Ecological Multimodal Freight Transport Optimization

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Abstract— **The increasing complexity of global supply chains, combined with the need for fast, cost-effective, and environmentally friendly deliveries, has reinforced the importance of multimodal freight transportation(MFT) as a key solution to meet modern demands. One of the main challenges in MFT is to develop an innovative optimization model to plan and manage the supply chain. In this work, we consider four modes of transportation (air, road, rail, and sea) and propose an innovative multi-objective optimization model, designed to simultaneously minimize transportation costs, transit times, and CO_2 emissions, while integrating the complex operational constraints inherent in current logistic systems. To address this problem, we adopt two well-known algorithms : Non-Dominated Sorting Genetic Algorithm III (NSGA-III) and Teaching-Learning Optimization (TLBO), through an experimental study demonstrating the effectiveness of these evolutionary solution methods in solving these complex optimization problem.**

The results show that TLBO optimization effectively reduces costs and environmental impact, while the NSGAIII algorithm improves delivery times.

Index Terms–multimodal transport, optimization, multi-objective optimization, metaheuristics...

I. INTRODUCTION

Global economic development and advances in information technology have profoundly simplified and accelerated global communications.

Growing transport market demand can no longer be met by a single mode of transport. MFT optimization, which could be a classical continuation of logistics problems, involves the efficient integration of multiple modes of transport and multiple factors such as time, service reliability, cost and CO_2 emissions to improve the overall efficiency of the transport system by adapting to changing conditions (delays, congestion...) and satisfying customer needs [1]. The researchers evaluated various algorithms and models to mitigate the complexity of multimodal transport networks and improve decision-making.

Selecting the most reliable stochastic routes requires the development of flexible, real-time, single-objective and multi-objective approaches based on technology and data analysis.

In the current literature, numerous optimization models have been developed, based on single or multiple objective functions, within a deterministic framework [2]. However, in reality, the expectations of customers and transport companies, as well as the operational constraints linked to delivery contexts, are very diverse. Some customers prioritize lower shipping costs, while others are willing to pay more for shorter delivery times [3]. On the other hand, some customers may seek a balance between cost and speed, trying to minimize expenditure and transit times simultaneously. This diversity of needs highlights the fact that route optimization in multimodal transport cannot be treated as a single-objective problem, but rather requires a multi-objective approach [4].

The multi-objective model is widely regarded as a realistic and relevant representation of optimization problems, as it effectively captures the complexity of real-life scenarios, where multiple, often conflicting, objectives need to be optimized simultaneously. Existing work on MFT optimization is often limited to two objectives (cost and time) and three transport modes. For a more global approach, we propose a model integrating three objectives (cost, time, and CO_2 emissions) while considering four modes of transport. This enables a more realistic and sustainable optimization of supply chains. This work propose to use TLBO and NSGAIII. The results show that TLBO effectively optimizes cost reduction and environmental impact. In contrast, the NSGAIII stands out for its ability to reduce delivery times.

II. STATE OF THE ART

The optimization of MFT relies on the combination of different transport modes to ensure the efficiency and profitability of logistics operations. This section is divided into two parts : the first provides an overview of the main transport modes, while the second is dedicated to a review of existing work in this field.

A. Transport modes

— *Road mode :* Road freight is flexible and accessible, ideal for short-distance door-to-door deliveries, but its emissions, reliance on fossil fuels and urban congestion require sustainable solutions [5].

— *Air mode :* Air freight ensures rapid deliveries of valuable or perishable goods, efficiently connecting remote locations, but it is expensive, vulnerable to weather and regulations, and polluting due to its high emissions [6].

— *Rail mode :* Rail freight, being both cost-effective and environmentally friendly, enables efficient long-distance transportation of goods. However, due to the inflexibility of its routes, it typically requires transshipment to trucks to reach the final destination. [7].

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— *Maritime mode :* Maritime transport offers an economical solution for transporting large volumes of freight over long distances with relatively low CO_2 emissions. However, its slow speed and associated risks, such as sulfur emissions, require the use of cleaner fuels and optimized routing strategies [8].

