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Optimizing Freight Cost Predictions with a Hybrid GRU-GA Model: Implications for Supply Chain Sustainability

Soroush Yousefi [1], **Babak Javadi** [2]

1. Computational Optimization and Smart Transformation Lab, Faculty of Engineering, College of Farabi, University of Tehran, Qom, Iran. E-mail: soroush.ut@gmail.com
2. Corresponding author, Computational Optimization and Smart Transformation Lab, Faculty of Engineering, College of Farabi, University of Tehran, Qom, Iran. E-mail: babakjavadi@ut.ac.ir

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ABSTRACT

Objective: Freight costs constitute a significant share of total supply chain expenses and play a critical role in operational efficiency and sustainability. Accurate freight cost forecasting is therefore essential for effective logistics planning and sustainable supply chain management. This study aims to develop a robust forecasting framework to improve the accuracy of freight cost prediction in real-world supply chain systems.

Methods: This research proposes a hybrid forecasting model that integrates a Gated Recurrent Unit (GRU) neural network with a Genetic Algorithm (GA) for hyperparameter optimization. The GRU model captures temporal dependencies in freight cost time-series data, while the GA optimizes key hyperparameters, including the number of neurons and dropout rate, by minimizing Mean Absolute Error (MAE). The model is trained and evaluated using a real-world healthcare supply chain dataset. Its performance is benchmarked against traditional statistical models, including Autoregressive (AR) and ARIMA models.

Results: The experimental results demonstrate that the proposed GRU-GA model significantly outperforms the benchmark models in terms of forecasting accuracy. The optimized GRU structure achieves lower MAE values compared to AR, ARIMA, and non-optimized deep learning models, indicating superior capability in modeling nonlinear and complex temporal patterns inherent in freight cost data.

Conclusion: The findings confirm that integrating evolutionary optimization with deep recurrent neural networks substantially enhances freight cost prediction performance. Improved forecasting accuracy can support better transportation planning, reduce operational inefficiencies, and contribute to economic, environmental, and social sustainability in supply chains. The proposed GRU-GA framework is flexible and can be extended to other logistics and transportation forecasting applications.

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1. Introduction

With the growth of the internet, the creation of more online stores, and an increase in online transactions, logistics have also become more active, leading to the growth of logistics-based businesses. With the outbreak of COVID-19 in 2020, people staying at home, and the rise in non-presential and online purchases, this trend has become more pronounced. By August 2020, the volume of traffic and vehicles used for transporting goods had increased compared to 2019 (Jang et al., 2023). This highlights the importance of freight, as market-induced freight can easily stimulate urban logistics.

On the other hand, freight costs, as one of the components of the supply chain, play an important role in the performance and sustainability of the supply chain. Ultimately, improving and reducing freight costs can help improve the environmental, economic, and social sustainability of supply chain systems.

From an environmental perspective, reducing freight costs can improve supply chain sustainability in various ways, including:

1. Less fuel consumption and fewer pollutant emissions: A significant portion of freight costs is related to fuel consumption. The use of fossil fuels in freight leads to the emission of greenhouse gases and air pollution, which have detrimental effects on the environment.
2. Optimal freight mode selection: Choosing freight modes with lower energy consumption, such as rail or maritime transport instead of road transport, can reduce pollutant emissions and improve environmental sustainability.
3. Route optimization: Using routing and freight planning software, routes can be optimized to reduce fuel consumption and emissions.
4. Better packaging: Lighter and recyclable packaging can help reduce weight, freight costs, and fuel consumption.

From an economic perspective, reducing freight costs can improve supply chain sustainability in various ways, including:

1. Overall cost reduction: Lower freight costs can lead to reduced overall supply chain costs and increased profitability for companies.
2. Increased productivity: Optimizing routes, reducing freight time, and using new technologies can help increase supply chain productivity.
3. Increased customer satisfaction: Providing faster and more reliable freight services can help increase customer satisfaction.

