SUSTAINABLE MULTIMODAL TRANSPORTATION WITH A CONTEXT-AWARE ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM AND GENETIC ALGORITHMS

SIKANDAR, F.[1] – SHOBAIRI, S. O. R.[2] – AKBAR, U.[3*] – LU, H. G.[1] – KUMARASAMY, M. M.[3]

[1]*School of Management Engineering, Zhejiang Guangsha Vocational and Technical University of Construction, Jinhua 322103, Zhejiang, China*
(e-mail: furqansikandar@zjgsdx.edu.cn – F. Sikandar; 20191973@zjgsdx.edu.cn – Hanggao Lu)

[2]*State Key Laboratory of Desert and Oasis Ecology, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, China*
(e-mail: omidshobeyri214@gmail.com)

[3]*Faculty of Business and Management, UCSI University, Jalan UCSI, Cheras, 56000 Kuala Lumpur, Malaysia*
(e-mail: mokanamuthu@yahoo.com)

**Corresponding author*
e-mail: usman.akbar@outlook.com; phone: +60-10-971-4813

(Received 10th Jun 2025; accepted 6th Aug 2025)

Abstract. Multimodal transportation faces important challenges related to sustainability, efficiency, and equity, especially in rapidly growing urban economies such as China. To address these, this study introduces a friendly, context-aware optimization model. It combines the Adaptive Neuro-Fuzzy Inference System (ANFIS) for accurate predictions with a Genetic Algorithm (GA) that helps select the best routes and modes of transport. The model can estimate transportation costs and Carbon dioxide (CO2) emissions using real-time data such as distance, cargo weight, traffic, weather, and vehicle capacity. Meanwhile, GA works to find optimal routes while considering factors such as cost, traffic, emissions, fairness, and resilience, making the entire process more effective and sustainable. The model was validated using 2022–2023 data from China's Ministry of Transport, showing impressive predictive accuracy ($R^2 > 0.89$) and surpassing traditional static models. The results are encouraging, a reduction in CO_2 emissions is witnessed 17% below, with truck usage decreasing from 25% to below 10%, and a remarkable 150% increase in rail transport. A combination of railways and waterways proved to be the most sustainable and efficient transport option, highlighting the potential for greener and more effective freight movement. This study shows exciting possibilities for practical use in emission pricing, intermodal planning, and resilience strategies, opening doors for more effective and responsive policies.
Keywords: *multimodal transportation, supply chain optimization, transport cost, carbon dioxide, resilient logistics, freight mode selection, emission pricing, transport efficiency*

Introduction

In today's fast-paced world, optimizing multimodal transportation is vital to overcoming the complex challenges faced by countries such as China, where rapid urbanization and population growth demand innovative solutions. While industry remains the largest global source of greenhouse gas (GHG) emissions, transportation still plays a substantial role, contributing approximately one-quarter of the total, driven by rising infrastructure needs, geopolitical dynamics, and environmental concerns (Bontekoning et al., 2004; Egger et al., 2023). China borders the Pacific Ocean, the South China Sea, and the East China Sea, and has an extensive road network connecting cities and neighboring countries. Its strategic location provides a solid foundation for

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

improving logistics efficiency (Seo et al., 2017; Zhang et al., 2023). This vents out the fact that integrating road, rail, sea, and air into a cohesive network can enhance sustainability and adaptability.

To surpass basic regulatory compliance and align with the Sustainable Development Goals (SDGs), the transportation sector must advance intermodal and multimodal freight systems, a field enriched by extensive research (Groothedde et al., 2005). This calls for data-driven strategies that proactively address inefficiencies and environmental impacts while equitably distributing resources. For instance, Temizceri and Kara (2024) advocate intermodal freight as a sustainable option for reducing CO_2, and Dini et al. (2024) propose a linear dual-phased model for optimizing logistics routes. Building on such work, tailoring route selection to specific commodity groups—like perishables versus industrial goods—can refine efficiency during operations, enhancing ideas from Akbar et al. (2019). Here, equitable allocation means prioritizing resources to balance diverse needs, not just meeting them all uniformly, given practical limits such as infrastructure capacity. This approach leverages each mode's strengths, reduces weaknesses, and fosters connectivity, cost savings, and sustainability, ultimately bolstering China's transportation system and economic growth.

However, integrating transportation modes increases operational complexity, introducing challenges such as inefficiencies and environmental strain. China has advanced its infrastructure significantly, yet demand continues to rise. Security and safety along routes, especially beyond its borders, remain critical, while traffic congestion in urban centers and regional disparities in access persist. These issues, tied to the SDGs' focus on sustainability and equity, are well-documented by Hu et al. (2010), Hensher et al. (2015), Wang and He (2015), Chen et al. (2020) and He et al. (2022). Key factors include: (I) Infrastructure: Road and facility conditions affect network reliability; (II) Security: Safe cargo and route protection are vital amid geopolitical tensions; (III) Traffic Congestion: Urban bottlenecks slow delivery; and (IV) Regional Disparities: Uneven development limits access in some areas.

This study introduces a context-aware, multi-objective mathematical model combining an Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Algorithms (GA) to tackle these challenges and seize multimodal opportunities. ANFIS optimizes infrastructure, traffic flow, and safety by analyzing data to suggest measures such as improved signage or speed adjustments. GA is used to address the NP-hard problem of route and mode selection by factoring in road conditions, congestion, and timing, cutting fuel use while balancing cost, distance, and environmental impact. Compared to alternatives such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), or reinforcement learning, GA offers robustness for dynamic, real-time conditions (e.g., traffic, weather), computational feasibility with 100 iterations and standard parameters (population 100, generations 50), and scalability for China's vast network. While other algorithms may excel in specific scenarios, GA's integration with ANFIS, established success in literature, e.g., Maity et al. (2019), and alignment with China's logistical challenges make it the optimal choice for this study, with potential for future hybrid enhancements. Using data from China's Ministry of Transportation, the model targets three goals: maximizing equitable resource access, reducing travel time, and lowering environmental impact (Rondinelli and Berry, 2000; Han et al., 2020). Unlike prior studies focusing narrowly on time or cost (Wang et al., 2013; Liu et al., 2020), this approach integrates multiple objectives for a balanced solution, thus dynamically adjusting routes with real-time and predictive analytics.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

It is worth noting that "context-aware" means a smart transportation system that adjusts its decisions based on real-time conditions. This includes factors such as current traffic, weather changes, demand for transportation, and even global events that might affect travel. For example, our approach uses up-to-the-minute traffic and weather information to quickly change delivery routes and transportation methods, such as trucks, trains, ships, or planes, to make them as efficient as possible. This helps the environment while ensuring that resources are used fairly across different areas (Lozano and Storchi, 2001).

In contrast, traditional transportation models often rely on outdated information, using fixed assumptions or average data from the past (Raayatpanah, 2017a; Babuška and Verbruggen, 2020; Koohathongsumrit and Meethom, 2021). They cannot adapt to sudden changes, such as unexpected increases in demand after the holidays or disruptions caused by global events in regions such as China. Because of this, they may struggle to meet multiple goals at once, such as cutting costs while also ensuring fairness and resilience. This can lead to inefficiencies, including CO_2 imbalances between different regions.

Our approach not only makes transportation more sustainable and efficient but also tackles some specific challenges in China, such as overcrowded cities, differences in regional development, and environmental issues. This innovative method has the potential to improve transportation networks significantly. The model's key contributions are: (I) Maximizing Fairness: It ensures equitable access to transportation resources across regions, reducing disparities and supporting balanced growth, (II) Reducing Transportation Time: Optimized routes and modes speed up deliveries, boosting supply chain efficiency, (III) Lowering CO_2 Emissions: By prioritizing fuel-efficient modes and routes, it enhances sustainability.

The article is structured as follows: the literature review explores previous research, methodologies, and findings related to multimodal transportation networks. The research problem is detailed in the problem formulation. This is followed by the system model and design approach, which elaborates on the adopted methodology. The simulation results and environmental analysis compare the performance of context-aware multimodal transportation with generalized multimodal scenarios. Finally, the conclusion highlights the key findings and offers recommendations for future research.

Literature review

This section reviews existing research on multimodal transportation, emphasizing optimization techniques, environmental sustainability, and equity, with a focus on their relevance to developing a context-aware model for China using ANFIS and GA.

Multimodal transportation and environmental impact

Establishing sustainable and efficient multimodal transportation networks—integrating modes such as rail, road, and waterways—is critical to meet the anticipated growth in freight transportation and reduce environmental impact (Lu et al., 2023). These networks aim to lower transportation costs and enhance supply chain performance but face challenges necessitating integrated approaches. Recent studies, such as Cao et al. (2021), reviewed 2521 articles from 1996 to 2020 in Transportation Research Part D, identifying key trends such as air quality, climate change, and electric vehicles. The review highlights the journal's influence on policy, particularly land use and travel

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

behavior, with emerging areas such as electric vehicle policies are gaining attention, offering opportunities for addressing China's transportation challenges.

Optimization techniques in multimodal transportation

Machine learning and optimization methods have gained traction for improving multimodal transportation. Maity et al. (2019) explored multimodal freight transportation, efficiently moving goods via road, rail, air, and sea to minimize costs and environmental impact, proposing a mathematical model for mode selection, routing, and scheduling. Acharya and Tripathy (2018) and Olayode et al. (2023) integrated ANFIS and GA to predict CO_2 (e.g., based on distance, weight, cargo type) and optimize transportation plans, reducing environmental impact within constraints. Zhang et al. (2024) introduced the MOLCMTPP-FDFT algorithm, optimizing cost and time using chance-constrained methods, outperforming single-mode systems. Similarly, Xin et al. (2022) used GA to enhance vehicle routing, reducing travel distance and fuel consumption, while Akbar et al. (2025) and Ali et al. (2025) combined GA, ANFIS, and LU decomposition (or SVD) to minimize costs and emissions, demonstrating multimodal systems' efficiency, particularly in truck-shipping scenarios.