B. Multi-model transport optimization approaches

In multi-modal transport optimization approches, the harmonious integration of different modes of transport is central to leveraging their strengths without their weaknesses. By integrating air, road, rail, and sea transport, this approach enables route optimization, reduces costs, shortens lead times, and minimizes environmental footprints. It thus contributes to making supply chains more efficient and sustainable. Nevertheless, most previous studies focus on two or three transport modes due to the increased complexity of models when integrating multiple modes.

Sun et al. (2018) [9] have solved the problem of green multimodal routes, taking into account rail mode capacity constraints and road mode congestion, using a time-dependent fuzzy programming method.

Wang et al. (2020) [10] used the Ant Colony Optimization (ACO) algorithm to develop an efficient system for minimizing CO_2 emissions and limiting risks. The application of ACO enables the intelligent study of different route combinations, offering equilibrium solutions that take into account both safety requirements and environmental issue.

Archetti et al. (2022) [2] carried out an in-depth study of complex strategic, tactical and operational problems, demonstrating that existing studies are limited to using a maximum of three modes of transport : road, rail, and sea.

Lu et al. (2022) [11] found an optimal solutions for optimizing multiple objectives related to freight volumes, costs, delays, and carbon emissions, using the NSGA-III algorithm.

Peng et al. (2023) [12] explored the advances of a data-driven multi-objective simulation algorithm (DDMSAC) to search for efficient results for minimizing transport costs and delays in three different transport modes : road (freeway), rail (railroad), and sea (inland waterway).

GUO et al. (2023) [13] minimized cost and CO_2 emissions. They used a mixed nonlinear programming model based on particle swarm optimization (PSO).

Rejeb et al. (2023) [14] covered the four major modes of transport (air, road, rail, and maritime). They aim to minimize three different objectives : the overall cost of transport, delivery time, and CO_2 emissions. To solve this complicated problem, they employed two well-known metaheuristics : the tabu search(TS) and the genetic algorithm(GA). These methods enabled the problem's multi-objectivity to be dealt with successfully and to suggest equilibrium solutions that served the economic, time, and environmental aspects. This study represents a significant breakthrough, as it introduces an innovative approach that simultaneously incorporates all four major transport modes. The overall objective is to develop a multi-objective model for multimodal freight transport (MFT) that effectively manages the trade-offs between transportation costs, delivery time, and CO_2 emissions.

Brar et al. (2024) [15] applied the TLBO algorithm to solve complex challenges in multimodal transport systems (MTS), focusing on minimizing total costs as the main objective. This approach integrates the four transport modes : rail, road, air, and sea.

Haghgoei et al. (2024) [16] introduced a multi-objective optimization approach using NSGA-II and Non-Revisiting Genetic Algorithm (NRGA) algorithms to address truck operations planning in cross-docks under uncertainty and fuzzy logistics. The study focuses on three objectives : minimizing the maximum product reception time, reducing gas emission costs, and decreasing the number of trucks assigned to entry and exit gates. This method enhances the efficiency and sustainability of cross-docking operations by integrating environmental and operational constraints.

Derpich et al. (2024) [17] proposed an innovative approach based on centralized load concentration, particularly suited to regions with specific geographical constraints. The objective is to reduce CO_2 emissions, optimize operational efficiency, and decrease high logistics costs, while aligning with sustainable development goals through the use of a genetic algorithm.

Zhao et al. (2024) [18] used the NSGA-III algorithm to develop a new multi-objective optimization approach for road transport. This method simultaneously addresses the three essential components of logistics performance : transport time, operating costs, and environmental impact. Unlike traditional approaches which often reduce these conflicting objectives to a single-objective problem, the NSGA-III algorithm preserves the multi-objective nature of the problem and generates a Pareto optimal set of solutions. Using a selection mechanism based on reference points, the algorithm ensures both convergence towards high-quality solutions and diversity reflecting the many trade-offs between objectives. Results show that this approach is capable of identifying reasonable and balanced operational configurations.

Zhang et al. (2024) [19] covered the four main modes of transport (air, road, rail, and sea) and used the Sparrow Search Algorithm (SSA) to limit CO_2 emissions.