From a social perspective, reducing freight costs can improve supply chain sustainability in various ways, including:

1. Supporting local communities: Using local freight services and supporting small local companies in this sector can lead to the development of local communities.
2. Job creation: Developing sustainable freight infrastructure can help create jobs in different regions.
3. Worker safety: Improving working conditions and safety for workers can help improve the social status of workers in the freight sector.

On the other hand, better and more accurate prediction of freight costs can significantly increase sustainability in the supply chain, and these two are interconnected. For reasons including:

1. Optimization of routes and modes of freight: With more accurate cost predictions, freight routes can be optimized to be both cost-effective and environmentally friendly. For example, rail transport may be less costly and cause less environmental harm than road transport.
2. Reduction of unnecessary freight: better prediction of freight costs, demand management, and inventory levels can help avoid unnecessary freight. This not only reduces costs but also decreases fuel consumption and hence pollutant emissions.
3. Selection of more sustainable suppliers: Knowing freight costs allows for the selection of suppliers who produce and transport their products sustainably.
4. Better fleet management: By accurately predicting costs using shipment volumes and routes, the freight fleet can be optimized, making the best use of vehicle capacities. This reduces costs, fuel consumption, and increases the lifespan of vehicles.
5. Reduction of overall costs: Lower freight costs lead to lower overall supply chain costs. This allows companies to invest more financial resources in sustainable technologies and improve production processes.

The conventional time-series methods of forecasting, such as the use of ARIMA models, are inadequate in capturing the fundamentally complex, nonlinear, and dynamic behavior of freight markets. These markets are influenced by a set of interacting variables: volatile fuel prices, changing almost overnight because of geopolitical events or disruptions to supply chains; fluctuating economic conditions that have an impact on demand and shipment volumes; global and regional geopolitical events that increase uncertainty and influence trade routes; seasonal demand; technological advances in transportation; and changing regulatory environments. Most ARIMA models rely on linear assumptions of the data and thus cannot capture these complex, usually unpredictable dynamics; hence, the models tend to be less accurate in their forecasts.

On the other hand, deep learning techniques, especially RNNs and their more advanced variants such as Gated Recurrent Units, have started to show promising alternatives in handling complex time-series data. RNNs are designed to process sequential data by maintaining an internal state, enabling them to "remember" past information. It is therefore particularly suitable for time-series forecasting, where a value at some point in time depends on its previous values. GRUs extend the RNN architecture with gate mechanisms that can regulate the information flow and somewhat alleviate the problem of vanishing gradients during training of traditional RNNs. These mechanisms for gating in GRUs allow them to filter information over even longer sequences to capture long-range patterns, proving much more practical and effective for time-series forecasts, such as freight costs, where history in the forms of trends or seasonal cycles makes quite a lot of difference.

On the other side, this performance of the networks depends substantially on how good an appropriate choice of their hyperparameters parameters which influence learning and changing network architecture or parameters-proves. The set includes the number of layers, the number of neurons in each layer, the learning rate, batch size, the types of activation functions, and various regularization parameters. Tuning these hyperparameters by trial and error is really an inefficient and time-consuming method. It cannot very often give an optimal combination of these. In this paper, GAs present a strong and efficient technique to optimize the aforesaid hyperparameters. Genetic algorithms take inspiration from the principle of selection and evolution. They start by generating a population of candidate solutions; in our context, this can be various sets of hyperparameters. They evaluate their performance using a fitness function that could be forecasting accuracy, then evolve that population to higher quality using genetic operators like selection, cross-over, and mutation. This allows GAs to efficiently scan the complex hyperparameter space and find that combination leading to a large increase in the performance of the GRUs.

This study proposes a hybrid model that combines GRU networks with a Genetic Algorithm for optimized freight cost forecasting. The GRU network is used to model temporal dynamics and nonlinear relationships that exist within freight cost data, while the GA optimizes the hyperparameters of the GRU toward the maximum forecasting accuracy of the GRU. Next, the results of the suggested GRU-GA model, when compared strictly to the capture of the conventional ARIMA, present superior performances for the description of the complexities of freight cost fluctuation. This paper bases the conduct of its study on a real dataset related to logistical pricing; numerous similarities exist among the Price and Quality Reporting and international transportation costs data developed by the Global Fund for its health supply chains. This dataset has very detailed freight costs, which will allow a realistic assessment of the performance of the model. Finally, the research discusses how improved forecasting accuracy may affect supply chain sustainability by investigating how better cost predictions can lead to optimized logistics, reduced waste, and greener transportation methods.