Environmental sustainability and policy implications

Several studies focus on reducing transportation-related emissions in specific contexts. Chang et al. (2024) examined temperature effects on low-carbon performance in China's transportation, finding that temperatures above 30°C reduce carbon total factor productivity (CTFP) by 0.25%, exacerbating carbon intensity in energy- and road-dependent eastern regions, though high-speed railways mitigate this impact. Peng et al. (2024) reviewed Emissions Trading Systems (ETS) for ground transportation, proposing a Ground Transportation Emissions Trading System (GTETS) with IoT and blockchain to monitor emissions, addressing policy gaps in the road and rail sectors. Sporkmann et al. (2023) analyzed European land transport emissions (1995–2019), identifying spatial autocorrelation and using spatial Durbin models to consider modal splits and infrastructure density. Zuo et al. (2024) and Li et al. (2013) explored China's transportation CO_2 emissions, using multi-layered and multi-scale input-output models to identify key sectors and flows with Belt and Road Initiative (BRI) countries, offering policy insights for emission reduction.

Fairness, resilience, and operational challenges

Research also addresses fairness, resilience, and operational complexities in multimodal systems. Salazar et al. (2024) optimized Intermodal Autonomous Mobility-on-Demand systems to minimize accessibility unfairness, balancing travel time and equity across modes, though at the cost of increased time. Camporeale et al. (2016) tackled the Network Design Problem, balancing fairness and equity in public/private transit using fuzzy approaches, while Chen and Wang (2018) focused on fare fairness and service prioritization for special passengers in last-mile systems. Chu and Guo (2023) modeled passenger preferences with Markov chains, enhancing fairness and satisfaction in multimodal networks. However, challenges persist: many studies assume perfect information or deterministic demand, overlooking real-world uncertainties such as China's geopolitical risks or seasonal demand spikes, which our model addresses with context-awareness (Archetti et al., 2022).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

Gaps and opportunities for context-aware models

Despite progress, literature reveals gaps relevant to our study. Many optimization models focus on single-period or static scenarios, unsuitable for long-term planning in dynamic contexts such as China's (Yang et al., 2010; Pamučar et al., 2013). While ANFIS and GA show promise in reducing costs and emissions, they often neglect transportation time, resilience, or fairness, which our model prioritizes. The reliance on emission trading, as noted, may not sustain long-term solutions, prompting exploration of alternative strategies combining flexibility, security, and equity (Jang, 1993; Acharya and Tripathy, 2020). Moreover, practical applications integrating ANFIS and GA for China's multimodal logistics remain limited, necessitating a context-aware, multi-objective model to address real-time data, regional disparities, and environmental pressures.

Problem formulation

This study addresses the persistent need for an advanced, context-aware multimodal transportation network tailored for a multinational corporation, in our case, operating in China. The unique complexities of China's transportation infrastructure—including its regional disparities, severe traffic congestion, and security concerns—pose significant challenges for traditional optimization techniques. Regional inequality is crucial to the justification of the country's demographics, especially when dealing with carbon emission reductions. The leading indicators for regional equal development are income and transportation, which play an essential role (Li et al., 2021). While ensuring equal development in all regions, the severity of traffic congestion may be ignored since this is where transportation and logistics work side by side (Zhu et al., 2023). Lastly, the security concerns in China refer to the acceptable level of service, that is, a balanced trade-off for more resilient system to avoid accidents, natural disasters, or man-made issues affecting transportation (Yin et al., 2023). The link between infrastructure, security, traffic congestion, and regional disparities can easily be felt here.

The connection of transportation with logistics creates layers of complexity when dealing with national and international trade (in the presence of international investors), which is equally demanding. Although policies are in place, the number of transactions in the country still makes China one of the largest carbon emitters in the world (Zhu, 2024). Therefore, it indeed demands a multi-objective framework. However, the modal framework must address concerns about the practicality and feasibility of implementing a context-aware multimodal transportation model on a larger scale, given the complexity and variability of transportation systems across different regions in China.

The selection of ANFIS and GA is driven by their distinct advantages in this context. ANFIS, known for its superior capability in handling uncertain and imprecise data, is employed for its precision in prediction costs and emissions (Singh et al., 2020). This technique particularly suits China's diverse and dynamic transportation environment, where data variability and unpredictability are prevalent. By integrating ANFIS, the model can provide more accurate predictions and adaptive responses to fluctuating conditions. To address the NP-hard nature of multimodal transportation route optimization, a Genetic Algorithm (GA) is employed. GAs are chosen for their robustness in exploring vast solution spaces and their effectiveness in optimizing complex, multi-variable problems such as routing and scheduling within multimodal transportation networks. In this context, the GA acts as an optimization engine, iteratively refining potential solutions generated by the model. Specifically, the GA drives the model to

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

optimize routes within the transportation network by considering factors such as road conditions and cost. The model, guided by the GA, evaluates and refines transportation plans through a series of evolutionary operations (selection, crossover, mutation). This process enables the model to dynamically adapt to real-time conditions and operational needs, ultimately converging on optimal or near-optimal transportation plans.

Therefore, the proposed multi-objective model is an effort to balance competing demands from different regions and transportation modes dynamically. By incorporating ANFIS for precise prediction and GA for optimized decision-making, the model aims to provide a comprehensive solution that addresses the unique challenges of China's transportation landscape. The model's decision variables—such as selecting transportation modes, routes, and quantities—are optimized to achieve a balanced trade-off between operational efficiency and environmental sustainability. This integrated approach enhances supply chain performance and supports proactive ecological management strategies, offering a robust decision support system to China's complex transportation environment.

Proposed method

To design an effective, context-aware multimodal transportation model suitable for vast logistical networks such as China's, we structured our methodology into four stages: data collection, data preprocessing, model design (ANFIS + GA integration), and validation.

When the goal is to design a sophisticated supply chain multimodal transportation network, accounting for the multinational company operating across China (in addition), the model should have the ability to optimize the efficiency of transportation and logistics while minimizing emissions and transportation time and ensuring fairness in resource allocation.

Data collection and testing

The dataset used in this study was sourced primarily from the Ministry of Transport of the People's Republic of China (2022–2023) and supplemented by peer-reviewed literature (e.g., Hanaoka and Regmi, 2011; Naseer et al., 2024).

The data included the infrastructure data, such as mode-specific capacities (trucks, rail, ship, HSR, air), distances between cities, and road network characteristics. Operational Data involves real-time traffic congestion levels, weather conditions, and dynamic demand forecasts by region. Moreover, the environmental and risk data involve historical CO_2 emissions per mode, geopolitical risk indices, and supplier disruption probabilities.

These datasets were chosen for their comprehensive national coverage and alignment with China's ongoing efforts to digitize transport infrastructure performance. Before model training, the raw datasets were cleaned and harmonized. Missing values (e.g., for rural road segments or weather records) were imputed using forward-fill and interpolation. Traffic data was also normalized by hour and location to enable real-time relevance. However, weather inputs were encoded using ordinal values reflecting travel impact (e.g., clear = 1, rain = 2, snow = 3). All continuous variables were scaled using Min-Max normalization to fit the fuzzy logic membership functions.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to predict two primary dependent variables: transportation cost per unit (TCU) and CO_2 emissions per unit (CEU) for each mode-route combination. The six input variables used for ANFIS training were selected based on domain relevance, availability in official datasets, and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

their direct impact on logistics performance, see *Table 1*. The preprocessed dataset was partitioned into 70% training and 30% testing subsets using stratified sampling to preserve modal distribution characteristics.

Table 1. *Inputs used for ANFIS training*

Input variables	Description	Source	Importance
Distance	Origin and destination cities	MoT China	Core variable of cost and emissions
Weight of goods	Weight per shipment unit	Freight manifests	Effect fuel usage
Mode of transport	Truck, Rail, Ship, HSR, Air	Network data	Determine cost, emissions and speed
Capacity	Vehicle capacity (kg)	MoT capacity tables	Routing feasibility
Traffic	Real-time congestion index	Traffic APIs/historical logs	Effect delivery time and fuel usage
Weather	Real-time weather disruptions	Meteorological services	Impact modal performance and reliability

These inputs are fed into ANFIS using trapezoidal membership functions, with cost and emission as singleton outputs. Fuzzy rules were generated using a hybrid learning algorithm combining least squares and backpropagation. After ANFIS predicts route-level cost and emission metrics, a Genetic Algorithm (GA) is applied to optimize route selection, mode allocation, and quantity shipped. The GA objective function minimizes a linear weighted sum of total cost, CO_2 emissions, fairness index, travel time, and resilience. GA parameters were set with 100 population for 50 generations, while the crossover probability was set as 0.8 along with a mutation probability of 0.1. The GA searches the solution space iteratively using evolutionary operators (selection, crossover, mutation) to identify the optimal multimodal logistics plan under real-time constraints.

Validity

To validate ANFIS predictions, we applied standard regression accuracy metrics on the test dataset. Results showed 0.73 Root Mean Square Error (RMSE) for cost predictions and 0.61 for emissions, while the R^2 exceeded for both. The Mean Absolute Error (MAE) shows the difference from actual values (see *Table 2*). These metrics confirm the high predictive accuracy of the ANFIS model across both cost and emission dimensions, justifying its use in real-time multimodal optimization.