MFT optimization seeks to efficiently combine different modes of transport to improve logistics performance while meeting environmental and economic challenges. Recent research proposed a variety of algorithmic approaches (ANT Colonies, NSGA-II, NSGA-III, PSO, TLBO, SSA, etc.) to minimize costs, lead times, CO_2 emissions, and risks, while managing uncertainties (capacity, congestion, and freight volumes). These studies were limited to two or three modes due to the complexity involved. Generally, recent research has developed a single or bi-objective model linked to one or two transport modes, but it is rare to find research that has proposed a multi-objective model applied to several transport modes.

III. Overview of the Multimodal Freight Transport (MFT)

We adopt the same mathematical model used by Rejeb et al. [14], but with more advanced optimization models such as the NSGA-III and TLBO algorithms, for the reasons mentioned above, instead of traditional algorithms such as tabu search (TS) and genetic algorithms (GA). Rejeb et al. [14] used a hybrid approach and a scalarization technique to formulate the multi-objective problem into a single-objective problem.

The implementation of the NSGA-III and TLBO algorithms poses several challenges : data quality and availability, the complexity of multimodal networks, and the variability of operational conditions. Our simulation, developed in this study, is highly feasible because it takes into account assumptions similar to real-world logistics conditions and realistic data. We have integrated these assumptions into our model to ensure a clear and efficient approach :

- The delivery method is set deterministically, which ensures that neither the delivery time nor the associated costs will be affected by unforeseen or random events.
- The amount of goods transported is limited by the capacity of the containers. Although the volume can be split according to needs, the model does not take into account the optimization of the arrangement of goods inside the containers.
- The model focuses on major road infrastructure and excludes the first and last miles, i.e., journeys connecting final shipping and receiving points, such as travel between warehouses and customers.
- Each pair of ports is served by a single intermediate mode of transport. Specifically, it is not possible to provide a direct journey by ship, train, or truck between two airports located in different cities, even if a direct flight is possible.

A. Objectives

1) The primary objective is to reduce the total cost of transportation, which encompasses trip expenses, tax costs, and warehouse costs.
2) The second objective focuses on reducing the overall travel time from the starting port to the destination port.
3) The third objective is to reduce the total CO_2 emissions, which includes minimizing both the emissions generated during transportation along the routes and those produced during transshipment at intermediate nodes.

B. Constraints

- The shipping process requires each good to be transported from its origin to an intermediate node before reaching its final destination, with the origin and destination nodes prohibited from serving as intermediate points to prevent circular routing.
- Transshipment operations are restricted to intermediate nodes only, where ship-in and ship-out times must be synchronized to ensure seamless transfers.
- Each good can undergo at most one transfer (either into or out of a port) to maintain efficiency.
- Ship-out times must logically follow ship-in times at transition ports.
- For goods originating from a port, ship-out times must occur after the order date.
- Container capacities on all routes must exceed or match the total volume of goods transported.
- Road usage is explicitly decided to ensure active or inactive flow status.
- Deliveries must adhere to specified deadlines and transit time limits.
- No transshipping is allowed at origin or destination nodes.
- Only a single transport mode is permitted between any two nodes to streamline operations.

IV. The solving method

To address the MFT problem, we employ two advanced optimization algorithms : TLBO and NSGA-III. TLBO algorithm introduced by Rao et al. [24], in 2011. It is a simple yet efficient global optimization method inspired by educational teaching-learning processes, requiring only general parameters like population size and iteration count. It also requires no parameters to be optimized, no crossover operators and no mutation. It offers a good balance between exploration and exploitation in the logistics system, minimizing any risk of unexpected convergence. In contrast to genetic algorithms [22], it has proved effective in solving complex problems such as neural network planning and optimization.

NSGA-III [25] excels in multi-objective optimization, particularly for more than two objectives, using reference points to ensure diverse and well-distributed solutions. Its robust exploration of Pareto frontiers makes it ideal for balancing MFT objectives like cost, time, and CO_2 emissions.

In the following sections, we detail the key steps of each method, highlighting their specific application to the context of MFT.

A. TLBO Algorithm

TLBO relies on the natural diversity of the population and the progressive improvement of solutions to deliver efficient and optimal results.