2. Literature Review

In a paper prepared by (Kovács, 2017), road freight costs were calculated using factors such as distance, fuel, price, and highway tolls. The Multiple Regression algorithm was used for this purpose. Following him, Sternad (2019) attempted to identify the main influential factors and considered two types of costs: fixed costs related to the vehicle and driver, and variable costs such as fuel.

Khajeh et al., (2023) presented three innovative methods for predicting freight rates and conducted a comprehensive analysis in a paper. Their innovative method included extracting and classifying disruptive events and using predictions to improve freight. This study also considered external factors such as excess capacity and the impact of events like COVID-19. Future studies for this research include completing and further improving container transport rate prediction methods.

Díaz-Ramírez et al., (2023) provided a new approach to freight prediction using soft facts. Soft facts are indices extracted from expert surveys regarding their sentiments, beliefs, or perceptions of current and future market developments. An integrated moving average with an autoregressive (ARIMA) model was used as the baseline, and the results were compared with ARIMAX and VAR models.

Díaz-Ramírez et al., (2023) reviewed several decades and showed that policymakers have supported modal shift in the freight sector as an important basis for achieving greenhouse gas reduction targets in freight. The results showed that while modal shift policies have effectively increased the share of rail and sea transport in Sweden, the actual impact of this shift on emission reduction is limited. Several factors influence this, including the high level of carbonization of road transport and the low emission intensity of road transport in Sweden. The study ultimately demonstrated that challenges related to modal shift, such as infrastructure limitations and increased costs for some industries, exist, and suggests that merely focusing on modal shift as an emission reduction strategy may not be the most efficient approach. Instead, moving toward other strategies, such as the use of electricity and electric vehicles, as well as fuel efficiency, should be considered.

Ehtesham Rasi & Sohanian, (2020) in the “A multi-objective optimization model for sustainable supply chain network with using genetic algorithm”, developed a mixed-integer linear programing (MILP) model to incorporate economic and environmental data for multi-objective optimization of the sustainable supply chain network network.

Taş et al., (2013) drived studies for a vehicle routing problem with soft time windows and stochastic travel times. This paper addresses the sustainable vehicle routing problem, considering factors like fuel consumption, emissions, and traffic congestion. A model is developed that considers both transportation costs (total distance traveled, number of vehicles used and drivers' total expected overtime) and service costs (early and late arrivals). They propose a Tabu Search method to solve this model.

Tang et al., (2020) had a study. This study explores how growth in environmental sustainability has influenced the logistics industry to pursue sustainable development, with carbon tax policies being a key approach to reducing emissions. The research aims to optimize sustainable transportation and inventory under a carbon tax policy and finds ways to balance the interests of governments and businesses. Using a Stackelberg game model and a three-stage dynamic game model, the study seeks to optimize transportation costs, carbon tax rates, and sustainable investments. Simulations indicate that while carbon tax policies improve social welfare and sustainability, they may reduce corporate profits. However, sharing sustainable investments between governments and businesses can mitigate these drawbacks and yield positive outcomes for both parties.

Mao et al., (2023) proposed a study which designs a reverse logistics network for express packaging recycling in China to address environmental pollution and resource waste. Using K-means and NSGA-II algorithms, the researchers optimized the selection of recycling and processing centers to minimize costs and carbon emissions. The solutions were categorized based on priority for cost or environmental benefits. The findings suggest that with proper planning and algorithmic support, sustainable logistics networks can be effectively designed to balance economic and environmental considerations.

Panigrahi et al., (2019) in “Sustainable supply chain management: A review of literature and implications for future research” discussed crucial issues about sustainable supply chain and minimizing negative impacts on the environment, society, and economy.