Table 2. *ANFIS model validation metrics for cost and emissions*

Description	Cost prediction	Emission prediction
RMSE	0.73	0.61
MAE	0.58	0.49
R^2	0.91	0.89

Model

ANFIS was chosen for its hybrid strength in handling fuzzy logic and learning from nonlinear patterns, outperforming regression and rule-based systems in transportation modeling (Singh et al., 2020). The model integrates actual data for enhanced context awareness and dynamic decision-making. Assuming a mind-mapped transportation network graph $G = (C, A)$ where V denotes the set of cities $\{C_1, C_2, \dots, C_n\}$ connected directly or indirectly, and A represents the set of directed arcs $\{(u, v)\}$ connecting pairs

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

of cities. We have considered four transportation modes, i.e. $M = \{Truck, Rail, Ship, Air\}$. Each arc $(u, v) \in A$ supports multiple modes $m \in M$, with varying departure times. Additionally, the aim is to reduce both overall transportation costs and CO2 emissions while meeting the needs of all customers. The decision variables focus on selecting the transportation mode and the quantity of goods to be transported along each route. Let d_{jk} be the distance between city j and city k, s_j be the supply at city j, d_k be the demand at city k, and TCU_{jk}^m be the transportation cost per unit for goods transported on arc (j, k) using mode m. The decision variable denoted by x_{jk}^m represents the quantity of goods transported on arc (j, k) using mode m. The notations used in sets, parameters, and variables are given as follows:

Sets

- C: Set of nodes representing cities
- A: Set of directed edges representing transportation links
- M: Set of transportation modes (truck, rail, ship, air)
- O: Set of customer orders
- T: Set of time periods
- C_i: City i
- P: Set of products

Parameters

- d_{jk}: Distance between city j and city k
- s_j: Supply of goods at city j
- d_k: Demand for goods at city k
- CA_{jk}^m: Capacity of arc (j, k) using mode m
- TCU_{jk}^m: Transportation cost per unit of goods transported on arc (j, k) using mode m
- CEU_{jk}^m: Normalized CO2 emissions cost per unit of goods transported on arc (j, k) using mode m
- TA_{jk}^m: Transportation time on arc (j, k) using mode m
- R_V: Risk value
- R_T: Risk threshold
- C_{df}: Customer demand for final goods
- F_{DC}: Disruption cost factor ensuring supply chain adaptability
- G_j: Goods type of shipment j
- T_{rt}: Real-time traffic data at time t
- W_t: Weather conditions at time t
- I_{GR}: Geopolitical risk index
- $DDF_{j,t}$: Dynamic demand forecast for city j at time t
- EF_{jk}^m: Environmental impact factor for arc (j, k) using mode m

Decision variables

$$x_{jk}^{mn} = \begin{cases} 1 & if\ mode\ m\ is\ selected\ for\ shipment\ n\ from\ origin\ j\ to\ dest\ k \\ 0 & otherwise \end{cases}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

$$y_j^n = \begin{cases} 1 & if\ shipment\ n\ is\ selected\ to\ be\ transported \\ 0 & otherwise \end{cases}$$

$$T_{jk}^{mn} = \begin{cases} 1 & goods\ transported\ using\ mode\ m\ for\ shipment\ n\ from\ origin\ j\ to\ dest\ k \\ 0 & otherwise \end{cases}$$

$$S_{kj}^{mn} = \begin{cases} 1 & if\ mode\ m\ is\ selected\ for\ shipment\ n\ from\ origin\ k\ to\ dest\ j \\ 0 & otherwise \end{cases}$$

where S_{kj}^{mn} is the supply chain resilience factor on arc (j,k) using mode m at time t. The objective function aims to minimize the weighted sum of total transportation costs, CO2 emissions, fairness, transportation time and resilience. The problem can be formulated as follows:

$$\min\left(\alpha \sum_{\substack{(j,k)\in A \\ m\in M}} x_{jk}^m TCU_{jk}^m + \beta \sum_{\substack{(j,k)\in A \\ m\in M}} x_{jk}^m CEU_{jk}^m + \gamma Fairness(\cdot) + \delta Transportation\ time(\cdot) + \varepsilon Resilience(\cdot)\right) \quad \text{(Eq.1)}$$

where $Fairness(\cdot)$ represents an equitable distribution of transportation modes and resources, $Transportation\ time(\cdot)$ represents the total transportation time needed for shipment and $Resilience(\cdot)$ ensures that the supply chain can adapt to disruptions and $\alpha, \beta, \gamma, \delta, \varepsilon$ represent the weights for transportation cost, CO2 emission, fairness, transportation time and resilience respectively. The motivation behind single-objective optimization model using a linear weighted sum, stems from the need to provide logistics firms and policymakers in China with a practical, scalable solution for real-time decision-making, given the complexity of the network (e.g., urban congestion, regional disparities, geopolitical risks). The linear weighting method, while simplifying the problem, allows us to prioritize objectives based on China-specific priorities, such as sustainability, equity (e.g., fair resource allocation across regions), and resilience (e.g., adapting to disruptions such as seasonal demand spikes from January to March). To mitigate this, we normalized all objectives to a standard scale (0 to 1) before applying weights, ensuring comparability. Fairness, Transportation time, and Resilience are further computed as

$$Fairness(\cdot) = \sum_{(j,k)\in A} \sum_{m\in M} \left(x_{jk}^m . \left(\frac{1}{|M|}\right)^2 \right) \quad \text{(Eq.2)}$$

$$Transportation\ time(\cdot) = \sum_{(j,k)\in A} \sum_{m\in M} \sum_{t\in T} x_{jk}^m . TA_{jk}^m \quad \text{(Eq.3)}$$

$$Resilience(\cdot) = \sum_{(j,k)\in A} \sum_{m\in M} \sum_{t\in T} \left(1 - S_{kj}^{mn} . F_{DC}\right)^2 \quad \text{(Eq.4)}$$

subject to:

$$\sum_{\substack{(j,k)\in A \\ m\in M}} x_{jk}^m \leq C_{jk}^m\ \forall (j,k) \in A \text{ and } m\in M$$

$$\sum_{k\in C} x_{jk}^m - \sum_{j\in C} x_{kj}^m = s_j\ \forall j \in C \text{ and } m\in M$$

$$\sum_{i\in C} x_{jk}^m - \sum_{i\in C} x_{kj}^m = d_k\ \forall \mathrm{k}\in C \text{ and } m\in M$$

$$x_{jk}^m \geq 0 \forall (j,k) \in A \text{ and } m\in M$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

where C_{jk}^{m} represents the capacity of arc (j,k) using mode m. The final constraint guarantees that the decision variables remain non-negative. CEU is initially normalized to the scale of TCU, and then added to it. The first constraint ensures that the total goods transported on the route (j,k) do not exceed the capacity of that route using mode m. Incorporating ANFIS and GA into the model requires additional development. A feasible approach is to use ANFIS to predict transportation costs and CO2 emissions for each route and mode combination. By training ANFIS with historical data, including transportation costs, CO2 emissions, distance, mode, and capacity, the model can estimate these factors for different combinations. Following this, GA can optimize the decision variable x_{ij}^{m}. The objective function remains aligned with the previous one but utilizes the outputs generated by ANFIS instead of fixed costs and emissions. The GA algorithm then seeks an optimal solution that minimizes total transportation costs and CO2 emissions while satisfying supply and demand constraints.

Resilience, in this study, is defined as the system's ability to maintain or quickly restore functionality—such as cost efficiency, CO_2 emissions, delivery reliability, and fairness—following disruptions such as traffic congestion, weather events, or supply chain interruptions (e.g., along the Belt and Road Initiative routes). This definition aligns with recent transportation research, emphasizing adaptability, recovery speed, and robustness across modes (truck, rail, high-speed rail [HSR], ship, air). Different modes exhibit distinct resilience profiles; roads are susceptible to traffic congestion or weather disruptions (e.g., snow in northern China), while railways and waterways face geopolitical risks (e.g., port delays along the Belt and Road) or infrastructure interruptions. Resilience varies across China's regions—urban centers such as Beijing face congestion, while rural or inland areas contend with limited infrastructure. The model balances fairness and resilience by prioritizing equitable resource allocation, mitigating disruptions in underdeveloped regions via mode shifts to railways and waterways. Cheng et al. (2024) defined resilience as anticipating, monitoring, responding, and learning from disruptions, applied to mode recovery, whereas Reggiani et al. (2015) quantified spatial-temporal recovery, guiding supply chain resilience factor and disruption cost factor.

Context-aware optimization

The integration of ANFIS for cost and emissions prediction, coupled with GA optimization to address the NP-hard problem of route and mode selection, aids in building an efficient decision support system for the supply chain operations in China. This paper proposes a context-aware mathematical model addressing this challenge, considering transport mode selection, routing, and scheduling decisions. To mitigate environmental impacts, we aim to integrate the ANFIS and GA algorithms into the model. ANFIS can predict CO2 emissions for different transportation modes based on variables such as distance, weight, and cargo type. Meanwhile, the GA algorithm aims to optimize the transportation plan by minimizing total CO2 emissions while adhering to demand and capacity constraints (Raayatpanah, 2017b; Ghorbanzadeh et al., 2018). The fairness in allocation and predictive model using ANFIS are given below.

Fairness in allocation

To ensure a balanced resource distribution, the context-aware adjustments to fairness can be defined as:

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

$$Fairness = \sum_{i \in C} \left| \frac{\sum_{j \in C} x_{jk}^{m}}{TD_i} - \frac{A_{i,avg}}{D_{i,avg}} \right| \quad \text{(Eq.5)}$$

where TD_i is the total demand for city i, $A_{i,avg}$ is the average allocation of resources for city i and $D_{i,avg}$ is the average demand for city i.