Algorithm 1 TLBO implements a classroom-inspired optimization process with two phases : Teacher Phase and Learner Phase.

- **Initialization :** Generates N candidate solutions $P = \{S_1, ..., S_N\}$ representing multimodal routes through nodes $\{n_1, ..., n_N\}$ of V and edges $\{e_1, ..., e_N\}$ of E. Computes objective ranges ($[C_{\min}, C_{\max}]$ for cost, $[T_{\min}, T_{\max}]$ for time, $[E_{\min}, E_{\max}]$ for CO_2 emissions) and selects the initial best solution S^* via :

$$S^* = \arg\min_{S \in P} f_{\text{norm}}(S) \tag{1}$$

— **Normalization :**

$$f_{\text{norm}}(S) = \frac{1}{3}\left(\frac{C - C_{\min}}{C_{\max} - C_{\min}} + \frac{T - T_{\min}}{T_{\max} - T_{\min}} + \frac{E - E_{\min}}{E_{\max} - E_{\min}}\right) \tag{2}$$

— **Teacher Phase :** Each individual S_i in the population learns from the best individual S^* (the teacher) :

$$S_i' = S_i + r \times (S^* - TF \times M) \tag{3}$$

where $r \in [0,1]$ is a random value, $TF \in \{1,2\}$ is the Teaching Factor, and M is the population mean.

— **Learner Phase :** Each individual interacts with a randomly selected peer S_j. If S_i is better, it moves away ; otherwise, it moves toward S_j :

$$S_i' = S_i + r \times \begin{cases} (S_i - S_j) & \text{if } f_{\text{norm}}(S_i) < f_{\text{norm}}(S_j) \\ (S_j - S_i) & \text{otherwise} \end{cases} \tag{4}$$

The algorithm iteratively updates reference ranges and S^* until convergence (when $fe < FE$), then returns the optimal solution with its normalized performance metrics.

Algorithm 1 TLBO for Multimodal Optimization

Require: Transport network $G = (V, E)$, population size N, max evaluations FE
Ensure: Optimal solution S^* with objectives : cost, time and CO_2 emissions (C, T, E)
Initialize population $P = \{S_1, ..., S_N\}$ with random routes
Compute objective ranges $[C_{min}, C_{max}]$, $[T_{min}, T_{max}]$, $[E_{min}, E_{max}]$
$S^* \leftarrow$ best normalized solution in P
while evaluation count $fe < FE$ **do**
  Teacher Phase
  for each $S_i \in P$ **do**
    $S_i' \leftarrow S_i + r(S^* - TF \cdot M)$ $\triangleright$ $r \in [0,1]$, $TF \in \{1,2\}$
    if $f_{\text{norm}}(S_i') < f_{\text{norm}}(S_i)$ **then**
      $S_i \leftarrow S_i'$
    end if
  end for
  Learner Phase
  for each $S_i \in P$ **do**
    Select random $S_j \neq S_i$
    if $f_{\text{norm}}(S_i) < f_{\text{norm}}(S_j)$ **then**
      $S_i' \leftarrow S_i + r(S_i - S_j)$
    else
      $S_i' \leftarrow S_i + r(S_j - S_i)$
    end if
    if $f_{\text{norm}}(S_i') < f_{\text{norm}}(S_i)$ **then**
      $S_i \leftarrow S_i'$
    end if
  end for
  Update S^* and objective ranges
end while
return S^*

B. NSGA-III algorithm

NSGA-III relies on the concept of Pareto dominance to identify the best solutions. To better explore all possibilities, it uses a selection method based on reference points. This helps to find a set of diverse and high-quality solutions.