Sánchez-Flores et al., (2020) made a review on emerging economies in sustainable supply chain. This article reviews global literature on SSCM in emerging economies, analyzing 56 articles from 2010 to April 2020. The study highlights that while interest in SSCM is increasing, research in emerging economies lags behind that in developed ones. The context of developing countries is crucial in empirical studies, and integrating the three dimensions of sustainability is vital for enhancing supply chain performance. The article also identifies limitations and suggests future research opportunities, particularly in supply chain functions like collaboration, sustainable practices innovation, and supplier development.

Recent research on freight cost prediction increasingly leverages advanced time-series models and machine learning–based methods to address complex, nonlinear dynamics. For instance, Saeed et al., (2023) applied the Prophet forecasting method to container freight rates while explicitly incorporating disruptive events, achieving notable gains over classical ARIMA models. Comparative studies show that models like LSTM-GA and CNN-GA consistently outperform their non-optimized counterparts, substantiating the value of evolutionary metaheuristics in hyperparameter tuning (Wang et al., 2023). Although previous work has largely focused on single-objective optimization or domain-specific contexts, our approach generalizes the paradigm by integrating GRU-GA for diverse real-world freight operations while emphasizing interpretability and sustainability impacts. This synthesis highlights both the advances and current limitations in the field, providing the rationale for the architecture and methods selected in this study.

3. Methodology

In this research, a real-world dataset has been used. This dataset provides data related to the freight of health supply chain goods. Additionally, it includes pricing and related supply chain costs for transporting goods to countries. This dataset has fields similar to the Price, Quality, and Reporting (PQR) data of the Global Fund and includes 10,325 observations and 33 features.

Firstly, features not related to freight costs were removed, and variables related to the target variable were kept for the following reasons:

- Reducing model complexity: The fewer the inputs of a model, the simpler the model becomes, and the likelihood of overfitting decreases. Overfitting refers to excessive learning of details, causing poor model performance on new, unseen data.
- Improving training speed: By reducing the number of variables, training time improves due to less data processing.
- Improving model interpretability: By removing irrelevant variables, the final model becomes more understandable, and the relationship between input and output variables can be easily analyzed.
- Reducing noise: Irrelevant variables can act as noise in the data, reducing model accuracy. By removing these variables, the main signal strengthens, allowing the model to better identify patterns in the data.

In this research, we used the correlation method for this purpose. In this method, the correlation coefficient between each variable and the target variable (freight cost) is calculated. Variables with zero or low correlation are likely irrelevant and are removed from the dataset used for training.

Next, we address outlier data, which refers to data significantly different from other data points. Outliers can be due to data collection errors, measurement noise, or abnormal phenomena in the data. We remove or correct outliers for the following reasons:

- Reducing model impact: Outliers can significantly impact model performance, affecting mean, standard deviation, and other statistics, leading to incorrect results.
- Improving model accuracy: Models trained with outliers may have lower accuracy in predicting new data.
- Identifying real patterns: Removing outliers helps in identifying real patterns in the data.

We used a distance-based method to identify outliers. In this method, data points whose distance from the mean exceeds three standard deviations are considered outliers.

Next, we deal with missing data, a common challenge in data analysis, caused by human error, technical issues in data collection, or non-response. We used the observation deletion method, which is simple and removes rows containing missing values. Given the low percentage of missing data, this method is appropriate.

For model stability, 70% of the dataset was allocated for training, and the remaining 30% for testing.

In this study, a Genetic Algorithm (GA)-optimized Gated Recurrent Unit (GRU) model for time series prediction is proposed. The methodology consists of three main components: data preprocessing, hyperparameter optimization using Genetic Algorithm, and final model training and evaluation.

3.1. Data Preprocessing

3.1.1 Data Preparation

The dataset is first loaded and preprocessed to ensure data quality. Missing values are removed to prevent inconsistencies in training. The dataset consists of multiple features representing historical input variables, with the target variable being the prediction output. The feature set X is separated from the target variable Y.

3.1.2 Data Splitting

To evaluate the model's generalization capability, the dataset is split into training and testing sets using 70-30 ratio. The training set is used for model training, while the test set is reserved for performance evaluation.