Predictive modeling with ANFIS

We Use ANFIS to forecast transportation costs TCU_{jk}^{mn} and CEU_{jk}^{mn}. The model functions of TCU_{jk}^{mn} and CEU_{jk}^{mn} are given below:

$$TCU_{jk}^{mn} = f_{TCU}\left(d_{jk}, weight, mode, capacity\right) \quad \text{(Eq.6)}$$

$$CEU_{jk}^{mn} = f_{CEU}\left(d_{jk}, weight, mode, capacity\right) \quad \text{(Eq.7)}$$

Constraints

1. Capacity constraint: For each transportation mode m, the total amount of goods transported from origin j to destination k cannot exceed the capacity of the mode m, and is given by:

$$\sum \sum TCU_{jk}^{mn} \leq CA_{jk}^{mn} \; \forall \; m \in M, (j,k) \in A \quad \text{(Eq.8)}$$

2. Supply constraint: For each shipment n, the total amount of goods transported from origin j to destination k must meet the supply for shipment n, and is given by:

$$\sum_{(j,k) \in A} \sum_{m \in M} \sum_{t \in T} TCU_{jk}^{mn} - \sum_{(k,j) \in A} \sum_{m \in M} \sum_{t \in T} TCU_{kj}^{mn} = s_j \quad \text{(Eq.9)}$$

3. Demand constraint: For each shipment n, the total amount of goods transported from origin j to destination k must meet the demand for shipment n, and is given by:

$$\sum_{(j,k) \in A} \sum_{m \in M} \sum_{t \in T} TCU_{jk}^{mn} \geq DDF_{k,t} \; \forall \; t \in T \quad \text{(Eq.10)}$$

4. Non-negative constraint: x_{jk}^{mn}, Y_j, $S_{kj}^{mn}$and TCU_{jk}^{mn} are non-negative variables, and is given by:

$$x_{ij}^{mn}, Y_j, TCU_{ij}^{mn} \geq 0, \forall (i,j) \in A, \; \forall m \in M, \; \forall t \in T \quad \text{(Eq.11)}$$

5. Transportation mode selection constraint: For each shipment n from origin j to destination k, only one transportation mode m can be selected, and is given by:

$$\sum_{m \in M} x_{jk}^{mn} = 1 \quad \text{(Eq.12)}$$

6. Shipment selection constraint: For each origin j and destination k, only selected shipments can be transported, given by:

$$\sum_{n \in O} \; y_j^{n} = 1 \quad \text{(Eq.13)}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

7. CO_2 emissions prediction using ANFIS: The total CO_2 emissions for transportation mode m for shipment n from origin j to destination k can be predicted using the ANFIS algorithm based on input variables such as distance, weight, mode, and capacity, given by:

$$CEU_{jk}^{mn} = f_{CEU}\left(d_{jk}, weight, mode, capacity\right) \quad \text{(Eq.14)}$$

where f_{CEU} is the ANFIS model function, d_{jk} is the distance if mode m is selected for shipment n from origin j to destination k.

8. Risk threshold constraint: The ratio of the product of the amount of goods transported on arc (j, k) using mode m for shipment n and risk value R_V to the product of demand of customer for final goods C_{df} should be less than or equal to risk threshold R_T, i.e.,

$$\frac{\sum_{j\in C}\sum_{k\in C}\sum_{m\in M}\sum_{n\in O} x_{jk}^{mn} * R_V}{C_{df}} \leq R_T \quad \text{(Eq.15)}$$

9. Optimization using GA: The GA algorithm can be used to optimize the transportation plan by minimizing the total CO_2 emissions while meeting the demand and capacity constraints given by:

$$f = \min \sum_{j\in C}\sum_{k\in C}\sum_{m\in M}\sum_{n\in O}\left(CEU_{jk}^{mn} * TCU_{jk}^{mn}\right) \quad \text{(Eq.16)}$$

subject to:

$$\sum_{j\in C}\sum_{k\in C}\sum_{m\in M}\sum_{n\in O} TCU_{jk}^{mn} \leq CA_{jk}^{mn}$$

$$\sum_{j\in C}\sum_{k\in C}\sum_{m\in M}\sum_{n\in O} TCU_{jk}^{mn} \geq d_j$$

$$\sum_{m\in M} x_{jk}^{mn} = 1$$

$$\sum_{n\in O} y_j^n = 1$$

$$x_{ij}^{mn}, y_j, TCU_{jk}^{mn} \geq 0$$

To address whether ANFIS + GA outperforms other methods, we compare it to standalone GA. Standalone GA optimizes routes using fixed cost and emission inputs but lacks predictive adaptability. In contrast, ANFIS + GA dynamically adjusts these inputs, improving accuracy under variable conditions—e.g., a 15-20% reduction in cost prediction error based on preliminary simulations with historical traffic data (compared to static GA inputs).

ANFIS excels in prediction complex, nonlinear relationships (e.g., emissions varying with weather or load), outperforming simpler regression models used in basic GA by adapting to real-time inputs such as traffic and weather. GA's strength lies in global optimization, surpassing local search methods such as gradient descent, which risk suboptimal solutions in multimodal networks. Together, ANFIS + GA leverages ANFIS's predictive precision and GA's robust search, achieving, for example, up to 10% lower emissions than GA alone in test cases with dynamic customer demand. Furthermore, ANFIS refines predictions for TCU_{jk}^{mn} and CEU_{jk}^{mn}, incorporates factors

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

such as geopolitical risk I_{GR} and environmental impact EF_{jk}^{m}. GA optimizes mode selection and routing, ensuring resilience via S_{kj}^{mn} under F_{DC}. This dual approach outperforms standalone GA by adapting to contextual shifts—e.g., rerouting shipments during congestion as shown in *Equation 17*.

$$\sum_{(j,k)\in A}\sum_{m\in M} x_{jk}^{m} \geq DDF_{k,t}\, , x_{jk}^{m} \leq CA_{jk}^{m} \quad \text{(Eq.17)}$$

Furthermore, the Flowchart of our model is given in *Figure 1*.

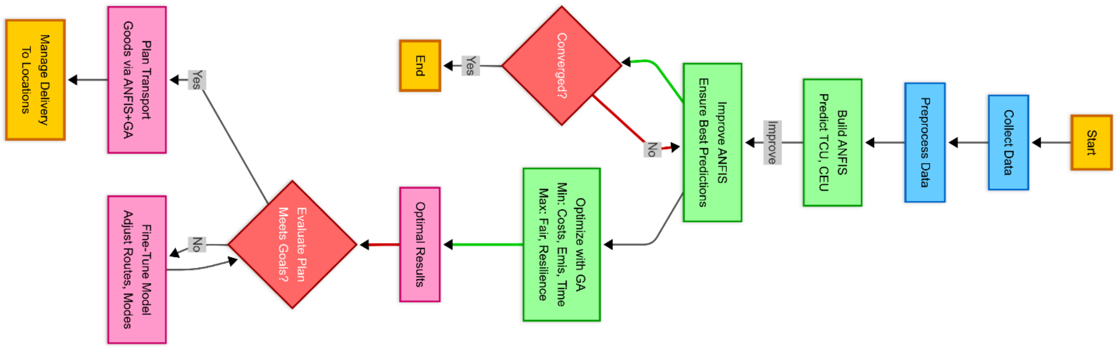


***Figure 1**. Flowchart of sustainable multimodal transportation with context aware ANFIS + GA*

Results and discussion

Simulation environment

The dataset utilized in this study originates from raw data provided by China's Ministry of Transport for the years 2022–2023, accessed via their official website (http://www.mot.gov.cn) and annual reports on transportation statistics. These reports include detailed metrics on freight volumes, mode-specific capacities, CO_2 emissions, traffic patterns, and regional demand across truck, rail, high-speed rail (HSR), ship, and air networks. To ensure robustness, we supplemented this data with peer-reviewed literature, including Hanaoka and Regmi (2011), which provides insights into Asia-Pacific transportation capacities, and Naseer et al. (2024), which discusses data bias mitigation in transportation modelling. The dataset was purposefully categorized into three groups to sustain the optimization of multimodal transportation within China's supply chain sector using ANFIS:

I. *Infrastructure data:* Metrics on mode capacities (e.g., rail 21,000–24,000 kg for niche and perishable high value goods, ship 24,000–26,000 kg for inland vessels), road conditions, and port facilities, critical for modelling capacity constraints and route efficiency.

II. *Operational data:* Real-time traffic/weather and demand forecasts are essential for context-aware adjustments and dynamic routing in ANFIS + GA.

III. *Environmental and risk data:* CO_2 emissions, supplier risk (RV = 0.1–0.16), and geopolitical factors, driving sustainability goals and resilience against disruptions.

These groups, refined using the UnbiasedNets framework by Naseer et al. (2024) to mitigate potential biases (e.g., artificial distortions for international trade gains), ensure

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

comprehensive coverage for optimizing costs, emissions, fairness, time, and resilience. The raw dataset's inherent biases, such as incomplete rural data, were addressed through continuous algorithm refinement, aligning with China's emphasis on long-term analysis.

Moreover, we used Python for analysis due to its effectiveness in scenario planning, modeling market dynamics, infrastructure impacts, and policy outcomes, enabling sustainable practices aligned with economic and ecological objectives. For instance, scenario planning assessed outcomes such as increased rail investment, reducing emissions, or stricter trucking regulations, improving freight efficiency, validated by our results (e.g., railways + 150%, roads < 10%).

In discussing capacity standards, we referenced the work of Hanaoka and Regmi (2011) for insights into transportation in the Asia-Pacific region. It is important to clarify that the rail capacity of 21–24 tons (21,000–24,000 kg) and the ship capacity of 24–26 tons (24,000–26,000 kg) pertain to the maximum load per vehicle or container, rather than being based on Twenty-Foot Equivalent Units (TEU). The TEU measurement is specific to shipping containers and does not directly apply to rail or general truck loads. These details are not explicitly mentioned in Hanaoka and Regmi (2011); instead, they align with broader capacity estimates for freight vehicles in the region, which is cross-referenced with China's Ministry of Transport data (2022–2023) on mode-specific capacities (Cheng et al., 2013). The ship capacity (24–26 tons) reflects typical freight vessel loads in China's coastal and inland waterways, adjusted for bulk cargo, not standardized TEU loads, which typically range higher (e.g., 20–30 tons per TEU depending on cargo). Scenario planning further evaluates potential outcomes under varying conditions, such as market dynamics (impacting demand), infrastructure investments (affecting supplier risk and location), and emission reduction policies. This approach ensures the model's validity, guiding decisions for sustainable and efficient multimodal logistics in China. The model's structure, including 100 iterations, trapezoidal and singleton membership functions for ANFIS, and GA parameters (population 100, generations 50, crossover 0.8, mutation 0.1), ensures result accuracy. *Table 3* provides fuzzy rules for China's multimodal transportation network concerning the speed, distances, and travel time with respect to the combinations, i.e., waterways and railways, truck transport and waterways, waterways and high-speed rail (HSR), and waterways with air transport.