Algorithm 2 implements NSGA-III to solve a multi-objective optimization problem in multimodal transport, minimizing three objectives : total cost (transport, storage, and taxes), total transport time, and CO_2 emissions, while respecting constraints such as deadlines and capacity limits. Input parameters include a transport graph $G = (V, E)$, where nodes represent ports, airports, and warehouses, an initial population N of random trajectories, a maximum number of generations g, and a mutation probability mp. The process begins by generating an initial population P_0 using the generate-initial-population method and employs directional reference points to guide the search toward diverse Pareto-optimal solutions. At each generation Q_t, the algorithm evaluates objectives and constraints for each individual, classifies solutions into non-dominated Pareto fronts $(F_1, F_2, \ldots)$, and applies genetic operators (crossover, mutation) to create new generations R_t. The optimization process employs a single-point crossover for each parent pair, selects random route segment point p_c and swaps subsequences after p_c while maintaining path continuity. Path validation ensures route feasibility and compliance with deadlines. After g generations or convergence, the algorithm returns Pareto-optimal solutions, providing trade-offs between objectives for informed decision-making.

Algorithm 2 NSGA-III for Multimodal Transport

Inputs : Transport graph $G = (V, E)$, origins O, destinations D, population size N, generations g, mutation probability mp
Initialization :
Generate population P_0 of N random solutions
Initialize reference points
Evolution :
for $i = 1$ to g **do**
  Evaluate objectives (cost, time, CO_2) for all solutions
  Perform non-dominated sorting $F_1, F_2, \ldots$
  Calculate crowding distance
  Reproduction :
  Select parents using binary tournament
  Apply single-point crossover :
  for each parent pair **do**
    Choose random crossover point p_c
    Swap segments after p_c to create offspring
  end for
  Apply mutation with probability mp
  Environmental Selection :
  Combine parents and offspring : $R_t = P_t \cup Q_t$
  Select new population P_{t+1} using elitism
end for
Output : Pareto-optimal transport solutions

V. Data description

The dataset provided by Ken Huang on GitHub [26] consists of two sheets : "Order Information" and "Route Information." The first sheet describes eight types of goods (honey, furniture, pharmaceutical drugs...), detailing their characteristics such as order number, weight, volume, and departure/arrival ports. The second sheet outlines 50 direct routes between ports in Wuxi, Singapore, Malaysia, and Shanghai, specifying transport modes, costs, durations, and weekly schedules. Each good has a well-defined departure and arrival point, with several possible routes and modes of transport, from which it is possible to choose those that best meet the optimization objectives. Cities have warehouses to facilitate transits or consolidate goods. The dataset focuses on optimizing transport costs and times but does not account for CO_2 emissions. This user-generated dataset offers realistic logistics scenarios, tested on optimization models. And because it doesn't take into account historical records, it doesn't reflect real-time variability or disruptions. While these data are useful in terms of simulation and method comparison, they require reflexive, intelligent use and real validation to confirm the robustness of the model.

A. Simulation parameters

The TLBO algorithm utilized 30 solutions and a maximum of 2000 evaluations, ensuring a balance between optimization efficiency and solution diversity. This setup allowed effective exploration of multimodal transport routes while keeping computation time reasonable. For NSGA-III, the parameters were determined experimentally, incorporating specific considerations for Pareto front management and solution distribution. Each experiment prioritized optimizing either cost, time, or CO_2 emissions, with the detailed parameters presented in Table I.

TABLE I
Parameters used for NSGA-III.

Parameter	Value
Population size	100
Number of generations	500
Crossover probability	0.9
Mutation probability	0.1
Crossover distribution index	20
Mutation distribution index	20
Reference points	the number of objectives

These parameter values are chosen based on the specific requirements of the multimodal transportation problem. The crossover and mutation parameters are based on default values in the multi-objective optimization literature, and implicitly tuned based on problem complexity.

B. Comparison of results

Tables II to V show the results of two different freight optimization approaches : TLBO and NSGA-III with two pareto front solutions : solution (P1) and solution (P2). Solutions (P1) and (P2) represent key trade-offs among cost, emissions, and time, illustrating distinct points on the Pareto front to facilitate analysis without excessive complexity.

TABLE II
Objective function values for each algorithm.

Indicator	TLBO	NSGAIII : P1	NSGAIII : P2
Total travel days	77	63	28
Total CO_2 emissions (kg)	7282.87	29 457.67	64 232.67
Total cost	194 895.00	195 175.00	267 210.00

TABLE III
TLBO : comparative results for each freight.