3.1.3 Data Normalization

Since neural networks perform better when input features are scaled within a uniform range, MinMax normalization is applied to transform the input variables between [0,1]. The transformation is performed as follows:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where X_{max} *and* X_{min} are the maximum and minimum values of each feature, respectively. The same transformation is applied to both training and test sets to maintain consistency.

3.1.4 Data Reshaping for GRU Input

Since the GRU model expects sequential data, the training and test sets are reshaped into three-dimensional tensors with the shape (samples, timesteps, features), where:

- Samples represent the number of data points
- Timesteps indicate the time dependency in sequences
- Features denote the number of input variables

This transformation ensures that the model can capture temporal dependencies effectively.

3.2. Hyperparameter Optimization Using Genetic Algorithm (GA)

Given the importance of hyperparameters in the performance of GRU models, a Genetic Algorithm (GA) is employed to optimize two key hyperparameters:

- Number of neurons (n) in the GRU layer
- Dropout rate (d) to prevent overfitting

GA is a population-based optimization technique inspired by natural selection, where the fittest individuals are selected and evolved over multiple generations. The process consists of the following steps:

3.2.1 Chromosome Representation

Each individual in the GA population represents a possible configuration of the GRU model's hyperparameters:

- n (number of neurons): an integer between [1, 100]
- d (dropout rate): a float between [0, 0.5]

Each individual (or solution) is represented as a chromosome in the form of:

$$I_i = (n_i , d_i)$$

Where n_i and d_i are the respective values for the i^{th} individual.

3.2.2 Initial Population Generation

An initial population of N individuals is randomly generated. Each individual is assigned random values within the predefined hyperparameter bounds.

3.2.3 Fitness Function Evaluation

Each individual's performance is assessed using a fitness function, which trains a GRU model with the given hyperparameters and evaluates its Mean Absolute Error (MAE) on the test set. The steps for fitness evaluation are as follows:

- Construct a GRU model with the individual's hyperparameters (n_i,d_i).
- Train the model on the training set ($Xtrain$,$Ytrain$) for a small number of epochs (E=10) to speed up the optimization process.
- Predict the output values $\hat{y}_i$ on the test set $Xtest$.
- Compute the MAE between predicted and actual values:

$$MAE = \frac{1}{n}\sum |y_i - \hat{y}_i|$$

Where n is the total number of test samples.

- Assign the MAE as the fitness score (lower values are better).

3.2.4 Selection

The selection process uses tournament selection to choose parents for reproduction. In each tournament, three individuals are randomly chosen, and the one with the lowest MAE (best performance) is selected.

3.2.5 Crossover

Selected parents undergo blend crossover, where offspring are generated by averaging the parents' hyperparameters with some randomness to introduce diversity. This allows for the exploration of new solutions while maintaining inherited properties from high-performing individuals.

3.2.6 Mutation

To further enhance diversity, Gaussian mutation is applied, which slightly perturbs the hyperparameter values by adding a small normally distributed noise. Mutation occurs with a probability P_m to prevent premature convergence to suboptimal solutions.

3.2.7 Iterative Evolution

The population evolves over G generations, with each iteration involving selection, crossover, and mutation. The best individuals are preserved for the next generation.

3.2.8 Best Solution Extraction

After evolution is complete, the best individual I^*=(n^*,d^*) with the lowest MAE is selected as the optimal hyperparameter set.

3.3 Final Model Training and Evaluation

3.3.1 Model Training

Using the optimized hyperparameters (n^*,d^*), a final GRU model is trained on the entire training dataset for Ef=50 epochs to ensure sufficient learning. The training process involves backpropagation and Adam optimization to minimize the Mean Squared Error (MSE).

3.3.2 Model Prediction and Evaluation

The trained model is used to predict outputs on the test set, and its performance is evaluated using MAE. The final MAE score is reported as the model's performance metric.