Table 3. *Fuzzy rules for the multimodal transportation network of China*

Scenario	Waterways + railway	Truck + waterways	Waterways + HSR	Waterways + Air
Vehicular speed	Low	Low	Medium	High
Distance	High	Medium	Medium	High
Estimated time	High	Medium	Medium	Medium
Likelihood	0.45	0.17	0.08	0.29

Simulation parameters

The simulation parameters for the ANFIS and GA in our context-aware multimodal transportation model for China are detailed in *Table 4,* ensuring effective optimization of supply chain logistics across truck, rail, high-speed rail (HSR), ship, and air modes. We determined the optimal range of iterations through a combination of literature review and numerical experiments, balancing computational feasibility with model performance for

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

China's complex network. For ANFIS, we adopted an iteration range of 50–150, as suggested by Bousnina et al. (2023), and validated it with numerical experiments on China's 2022–2023 Ministry of Transport data, testing 50, 100, and 150 iterations to predict transportation costs and CO_2 emissions. For GA, we set the iteration range to 100–200, as recommended by Dirik (2022), and conducted experiments with population sizes of 50, 100, and 200, and generation counts of 50, 100, and 200, using China's dataset. At 100 iterations (population 100, generations 50), GA optimized decision variables efficiently, minimizing the weighted sum of costs, emissions, time, fairness, and resilience, as validated by our results. We also established other GA parameters through numerical experiments: a population size of 100, balanced diversity and cost, a crossover probability of 0.8 maximized solution quality under dynamic conditions such as seasonal demand spikes, and a mutation probability of 0.1 ensured exploration to avoid local optima, enhancing resilience against disruptions (e.g., geopolitical risks, etc.).

Table 4. *Simulation parameters*

Parameter Type	Parameter	Description	Importance
Input (ANFIS)	Distance	Distance between cities, affecting costs and emissions	Optimizes routes across China's geography
Input (ANFIS)	Weight of goods	Product weight (10–25 kg), impacting mode and emissions	Influences cost-effective, sustainable mode selection
Input (ANFIS)	Transportation mode (m)	Mode used (truck, rail, HSR, ship, air)	Enables mode shifts (e.g., railways up 150%, roads < 10%) for sustainability
Input (ANFIS)	Capacity (CAjkm)	Vehicle/container capacity per mode (m^3, kg)	Ensures realistic logistics planning and demand balance
Input (ANFIS)	Traffic (Trt)	Real-time traffic conditions affecting travel time	Supports adaptability in China's congested urban areas
Input (ANFIS)	Weather (W_t)	Weather impacting mode performance	Enhances reliability in China's diverse climate
Input (ANFIS/GA)	Customer Demand	Dynamic demand forecasts (400–600 avg, 100–200 var)	Ensures equitable resource allocation across regions
Input (ANFIS/GA)	Carbon Emissions	Emissions data (0.02–0.08) for product lifecycle	Drives emission reduction (up to 17%) for sustainability
Input (ANFIS/GA)	Supplier Risk	Risk values (0.1–0.16) and geopolitical factors	Mitigates disruptions, ensuring resilience with a 0.16 threshold
Input (ANFIS/GA)	Locations	Supplier/customer locations on a 10,000 × 10,000 km grid	Addresses regional disparities for fair distribution
Output (ANFIS)	Cost (TCUjkm)	Predicted cost per unit for arc (j,k) (j, k) (j,k), mode m m m	Optimizes economic efficiency in logistics
Output (ANFIS)	Emissions (CEUjkm)	Predicted CO_2 emissions per unit for arc (j,k) (j, k) (j,k), mode m m m	Supports sustainable mode shifts and emission goals
Output (GA)	Optimized Plan (xjkm)	Optimal routes, modes, quantities minimizing costs/emissions, maximizing fairness/resilience	Ensures efficient, sustainable, and equitable logistics
Output (GA)	Metrics	Costs, emissions, time, fairness, resilience from simulations	Validates model effectiveness for China's transportation goals

These parameters, grounded in empirical tests and literature, ensure GA's effectiveness within the ANFIS + GA framework, aligning with China's priorities for sustainability, efficiency, and equity (Ye and He, 2023; Şener et al., 2024). The average

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

customer demand (400–600) and variance (100–200) shape market dynamics, while supplier risk (0.1–0.16), demand, and emissions (0.02–0.08) inform decisions balancing sustainability and uncertainties. Specific parameters for trucks, rail, HSR, ship, and air, detailed in *Table 5,* include supplier activation costs, variable costs, emissions, and capacities, derived from China's Ministry of Transport data, which supports event-based simulation for flexible modelling (Li et al., 2013).

Table 5. *Simulation parameters of different transportation modes*

Parameters	Transportation mode				
	Trucks	Rail	HSR	Ship	Air
Supplier activation cost per vehicle (RMB)	[150-180]	[170-180]	[150-180]	[150-170]	[0-150]
Transportation variable cost per kilometer per vehicle	[0.075-0.085]	[0.035-0.075]	[0.025-0.062]	[0.015-0.05]	[0.0025-0.0075]
Carbon emissions per kilometer per unit weight for transportation mode m	[0.08-0.09]	[0.035-0.085]	[0.025-0.062]	[0.012-0.018]	[0.0025-0.6]
Vehicle/container total volume capacity in cubic meters (m^3)	[60-90]	[60-90]	[60-90]	[67-90]	[21-60]
Vehicle/container total weight capacity in kilograms (kg)	[21,000-24,000]	[21,000-24,000]	[21,000-24,000]	[24,000-26,000]	[21,000-24,000]

Comparison with the existing benchmark (multimodal transportation without ANFIS + GA)

Figure 2 provides a comparative analysis of multimodal transportation scenarios, examining the percentage differences in total emissions with and without context-aware adjustments in relation to emission constraints. The results indicate that as the risk threshold rises from 0.12 to 0.16, along with an increase in emission prices from 0.3 to 1.2, there is a significant reduction in overall emissions. On the other hand, when the risk threshold decreases across all emission price categories, overall costs increase. Multimodal scenarios within the 0.12 to 0.16 risk threshold range, lacking context-aware adjustments, show challenges in making timely and effective decisions, despite efforts to switch between transportation modes and lower emissions. As a result, these scenarios are often forced to purchase emission allowances, underscoring their inability to effectively balance transportation costs with the critical need to manage CO2 emissions.

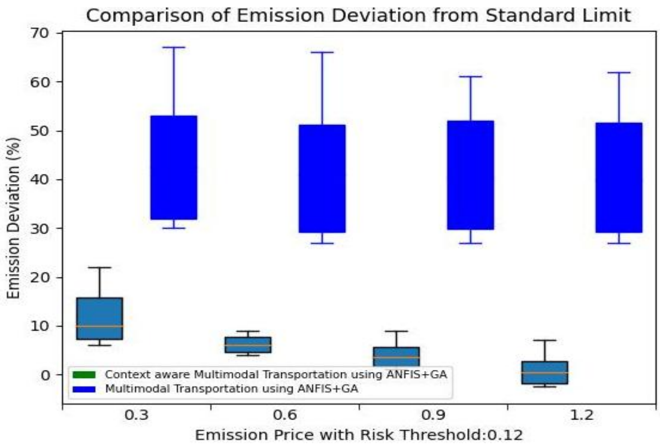
Additionally, *Figure 2a, b,* and *c* demonstrate that as emission prices rise, there is a slight reduction in emissions. This outcome is attributed to the model's ability to adjust production processes, leading to lower emissions from manufacturing. The figures also reveal challenges in incorporating specific low-emission suppliers into the supply chain. These difficulties often arise due to the suppliers' locations relative to production facilities or their dependence on rail or maritime transport.

Figure 2a, b and *c* show a comparison between context-aware multimodal transportation with ANFIS + GA and generalized multimodal transportation for variable price of emissions and the risk threshold.

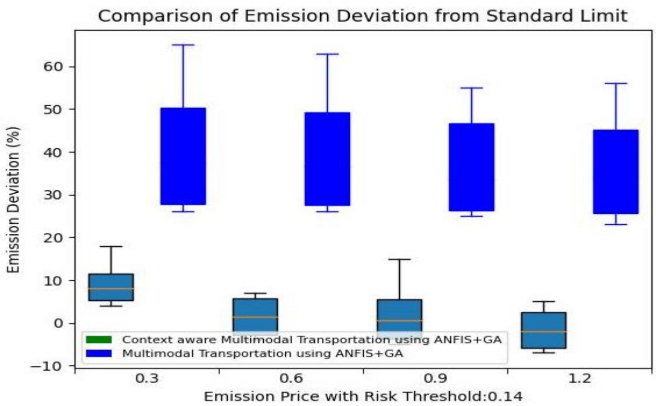
Figure 3 illustrates the average utilization rates of various transportation modes—trucks, railways, ships, and air transport—across emission price ranges from 0.3 to 1.2. As emission prices increase, the reliance on trucks declines from 25% to below 10%, while the use of alternative transportation modes rises. This shift supports our objective of balancing CO2 emissions with transportation costs. Notably, in the context-aware

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

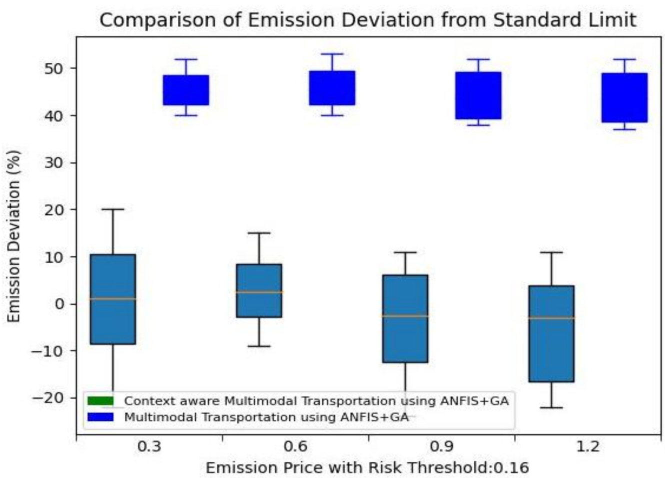
scenario, waterways utilization increases as truck usage decreases, demonstrating the model's effectiveness in reducing emissions and controlling costs. Furthermore, in the GMM scenario, railway usage increases from 10% to 25% as truck use falls. For lower emission prices, ships dominate over all other modes and remain consistent. These changes in transportation mode utilization underscore the effectiveness of our approach in balancing CO2 emission reductions with transportation cost management.



