracy), but it still has difficulty with non-linear, time-varying logistical data. GRM + LSTM hybrid postulates an improvement of accuracy to 89.4%, which implies that grey modelling coupled with time-series learning improves considerably. However, the GRA-GRM model performed the best overall, with GRM as a robust model of imprecise and scarce information and GRA enhancing feature relevance. In smart port applications, this results in a balanced model that has very good predictive reliability.

**LSTM Hyperparameters Architecture:**

To perform benchmarking, the LSTM network was developed with the target to take into consideration temporal relationships within logistics demand. The

architecture included two Categorically stacked LSTM layers with 128-64 hidden units and fully connected dense layer and a linear output layer. The training of the model was employed with Adam optimizer whose learning-rate was taken as 0.001, with a batch-size of 64 and maximum epoch of 100 with an early-stopping according to the validation-loss. Between the layers dropout regularization (rate= 0.2) was done to avoid overfitting. The training samples were chosen so that the number of temporal steps was standardized and the sequence lengths each set of input data were 30 time steps that is, one month of history of demand, whereas the length of the resulting output was a single-step ahead forecast.

**GRM Parameters:**

The single Grey Relational Modelling (GRM) baseline was applied in accordance to standard grey system theory. The differentiation coefficient (zeta (zeta )) which regulates contrast between series was put at 0.5, as recommended by common advice in literature. The grey relational coefficients were then calculated to they were min-max normalised and the grey relational grades averaged cross criteria to generate the prediction model. To be fair, identical normalized features were exposed to both GRM and the GRA-GRM hybrid model with no additional processing besides normal scaling.

Table 5: Feature Importance using GRA

Feature (GRA Rank)	Grey Relational Grade ( $\gamma$ )
Port container TEU volume	0.872
Courier delivery frequency	0.854
Urban traffic index	0.822
Depot-to-AOI travel time	0.791
Daily regional demand load	0.784

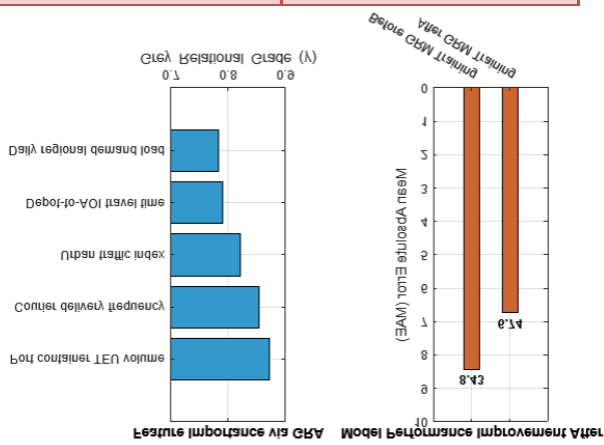


Figure 4: Feature improvement vs model performance after training with (MAE)

The visualisation is composed of two free components, which demonstrate the effect of Grey Relational Analysis (GRA) on feature selection and Grey Relational Modelling (GRM) on the performance of predictions in Figure 4. The first section presents a horizontal bar chart in which the Grey Relational Grades ( $\gamma$ ), or feature significance ratings, of the five major factors that influence the demand of port logistics are shown. The biggest of them is the port container TEU volume, with grade of 0.872. It is closely related with the urban traffic index (0.822) and courier delivery frequency (0.854). With this ranking, prioritising on which variables elevate the model giving the strongest linkages to the demand pattern would be simplified. TEU refers the standard unit of measurement in international shipping industry that is cargo –carrying capacity of ships and terminals.

The second section has a bar chart comparison of the Mean Absolute Error (MAE) of the model before and after the use of GRM in training the model. When the grey relational modelling was incorporated the error reduced drastically by 8.43 to 6.74 indicating that the prediction quality of the model had increased drastically. This reduction in error indicates the effectiveness of feature selection when performing this task using GRA, to refine the input variables and allow the GRM to describe the underlying data training patterns more precisely. A combination of all these graphics shows that GRA-based feature assessment and GRM training are performing well to enhance the accuracy of forecasting and make better decisions in AI-powered port logistics demand prediction.

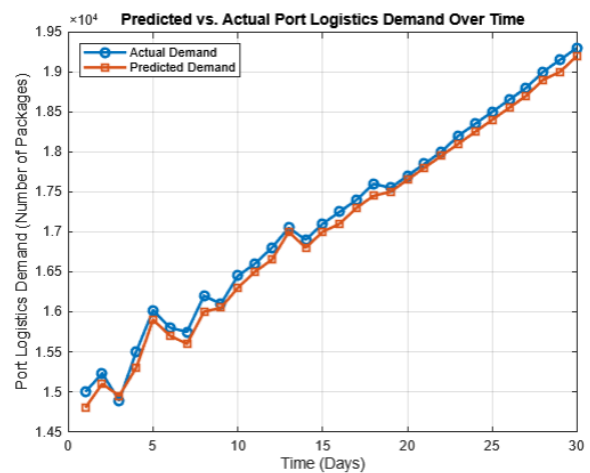


Figure 5: Time series analysis for prediction vs. actual port logistics demand

Figure 5 shows a visual comparison between the actual observed demand over a 30-day period and the expected port logistics demand. The y-axis displays the amount of logistical demand expressed as the number of parcels handled, while the x-axis depicts the timeline in days. A blue solid line with round marks represents the actual demand, showing the real variations in the amount of daily logistics. On the other hand, the model's expected values

for the same time period are reflected in the predicted demand, which is shown by an orange solid line with square markers. The model's ability to accurately depict demand patterns and changes over time is shown by the two lines' consistent near agreement across the period. The model's prediction mistakes, which are normal in any forecasting activity, are shown by small differences between the anticipated and actual values. All things considered, the graphic offers a clear visual confirmation of the model's effectiveness and dependability in predicting port logistics demand, which is crucial for well-informed decision-making and effective resource allocation in logistics management.