This research applies a GRU neural network to the dataset. Then, using a genetic metaheuristic algorithm, this algorithm is optimized. The optimization objective function is MAE, and the pseudo-code of this algorithm is as follows:

Pseudo-Code for Genetic Algorithm-Optimized GRU Model

Algorithm 1: GRU Hyperparameter Optimization Using Genetic Algorithm

Input:

- *Dataset (D)*
- *Population size (N)*
- *Number of generations (G)*
- *Crossover probability (P_c)*
- *Mutation probability (P_m)*

Output:

- *Optimized GRU model with the best number of neurons and dropout rate*

1. Data Preprocessing

- *Load dataset (D)*
- *Remove missing values*
- *Separate features (X) and target variable (Y)*
- *Split data into training set ((X_{train}, Y_{train})) and testing set ((X_{test}, Y_{test}))*
- *Normalize (X_{train}) and (X_{test}) using MinMaxScaler*
- *Reshape (X_{train}) and (X_{test}) into three-dimensional tensors for GRU input*

2. Genetic Algorithm Initialization

- *2.1 Define search space:*
  - *Number of neurons (n in [1, 100])*
  - *Dropout rate (d in [0, 0.5])*
- *2.2 Generate initial population (P) of size (N), where each individual (I_i) is represented as (I_i = (n_i, d_i))*
- *2.3 Evaluate the fitness of each individual using Algorithm 2.*

Algorithm 2: Fitness Evaluation

Input: Individual ($I_i = (n_i, d_i)$)

Output: Fitness score (MAE)

Begin

1. *Create a GRU model with (n_i) neurons and dropout rate (d_i)*
2. *Train the model on ((X_{train}, Y_{train})) for (E) epochs*
3. *Predict (Y_{pred}) on (X_{test})*
4. *Compute Mean Absolute Error (MAE) between (Y_{test}) and (Y_{pred})*
5. *Return MAE as fitness score*

End

3. Evolutionary Process

For each generation (g) in (G) do:

- *3.1 Selection: Select parents using tournament selection*
- *3.2 Crossover: Apply blend crossover with probability (P_c) to generate offspring*
- *3.3 Mutation: Apply Gaussian mutation with probability (P_m)*
- *3.4 Ensure neurons and dropout remain within bounds*
- *3.5 Evaluate fitness of new population using Algorithm 2*
- *3.6 Replace current population with new population*

4. Model Training with Best Parameters

- *4.1 Select the best individual (I* = (n*, d*)) from the final population*
- *4.2 Train a final GRU model with (n*) neurons and dropout rate (d*) for (E_f) epochs*
- *4.3 Evaluate the final model on (X_{test})*
- *4.4 Report the final MAE*

End of Algorithm

4. Numerical Results

This section presents the numerical results obtained from the experiments conducted using the proposed GRU-GA model for freight cost forecasting. The model's performance is evaluated and compared against the benchmark ARIMA model. The primary performance metric used is the Mean Absolute Error (MAE), which measures the average absolute difference between the predicted and actual freight costs. Lower MAE values indicate better forecasting accuracy.

Additionally, the results from the proposed GRU-GA algorithm are compared against those obtained from GRU, ARIMA, and AR models, demonstrating the improvements achieved by the proposed algorithm.

This study utilizes a freight pricing dataset from the health supply chain. This dataset contains information regarding freight and pricing for health supply chain goods, specifically focusing on the shipment of antiretroviral (ARV) drugs and HIV laboratory supplies to recipient countries. Critically, the dataset includes not only the price of the goods themselves, but also the associated supply chain costs incurred in delivering these goods internationally. This data shares structural similarities with the Price, Quality, and Reporting (PQR) data maintained by the Global Fund. Given that PEPFAR and the Global Fund are the two largest procurers of HIV health commodities, this dataset, when analyzed in conjunction with PQR data, offers a more holistic understanding of global costs associated with these essential health goods. This comprehensive view is particularly valuable for discerning pricing ranges, identifying cost trends, and analyzing the volume of products delivered to individual countries. The United States government has recognized the potential of this data to empower stakeholders in making more informed, data-driven decisions. However, it is important to acknowledge that contextual factors, specific to each country and supply chain, should be carefully considered when interpreting and utilizing this database.