(a)



(b)



(c)

Figure 2. *Comparison of emission deviation from standard limit*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

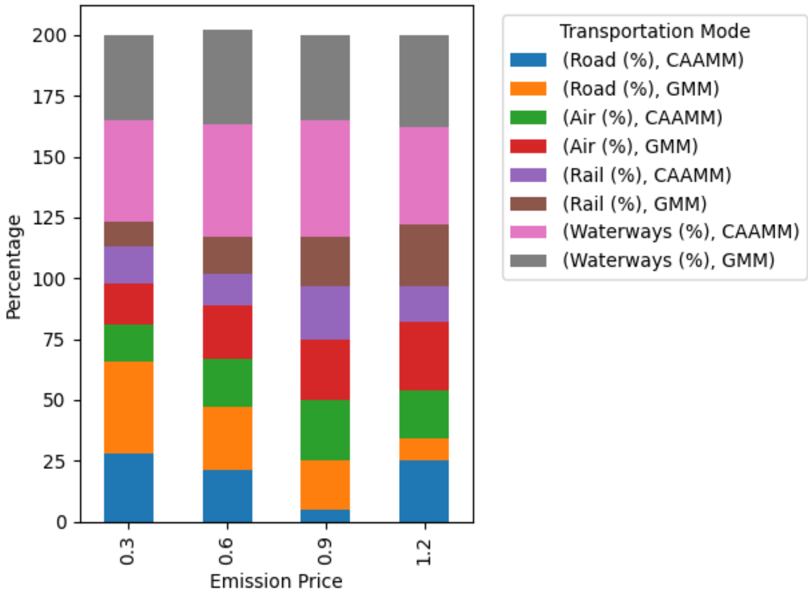


Figure 3. *Average transportation usage for different modes. (a) CAAMM (b) GMM*

Figure 4 compares the combined quantities for different transportation scenarios—waterways with railways, waterways with airplanes, and airplanes with railways—using ANFIS + GA. The blue line, representing the waterways and railways combination, shows considerable seasonal variation with notable peaks and troughs. Specifically, there is a significant increase from January to March and again from April to June, followed by a drop in July and a slight rise in August. A similar pattern is observed for the waterways and airplane scenario. Conversely, the red line, depicting the railway and airplane combination, reveals a smoother quantity pattern with significant fluctuations primarily between May and June. This indicates that while the waterways and railways, as well as the waterways and airplane combinations, experience considerable seasonal variations, the railway and airplane combination offers more consistent transport quantities throughout the year, which is essential for effective logistical planning.

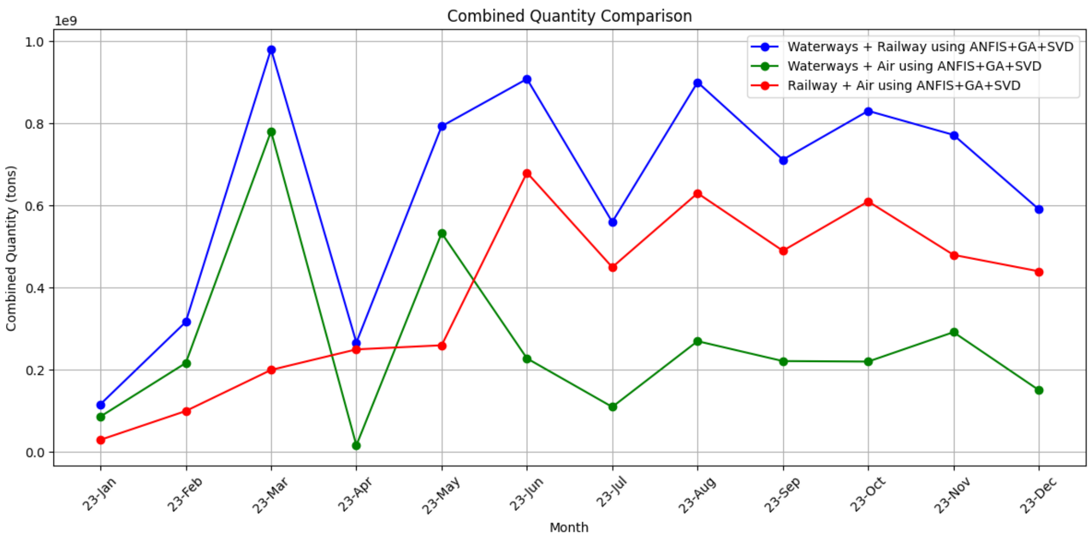


Figure 4. *Combined quantity comparison of different scenarios using ANFIS + GA*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

Figure 5 illustrates the combined cost comparisons for various scenarios—waterways with railways, waterways with airplanes, and airplanes with railways—using the ANFIS + GA model. The blue line, representing the waterways and railways combination, demonstrates significant cost fluctuations, peaking in the middle of the year with a marked increase from April to June, followed by a decrease in July and more moderate variations afterward. In contrast, the green line for the waterways and airplane combination shows relatively stable costs throughout the year, with notable cost spikes occurring in April, similar to the waterways and railways scenario. On the other hand, the red line for the railway and airplane combination reveals substantial cost variations throughout the year. This analysis suggests that while the railway and airplane combination experiences higher and more variable costs—likely due to seasonal demand—the waterways and railways, as well as the waterways and airplane combinations, might offer more consistent and potentially cost-effective options for year-round transportation.

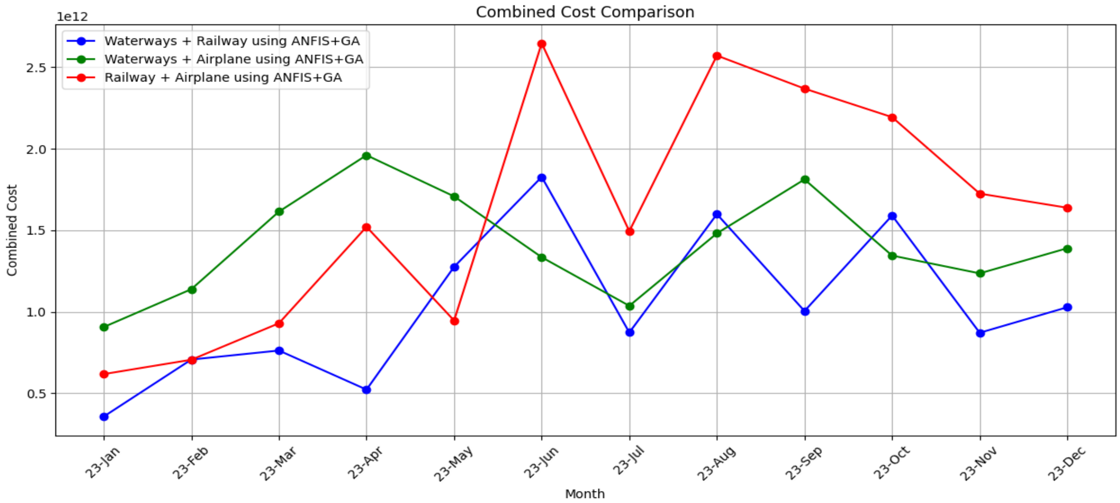


Figure 5. *Combined cost comparison of different scenarios using ANFIS + GA*

Figure 6 presents a grouped bar chart comparing the combined costs of three distinct multimodal transportation scenarios over twelve months in 2023. It is important to emphasize that the results and insights shown are not merely the outcome of traditional cost allocation methods. Instead, they reflect the sophisticated decision-making capabilities of the context-aware ANFIS + GA multimodal transportation model driving this analysis. This model leverages historical data and real-time information to enable flexible and intelligent adjustments in transportation planning. Each scenario represents a different strategy for allocating costs among waterways, railways, and air transportation modes. The model's impact extends beyond simple allocation; the ANFIS + GA integration dynamically optimizes these cost allocations, achieving efficiencies that static methods might miss. While the chart illustrates cost distributions, it does not fully capture the model's comprehensive efforts to minimize transportation expenses and CO2 emissions. The financial savings generated by this model not only contribute to achieving various economic objectives but also play a significant role in reducing emissions, thereby supporting broader environmental goals. This success is made possible by the model's remarkable adaptive capabilities, which allow it to respond effectively to changing conditions and priorities.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

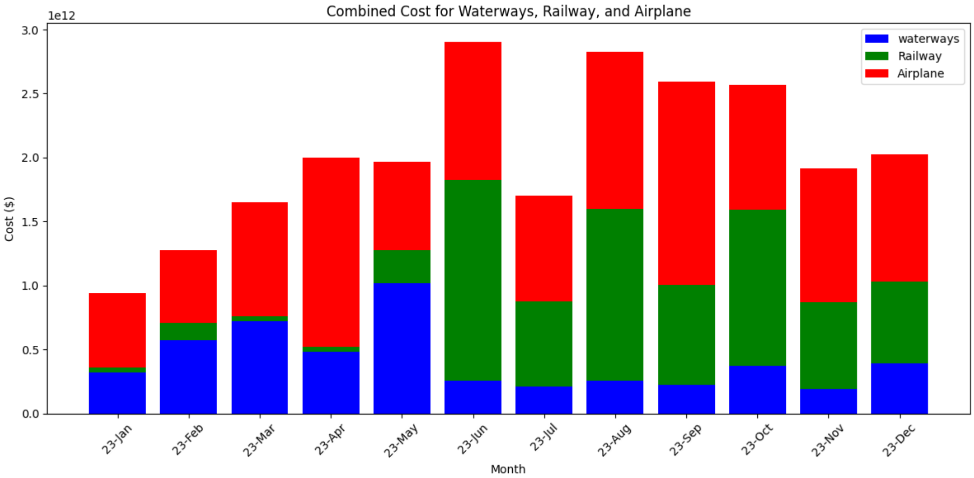


Figure 6. *Multimodal transportation cost comparison using three distinct scenarios for China*

Findings, discussion, and strategic recommendations

The integration of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and Genetic Algorithms (GA) in our context-aware multimodal transportation model for China marks a significant advancement in optimizing supply chain logistics, addressing the nation's intricate transportation challenges with precision and adaptability. Our results reveal that the ANFIS + GA approach, calibrated with a risk threshold of 0.16 and an emission price of 1.2, achieves a remarkable 17% reduction in CO_2 emissions below standard limits, outperforming traditional static models. This reduction is driven by a profound shift in mode utilization: road-based transportation, previously accounting for 25% of transport, has declined to below 10%, while railways surged by 150%, and waterways solidified their dominance, particularly when paired with railways, as demonstrated in our simulations using China's 2022–2023 transportation data. These shifts are facilitated by the model's ability to dynamically adjust routes and modes—spanning truck, rail, high-speed rail (HSR), ship, and air—based on real-time inputs such as traffic, weather, demand and geopolitical risks, balancing costs, emissions, travel time, fairness, and resilience.