Freight	Cost	CO_2 (kg)	Days	Modes
Honey	3001.875	1419.60	18	Truck-Sea-Sea-Truck
Furniture	1081.875	872.00	9	Truck-Sea-Truck
Paper plates	1271.875	1272.00	11	Truck-Sea-Truck
Pharmaceutical drugs	81151.875	1.27	10	Truck-Sea-Truck
Cigarette	106331.875	238.00	17	Truck-Sea-Sea-Truck
Apple	1451.875	1590.00	10	Truck-Sea-Truck
Durian	351.875	1350.00	1	Truck
Furniture	251.875	540.00	1	Truck

TABLE IV
NSGAIII P1 : comparative results for each freight.

Freight	Cost	CO_2 (kg)	Days	Modes
Honey	3056.25	1692.60	15	Truck-Sea-Sea-Truck-Truck
Furniture	1681.25	17772.00	5	Truck-Truck-Air-Truck
Paper plates	1026.25	3572.00	12	Truck-Truck-Sea-Truck
Pharmaceutical drugs	81581.25	15.07	4	Truck-Air-Truck
Cigarette	105906.25	353.00	10	Truck-Truck-Sea-Truck
Apple	1206.25	4465.00	10	Truck-Sea-Truck-Truck
Durian	276.25	1350.00	1	Truck
Furniture	441.25	232.00	6	Truck-Rail-Truck

TABLE V
NSGAIII P2 : comparative results for each freight.

Freight	Cost	CO_2 (kg)	Days	Modes
Honey	4063.88	15 825.60	4	Truck-Air-Truck
Furniture	2053.88	10 072.00	4	Truck-Air-Truck
Paper plates	2363.88	15 072.00	4	Truck-Air-Truck
Pharmaceutical drugs	82 243.88	15.07	4	Truck-Air-Truck
Cigarette	107 553.88	2518.00	4	Truck-Air-Truck
Apple	2543.88	18 840.00	4	Truck-Air-Truck
Durian	838.88	1350.00	2	Truck
Furniture	738.88	540.00	2	Truck

Table II presents NSGA-III (P2) delivers a reduced total time of 28 days, compared with 63 days (P2) and 77 days (TLBO), thanks to the extensive use of air transport (from Table V). In terms of total CO_2 emissions, and according to Table II, the NSGA-III algorithm presents a value (29457.67 kg for P1) and a high value of (64232.67 kg for P2) compared to TLBO which gives a low value reaching 7282.87 kg, thanks to the use of profitable and less polluting modes of transport such as truck and sea(from Table III). In terms of profitability, the TLBO has a low total cost of 194895 compared with the very high total costs provided by the NSGA-III (195175 (P1) and 267210 (P2)). TLBO is best suited to reducing cost and environmental impact, but NSGA-III is preferable for faster deliveries, as is the case for NSGA-III (P2). The aim of these results is to help decision-makers better select the algorithm that matches their operational priorities. The results confirm the possibility of integrating these approaches into other support systems to minimize time and improve economic and environmental efficiency, adding tangible value to logistics planning.

Figure 1 presents the transport routes for honey products under TLBO and two NSGA-III solutions (P1 and P2).

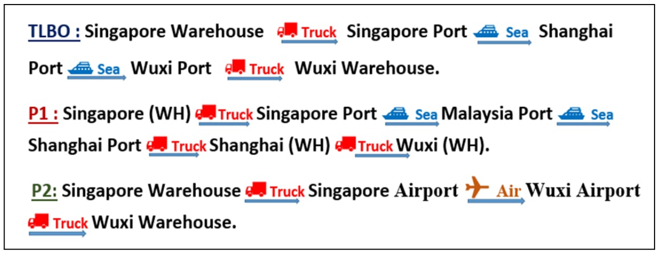

FIG. 1. Transport routes for honey products under TLBO and NSGA-III (P1 and P2).