4.1 Overall Performance Comparison

To further investigate the performance of the proposed GRU-GA model, we compared its performance with conventional time series models (AR, ARIMA) and two basic deep learning models: conventional GRU and LSTM - neither of which use hyperparametric metaheuristic optimization. The results are presented in Table 1, which shows the mean absolute error (MAE) of each method on the test set along with the relative improvement percentage.

Table 1. Model Performance Comparison (MAE and Relative Improvement)

Model	MAE	Improvement vs. AR (%)	Improvement vs. ARIMA (%)
AR	16,219.15	–	–
ARIMA	13,631.63	15.95	–
LSTM	11,823.70	27.12	13.27
Vanilla GRU	11,350.20	30.02	16.72
GRU-GA	**10,546.75**	**34.97**	**22.63**

As shown in Table 1, both deep learning models (LSTM and vanilla GRU) clearly outperform classical AR and ARIMA, highlighting their superiority in modeling complex, nonlinear temporal dependencies inherent in freight cost data. Notably, the proposed GRU-GA model achieves the lowest MAE among all methods, delivering a 22.63% improvement over ARIMA and a 34.97% improvement over AR. Furthermore, GRU-GA outperforms vanilla GRU and LSTM by 7.08% and 6.88% respectively, underscoring the added predictive value of the genetic algorithm optimization step.

This performance gap illustrates the crucial impact of metaheuristic hyperparameter tuning: while deep learning architectures possess the capacity to model dynamic cost patterns, their full potential is realized only when optimally configured for the task at hand. By allowing the GA to automatically explore the hyperparameter space, the GRU-GA approach consistently converges to network configurations that would be unlikely to emerge from manual tuning or default settings.

It is also worth noting that this gain in predictive accuracy comes at a reasonable computational cost. All training and optimization steps were conducted on an Intel Core i5 CPU with 8GB RAM, with the full GRU-GA process (100 generations, moderate population size) completing in approximately 10 minutes—well within practical bounds for many real-world forecasting environments. This trade-off between increased forecast accuracy and practical cost demonstrates the practical applicability of the proposed hybrid framework for supply chain decision-makers.

In summary, these comprehensive results demonstrate that the GRU-GA model not only outperforms traditional and deep learning benchmarks in terms of forecast accuracy, but also does so with manageable resource requirements. This establishes GRU-GA as a robust and scalable tool for reliable freight cost forecasting in complex and realistic logistics scenarios.

4.2 Impact of GA Optimization

To illustrate the impact of the GA optimization, Figure 1 shows the convergence of the GA during the hyperparameter search process. It plots the best fitness (lowest MAE) achieved by the population over generations.