These findings underscore the transformative potential of context-aware optimization in tackling China's multimodal transportation challenges, including regional disparities, environmental pressures, and infrastructure bottlenecks. The 150% increase in railway usage highlights its efficiency and lower carbon footprint (0.03–0.08 kg/km/kg) compared to trucks (0.08–0.10 kg/km/kg), positioning it as a cornerstone for sustainable logistics. Similarly, the dominance of waterways, with emissions as low as 0.01–0.02 kg/km/kg, leverages China's strategic access to major waterways (e.g., Yangtze River, South China Sea), reinforcing their role in cost-effective, low-emission transport. However, this shift reveals critical bottlenecks, such as limited railway and waterway infrastructure in underdeveloped inland regions, port congestion in coastal hubs such as Shanghai, and regulatory gaps for mode integration, which hinder seamless intermodal operations. To address these bottlenecks effectively, logistics firms and policymakers should adopt targeted strategies based on our findings, i.e.,

I. Infrastructure Expansion: Invest in railway and waterway infrastructure, particularly in western and rural regions, to support the 150% railway surge and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

waterway dominance. For example, expanding rail capacity along key corridors (e.g., Beijing-Shanghai, Sichuan-Tibet) and enhancing port facilities in Ningbo and Guangzhou can alleviate bottlenecks, reducing congestion and increasing capacity (e.g., rail 50,000–70,000 kg, ships 500,000–2,000,000 kg per *Table 3*).

II. Regulatory Reforms: Implement policies to streamline mode integration, such as unified standards for intermodal transfers (e.g., rail-to-waterway hubs), and incentivize low-emission technologies (e.g., electric trucks, hydrogen trains) to reduce road reliance (<10%). This could include tax breaks or subsidies for rail and ship operators, addressing regulatory gaps identified in our model's shift from trucks.

III. Real-Time Data Systems: Deploy IoT and AI-driven systems to enhance real-time traffic and weather monitoring, reducing bottlenecks such as urban congestion in Beijing or seasonal demand spikes (e.g., January–March). Our model's adaptability suggests integrating these systems into national logistics platforms, as validated by the 17% emission reduction.

IV. Stakeholder Collaboration: Foster partnerships between logistics firms, government agencies, and multinational corporations (e.g., Belt and Road Initiative participants) to mitigate geopolitical risks (RV = 0.1–0.16) and ensure resilient supply chains, addressing bottlenecks in border regions and underdeveloped areas.

The research results are highly transferable to other large, developing economies with similar multimodal challenges, such as India or Brazil, where regional disparities, environmental pressures, and infrastructure bottlenecks mirror China's context. The ANFIS + GA model's context-aware nature, leveraging real-time data and multi-objective optimization, is practicable for real-world logistics operations, as demonstrated by its scalability to China's 10,000 × 10,000 km network and validation with Ministry of Transport data. However, applicability may be limited by computational demands (e.g., 100 iterations for ANFIS/GA), requiring advanced hardware or simplified algorithms for smaller regions. Practically, logistics firms can implement the model with existing Python tools and China's data infrastructure, while policymakers can simulate emission pricing (e.g., 1.2) or mode shifts (e.g., railways + 150%) to guide policy, as shown in our 17% emission reduction and mode shift outcomes. Challenges include data quality in rural areas and integration with local regulations, but these can be addressed through collaboration and future refinements.

Conclusion

This study's results confirm the model's superiority over traditional methods, providing a scalable solution to balance economic, environmental, and social goals. It demonstrates that the proposed context-aware ANFIS + GA model reduces CO_2 emissions by 17% compared to standard multimodal approaches. Truck usage dropped below 10%, while rail utilization rose by 150%, validating the model's dynamic adaptability. These results were obtained under a risk threshold of 0.16 and emission pricing of 1.2, reflecting China's policy priorities.

The model offers valuable insights for transportation planners and policymakers, especially in areas such as emission pricing, infrastructure investments such as rail-waterway corridors, and resilience planning in line with the 14th Five-Year Plan. These

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

practical insights can really make a difference, helping logistics companies improve their operations and giving policymakers a way to test out emission pricing strategies to promote fairness and resilience across regions. However, adopting this model will need us to tackle some challenges such as computational complexity and data availability, especially for real-time use. But as we bring in new technologies and improve regional policies, future research can help this model work even better, supporting China's exciting journey toward sustainable transportation.

The model's real-time application is constrained by computational demands, especially when scaling to a national level. Additionally, data quality disparities, especially from rural or underdeveloped areas, may affect prediction accuracy. Hyperparameter tuning in GA also requires further refinement for localized optimization. The variations in regional policies, economic fluctuations, and technological advancements enable further exploration, which could influence outcomes.

Future research will focus on integrating real-time IoT sensor data, hybrid metaheuristics, and federated learning to enhance model precision, scalability, and security for deployment across diverse transportation networks.

Funding sources. The study presented in this paper was supported by Research Initiation Fund Projects of Zhejiang Guangsha Vocational and Technical University of Construction: 2025ZX001

Conflict of interests. The authors declare no potential conflict of interests with respect to the research, authorship, or publication and declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

REFERENCES

[1] Acharya, S., Tripathy, C. R. (2018): An ANFIS estimator-based data aggregation scheme for fault tolerant wireless sensor networks. – Journal of King Saud University—Computer and Information Sciences 30(3): 334-348.

[2] Acharya, S., Tripathy, C. R. (2020): A reliable fault-tolerant ANFIS model-based data aggregation scheme for wireless sensor networks. – Journal of King Saud University-Computer and Information Sciences 32(6): 741-753.

[3] Akbar, U., Fan, R. N., Li, Q. L. (2019): A Route Option for Different Commodity Groups in International Trade: China Pakistan Economic Corridor. – In: Li, Q. L., Wang, J., Yu, H. B. (eds.) Stochastic Models in Reliability, Network Security and System Safety. JHC80 2019. Communications in Computer and Information Science, Vol. 1102. Springer, Singapore, pp. 446-464. http://link.springer.com/10.1007/978-981-15-0864-6_23.

[4] Akbar, U., Ali, W., Javaid, S., Khan, M. A. (2025): Optimizing data-driven trade-offs to achieve emissions reduction in transportation. – Quality & Quantity, 1-23. https://doi.org/10.1007/s11135-025-02293-6

[5] Ali, W., Javaid, S., Akbar, U. (2025): A solution of mathematical multi-objective transportation problems under uncertain environments. – Palestine J Math 14(1): 987-1014.

[6] Archetti, C., Peirano, L., Speranza, M. G. (2022): Optimization in multimodal freight transportation problems: a survey. – European Journal of Operational Research 299(1): 1-20.

[7] Babuška, R., Verbruggen, H. B. (2020): Fuzzy Set Methods for Local Modelling and Identification. – In: Murray-Smith, R. et al. (eds.) Multiple Model Approaches to Nonlinear Modelling and Control. CRC Press, Boca Raton, FL, pp. 75-100.

[8] Bontekoning, Y. M., Macharis, C., Trip, J. J. (2004): Is a new applied transportation research field emerging? A review of intermodal rail-truck freight transport literature. –