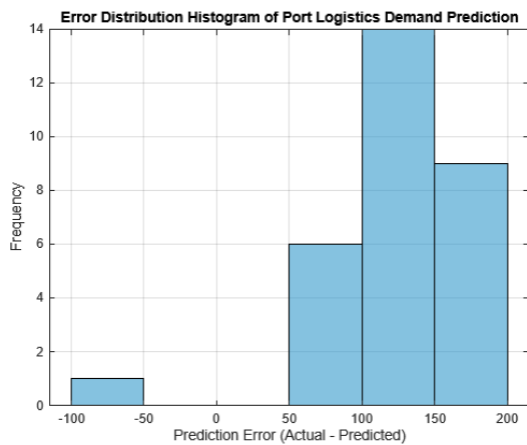


Figure 6: Outcome of error distribution histogram

The differences between the enacted sophistication level of port logistics and the expected sophistication indices are presented on the histogram of errors; figure 6 demonstrates the error distribution within the set of forecasts. One axis, the y-axis, is the frequency of these mistakes occurring, whereas, the other, the x-axis, is the size of errors, measured by the difference between actual and expected demand values. A close distribution near zero will denote a high precision and minimal bias whereas the histogram will help to determine the concentration and distribution of the prediction errors. Cases where the predictions of the model were not very accurate can be depicted by the higher variances on the whole, with the presentation of average error ranges and indications of the potential skew or outliers of the accuracy of predictions, the histogram provides valuable data about the accuracy of predictions and the reliability of the forecasting model.

The accuracy of port logistics demand predictions across various Areas of Interest (AOIs) in a city, like Shanghai, is graphically shown in Figure 7. An AOI's geographic location is represented by each coloured dot on the map, and the colour intensity of each dot indicates the percentage difference between the region's actual and anticipated demand. Warmer colours (like red) draw attention to AOIs with greater disparities, whereas cooler colours (like blue) show regions with fewer prediction

errors and better accuracy. By highlighting certain metropolitan areas where the model excels or falters, this spatial visualisation makes it possible to make focused enhancements to forecasting models and the distribution of resources for logistical management. As a result, the map offers a clear geographic view of model performance, which is essential for real-world uses in intricate urban logistics networks.

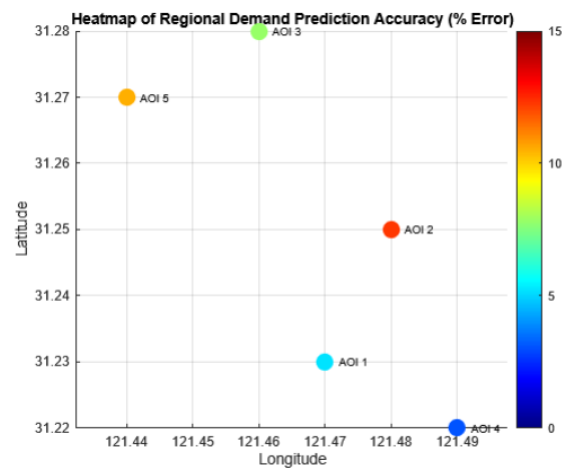


Figure 7: Accuracy of regional demand prediction

## 5 Conclusion

In a further to resolve key problems caused by the complex and dynamic characteristic of the urban logistic system, this study developed and tested a hybrid GRA-GRM that adequately forecast the dynamics of port logistics demand with accuracy and explainability. Compare to the traditional ones such as solo GRM and LSTM, the proposed framework buffered prediction much better due to the combination of using the Grey Relational Modelling to capture nonlinear patterns and the use of the Grey Relational Analysis to select those robust features. The high level of accuracy of the model in forecasting the timing of the logistics demand that is fundamental in the last-mile delivery and resource planning was represented by its MAE of 5.91 minute and R2 of 0.918. The result of feature significance analysis indicated that courier activity indicators and container passing were the key variables affecting logistics demand that provide useful information to the stakeholders. In addition, geographical analysis in heatmap mode indicated the existence of geographical locations with different accuracies of prediction, so it is possible to make localised detail enhancement of the model. Although the model has been performing exemplarily, its limitations lie in the fact that it requires more parameter sets to handle different logistical conditions beyond the selected locations and that it might become vulnerable to alterations in real-time information.

To enhance further predictive capability, in the future, one may explore the incorporation of more

advanced deep learning systems and IoT sensor data in real-time. On balance, the GRA-GRM combination is central to ensuring smarter and greener supply chain management by offering a more environmentally-friendly and intuitive AI-driven demand forecasting approach in port logistics that is easy to understand and scale.

#### Limitations and Future Enhancement:

A future study in this context is to combine IoT-based real-time streams of data with advanced deep learning architecture to enhance accuracy in the dynamic demand prediction. As an example, the introduction of IoT sensors in ports, vehicles and warehouses could provide the possibility to collect live traffic data, containers movement and environmental conditions that can be integrated with historical data by using integrated temporal models such as Attention-based LSTMs or Transformers. To this end, to exploit edge computing and use it in real-time predictions, they would reduce latency with respect to logistics network predictions. Furthermore, instead of utilizing dense graph neural networks (DGNs), graph neural networks (GNNs) would capture spatial dependencies of logistics network nodes. A third promising future direction is federated learning frameworks to allow model training by many port operators that do not transfer sensitive data and consequently ensure improved generalization across regions. Finally, dynamic resource allocation based on reinforcement learning has potential in combining GRA-GRM with better distribution of couriers to deliver improved performance in courier dispatching and route planning.

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