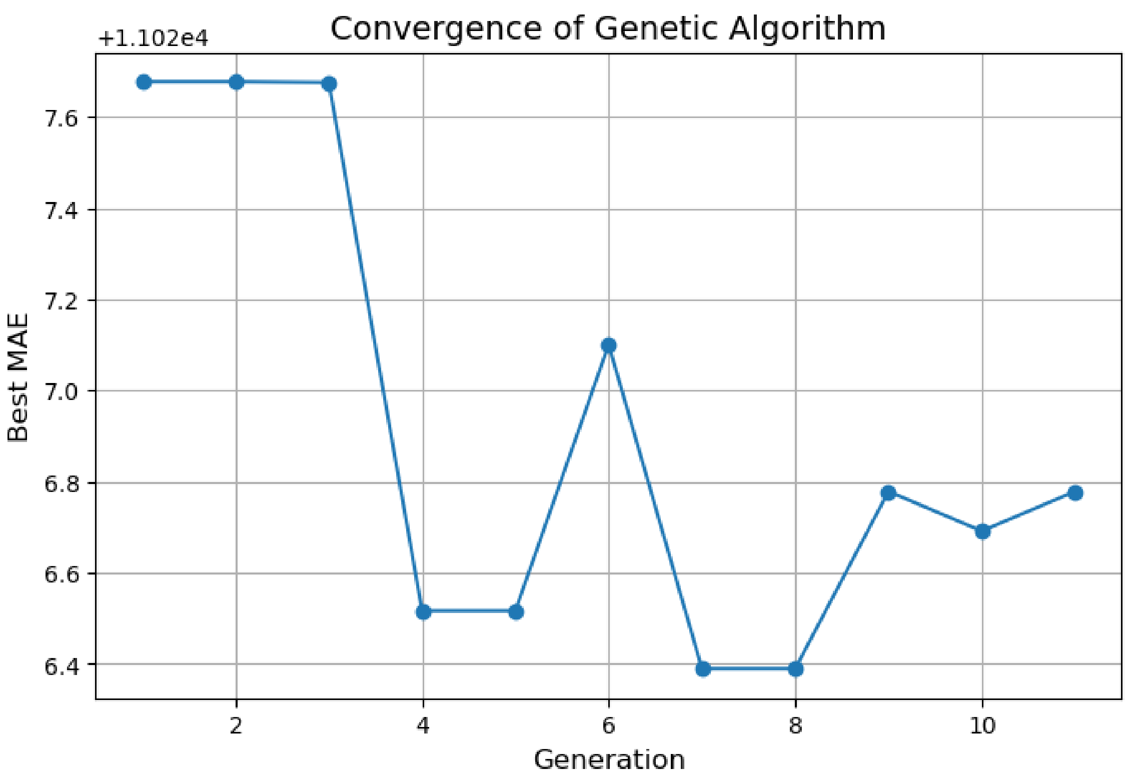

Figure 1. Convergence of the GA during hyperparameter optimization

The vertical axis in this chart represents the best Mean Absolute Error (MAE) value in each generation of the Genetic Algorithm. The MAE is a measure of the difference between the predicted and actual values, and is measured in dollars. The base number is 1.102 × 10^4 (i.e., about 11020), and the values shown represent the variations of this value. The hyperparameters that were optimized by the Genetic Algorithm were the number of neurons in the GRU layer and the dropout rate. The number of neurons was allowed to vary between 1 and 100, and the dropout rate was allowed to vary between 0 and 0.5. The Genetic Algorithm was run for 100 generations, and the best MAE value in each generation is shown in the chart.

As seen in Figure 1, the MAE decreases significantly over the generations, indicating that the GA effectively explores the hyperparameter space and finds increasingly better configurations for the GRU network. This highlights the importance of the GA optimization in enhancing the model's performance.

5. Conclusion

This study introduces a novel hybrid forecasting framework that synergistically integrates GRU recurrent units (GRUs) with a genetic algorithm (GA) to improve the accuracy of transportation cost forecasting, a key determinant of supply chain sustainability. Mixing the time modeling capability of GRUs and global search optimality of evolutionary algorithms, the ensuing GRU-GA model outperformed considerably both conventional statistical models (AR, ARIMA) and individual deep learning models (LSTM, simple GRU), with the highest mean absolute error (MAE) on all metrics.

In addition to the technical quality, this model has deep real-world significance for sustainability and logistics planning. Accurate transport cost forecasting enables logistics planners to optimize transportation routes, select cleaner transport modes, reduce operational inefficiencies, and actively manage inventories ahead of time. All of these map directly to the three pillars of sustainability: environmental (through reduced greenhouse gas emissions and fuel consumption), economic (through cost savings and efficiency), and social (through improved service reliability and labor outcomes).

While the current application is built with healthcare supply chain transportation data, its methodological underpinnings are generalizable. Future work might build on the framework by introducing exogenous variables such as macroeconomic shocks, geopolitical tensions, or weather shocks. Further research might also compare with other optimization methods such as particle swarm optimization (PSO), Bayesian optimization, or hybrid ensembles—and increase predictive robustness and interpretability of the model. Finally, incorporating the GRU-GA system into decision support systems can enable real-time feedback to stakeholders and enable adaptive counter-responses to developments in global logistics networks.

In conclusion, not only does the GRU-GA method improve the state of the art in the prediction of transportation cost, but it also illustrates how AI-based hybrid architecture can be effective enabler of sustainable, data-driven decision-making in supply chains.

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