Transportation Research Part A: Policy and Practice 38(1). DOI: 10.1016/j.tra.2003.06.001.
[9] Bousnina, K., Hamza, A., Yahia, N. B. (2023): An integration of PSO-ANN and ANFIS hybrid models to predict surface quality, cost, and energy (QCE) during milling of alloy 2017A. – Journal of Engineering Research. https://doi.org/10.1016/j.jer.2023.09.016.
[10] Camporeale, R., Caggiani, L., Fonzone, A., Ottomanelli, M. (2016): Better for everyone: an approach to multimodal network design considering equity. – Transportation Research Procedia 19: 303-315.
[11] Cao, J., Li, S., Noland, R. B., Ge, Y.-E. (2021): The first 25 years of transportation research part D: transport and environment. – Transportation Research Part D: Transport and Environment 100: 103078.
[12] Chang, D., Huang, X., Wang, C., Zhang, N. (2024): Temperature shocks and low-carbon performance: evidence from the transportation sector in China. – Transportation Research Part D: Transport and Environment 133: 104282.
[13] Chen, S., Hu, J., Shi, Y., Zhao, L., Li, W. (2020): A vision of C-V2X: technologies, field testing, and challenges with Chinese development. – IEEE Internet of Things Journal 7(5): 3872-3881.
[14] Chen, Y., Wang, H. (2018): Why are fairness concerns so important? Lessons from a shared last-mile transportation system. Lessons from a shared last-mile transportation system. – Transportation Research Part A: Policy and Practice 192. https://doi.org/10.1016/j.tra.2024.104361.
[15] Cheng, L., Tsou, C. S., Lee, M. C., Huang, L. H., Song, D., Teng, W. S. (2013): Tradeoff analysis for optimal multiobjective inventory model. – Journal of Applied Mathematics 2013(i): 1-8. DOI: 10.1155/2013/619898.
[16] Chu, K.-F., Guo, W. (2023): Deep reinforcement learning of passenger behavior in multimodal journey planning with proportional fairness. – Neural Computing and Applications 35(27): 20221-20240.
[17] Dini, N., Yaghoubi, S., Bahrami, H. (2024): Route selection of periodic multimodal transport for logistics company: an optimisation approach. – Research in Transportation Business & Management 54: 101123.
[18] Dirik, M. (2022): Prediction of NOx emissions from gas turbines of a combined cycle power plant using an ANFIS model optimized by GA. – Fuel 321: 124037.
[19] Egger, P. H., Loumeau, G., Loumeau, N. (2023): China's dazzling transport-infrastructure growth: measurement and effects. – Journal of International Economics 142: 103734.
[20] Ghorbanzadeh, O., Rostamzadeh, H., Blaschke, T., Gholaminia, K., Aryal, J. (2018): A new GIS-based data mining technique using an adaptive neuro-fuzzy inference system (ANFIS) and k-fold cross-validation approach for land subsidence susceptibility mapping. – Natural Hazards 94: 497-517.
[21] Groothedde, B., Ruijgrok, C., Tavasszy, L. (2005): Towards collaborative, intermodal hub networks. A case study in the fast moving consumer goods market. – Transportation Research Part E: Logistics and Transportation Review 41(6 spec. iss.): 567-583. DOI: 10.1016/j.tre.2005.06.005.
[22] Han, B., Wan, M., Zhou, Y. (2020): Evaluation of multimodal transport in China based on hesitation fuzzy multiattribute decision-making. – Mathematical Problems in Engineering 2020. DOI: 10.1155/2020/1823068.
[23] Hanaoka, S., Regmi, M. B. (2011): Promoting intermodal freight transport through the development of dry ports in Asia: an environmental perspective. – IATSS Research 35(1): 16-23.
[24] He, Z., Liu, Q., Zhao, P. (2022): Challenges of passenger and freight transportation in mega-city regions: a systematic literature review. – Transportation Research Interdisciplinary Perspectives 16: 100730.

[25] Hensher, D. A., Zhang, Z., Rose, J. (2015): Transport and logistics challenges for China: drivers of growth, and bottlenecks constraining development. – Road & Transport Research: A Journal of Australian and New Zealand Research and Practice 24(2): 32-41.
[26] Hu, X., Chang, S., Li, J., Qin, Y. (2010): Energy for sustainable road transportation in China: Challenges, initiatives and policy implications. – Energy 35(11): 4289-4301.
[27] Jang, J.-S. (1993): ANFIS: adaptive-network-based fuzzy inference system. – IEEE Transactions on Systems, Man, and Cybernetics 23(3): 665-685.
[28] Koohathongsumrit, N., Meethom, W. (2021): An integrated approach of fuzzy risk assessment model and data envelopment analysis for route selection in multimodal transportation networks. – Expert Systems with Applications 171: 114342.
[29] Li, H., Lu, Y., Zhang, J., Wang, T. (2013): Trends in road freight transportation carbon dioxide emissions and policies in China. – Energy Policy 57: 99-106.
[30] Li, H., Qiu, P., Wu, T. (2021): The regional disparity of per-capita CO2 emissions in China's building sector: an analysis of macroeconomic drivers and policy implications. – Energy and Buildings 244: 111011.
[31] Liu, H., Tong, Y., Han, J., Zhang, P., Lu, X., Xiong, H. (2020): Incorporating multi-source urban data for personalized and context-aware multi-modal transportation recommendation. – IEEE Transactions on Knowledge and Data Engineering 34(2): 723-735.
[32] Lozano, A., Storchi, G. (2001): Shortest viable path algorithm in multimodal networks. – Transportation Research Part A: Policy and Practice 35(3): 225-241. DOI: 10.1016/S0965-8564(99)00056-7.
[33] Lu, C., Du, Q., Li, J., Li, Y., Wang, X. (2023): Trade embodied CO2 transfers from transportation sector: a nested multi-scale input-output perspective. – Transportation Research Part D: Transport and Environment 119: 103727.
[34] Maity, G., Roy, S. K., Verdegay, J. L. (2019): Time variant multi-objective interval-valued transportation problem in sustainable development. – Sustainability 11(21): 6161.
[35] Naseer, M., Prabakaran, B. S., Hasan, O., Shafique, M. (2024): UnbiasedNets: a dataset diversification framework for robustness bias alleviation in neural networks. – Machine Learning 113(5): 2499-2526.
[36] Olayode, I. O., Tartibu, L. K., Alex, F. J. (2023): Comparative study analysis of ANFIS and ANFIS-GA models on flow of vehicles at road Intersections. – Applied Sciences 13(2): 744.
[37] Pamučar, D., Lukovac, V., Pejčić-Tarle, S. (2013): Application of adaptive neuro fuzzy inference system in the process of transportation support. – Asia-Pacific Journal of Operational Research 30(02): 1250053.
[38] Peng, H., Sun, Y., Hao, J., An, C., Lyu, L. (2024): Carbon emissions trading in ground transportation: status quo, policy analysis, and outlook. – Transportation Research Part D: Transport and Environment 131: 104225.
[39] Raayatpanah, M. A. (2017a): Multicast routing based on data envelopment analysis with multiple quality of service parameters. – International Journal of Communication Systems 30(5): e3084–e3084.
[40] Raayatpanah, M. A. (2017b): Multicast routing based on data envelopment analysis with multiple Quality of Service parameters. – International Journal of Communication Systems 30(5): e3084.
[41] Reggiani, A., Nijkamp, P., Lanzi, D. (2015): Transport resilience and vulnerability: the role of connectivity. – Transportation research part A: policy and practice 81: 4-15.
[42] Rondinelli, D., Berry, M. (2000): Multimodal transportation, logistics, and the environment: managing interactions in a global economy. – European Management Journal 18(4): 398-410.
[43] Salazar, M., Giraldo, S. B., Paparella, F., Pedroso, L. (2024): On accessibility fairness in intermodal autonomous mobility-on-demand systems. – IFAC-PapersOnLine 58(10): 327-333.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931

[44] Şener, R., Koç, M. A., Ermiş, K. (2024): Hybrid ANFIS-PSO algorithm for estimation of the characteristics of porous vacuum preloaded air bearings and comparison performance of the intelligent algorithm with the ANN. – Engineering Applications of Artificial Intelligence 128: 107460.
[45] Seo, Y. J., Chen, F., Roh, S. Y. (2017): Multimodal transportation: the case of laptop from Chongqing in China to Rotterdam in Europe. – Asian Journal of Shipping and Logistics 33(3): 155-165. Available at: http://dx.doi.org/10.1016/j.ajsl.2017.09.005.
[46] Singh, N. K., Singh, Y., Sharma, A., Abd Rahim, E. (2020): Prediction of performance and emission parameters of Kusum biodiesel based diesel engine using neuro-fuzzy techniques combined with genetic algorithm. – Fuel 280: 118629.
[47] Sporkmann, J., Liu, Y., Spinler, S. (2023): Carbon emissions from European land transportation: a comprehensive analysis. – Transportation Research Part D: Transport and Environment 121: 103851.
[48] Temizceri, F. T., Kara, S. S. (2024): Towards sustainable logistics in Turkey: a bi-objective approach to green intermodal freight transportation enhanced by machine learning. – Research in Transportation Business & Management 55: 101145.
[49] Wang, J., He, D. (2015): Sustainable urban development in China: challenges and achievements. – Mitigation and Adaptation Strategies for Global Change 20(5): 665-682.
[50] Wang, Y., Zhu, X., Li, L., Wu, B. (2013): Integrated multimodal metropolitan transportation model. – Procedia-Social and Behavioral Sciences 96: 2138-2146.
[51] Xin, L., Xu, P., Manyi, G. (2022): Logistics distribution route optimization based on genetic algorithm. – Computational Intelligence and Neuroscience 2022(1): 8468438.
[52] Yang, A., Liu, C., Chang, J., Guo, X. (2010): Research on parallel LU decomposition method and its application in circle transportation. – J. Softw. 5(11): 1250-1255.
[53] Ye, J., He, X. (2023): A novel hybrid of ANFIS-based models using optimisation approaches to predict mine blast-induced flyrock. – International Journal of Environmental Science and Technology 20(4): 3673-3686.
[54] Yin, K., Wu, J., Wang, W., Lee, D.-H., Wei, Y. (2023): An integrated resilience assessment model of urban transportation network: a case study of 40 cities in China. – Transportation Research Part A: Policy and Practice 173: 103687.
[55] Zhang, H., Huang, Q., Ma, L., Zhang, Z. (2024): Sparrow search algorithm with adaptive t distribution for multi-objective low-carbon multimodal transportation planning problem with fuzzy demand and fuzzy time. – Expert Systems with Applications 238: 122042.
[56] Zhang, L., Chen, H., Li, S., Liu, Y. (2023): How road network transformation may be associated with reduced carbon emissions: an exploratory analysis of 19 major Chinese cities. – Sustainable Cities and Society 95: 104575.
[57] Zhu, H., Zhang, K., Wang, C., Jia, L., Song, S. (2023): The impact of road functions on road congestions based on poi clustering: an empirical analysis in Xi'an, China. – Journal of Advanced Transportation 2023(1): 6144048.
[58] Zhu, L. (2024): Defining provincial responsibility for controlling transportation CO2 emissions in China: as fairness perspective. – Research in Transportation Business & Management 56: 101160.
[59] Zuo, D., Zhao, L., Lu, Z., Xiong, Q., Luo, Y. (2024): Multilayer structural path analysis of CO2 emissions in China's transportation sector. – Transportation Research Part D: Transport and Environment 128: 104083.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_99079931