VI. CONCLUSION

Optimizing freight transport systems represents a major challenge to meet the growing economic, environmental and operational demands of a globalized world. Optimization algorithms such as TLBO and NSGA-III offer promising solutions to these complexities. This study has shown that TLBO is particularly well suited to scenarios where cost reduction and environmental impact mitigation are priorities. NSGA-III, on the other hand, stands out for its ability to ensure rapid delivery, but at high cost and CO_2 emissions. These results underline the importance of selecting the algorithm best suited to the specific objectives of a company or logistics system. Prospects for this research include in-depth evaluation of the performance of the proposed model in real scenarios and exploration of new metaheuristic hybridizations to improve these results. In the future, these hybrid approaches could offer more balanced and versatile solutions to the multiple requirements of modern freight transport.

REFERENCES

[1] A. Godart, Optimisation de tournées de collecte et livraison avec transferts, Ph.D. dissertation, Université Bourgogne Franche-Comté, 2020.

[2] C. Archetti, L. Peirano, and M. G. Speranza, "Optimization in multimodal freight transportation problems : A survey," *Eur. J. Oper. Res.*, vol. 299, no. 1, pp. 1–20, 2022.

[3] A. Maneengam, "Multi-objective optimization of the multimodal routing problem using the adaptive ε-constraint method and modified TOPSIS with the D-CRITIC Method," Sustainability, vol. 15, no. 15, p. 12066, 2023.

[4] M. A. Rahman, "Choosing multimodal freight mix : An integrated multi-objective multicriteria approach," Journal of Transportation Technologies, vol. 14, no. 3, pp. 402–422, 2024.

[5] Z. He, K. Navneet, W. van Dam, et al., "Robustness assessment of multimodal freight transport networks," Reliability Engineering & System Safety, vol. 207, p. 107315, 2021. .

[6] D. Babić, M. Kalić, M. Janić et al., "Integrated door-to-door transport services for air passengers : From intermodality to multimodality," Sustainability, vol. 14, no. 11, p. 6503, 2022.

[7] C. Rong, X. Li, G. Zhang et al., "Analysis on the adjustment of transportation structure and the logistics transformation of railway freight," in Proc. Int. Conf. on Railway Sciences and Logistics Innovation, Beijing, China, Mar. 2025, pp. 45–52.

[8] X. Huang, Y. Wen, F. Zhang et al., "A review on risk assessment methods for maritime transport," Ocean Eng., vol. 279, p. 114577, 2023.

[9] Y. Sun, M. Hrušovský, C. Zhang et al., "A time-dependent fuzzy programming approach for the green multimodal routing problem with rail service capacity uncertainty and road traffic congestion," Complexity, vol. 2018, no. 1, p. 8645793, 2018.

[10] Z. Wang, M. Zhang, R. Chu et al., "Modeling and planning multimodal transport paths for risk and energy efficiency using and/or graphs and discrete ant colony optimization," IEEE Access, vol. 8, pp. 132642–132654, 2020.

[11] Y. Lu, F. Chen, and P. Zhang, "Multiobjective optimization of multimodal transportation route problem under uncertainty," Eng. Lett., vol. 30, no. 4, 2022.

[12] Y. Peng, S. H. Gao, D. Yu et al., "Multi-objective optimization for multimodal transportation routing problem with stochastic transportation time based on data-driven approaches," RAIRO-Oper. Res., vol. 57, no. 4, pp. 1745–1765, 2023.

[13] L. Guo, J. Du, J. Zheng et al., "Integrated planning of feeder route selection, schedule design, and fleet allocation with multimodal transport path selection considered," J. Mar. Sci. Eng., vol. 11, no. 7, p. 1445, 2023.

[14] L. Rejeb, A. Chaabani, H. Safi et al., "Multimodal freight transport optimization based on economic and ecological constraints," in Advances in Computational Logistics and Supply Chain Analytics, Cham, Switzerland : Springer Nature, 2023, pp. 99–127.

[15] T. Brar, T. Kumar, and M. K. Sharma, "Optimizing multimodal transportation systems using the teaching–learning-based algorithm," Int. J. Appl. Comput. Math., vol. 10, no. 1, p. 18, 2024.

[16] A. Haghgoei, A. Irajpour, and N. Hamidi, "A multi-objective optimization model of truck scheduling problem using cross-dock in supply chain management : NSGA-II and NRGA," J. Model. Manag., vol. 19, no. 4, pp. 1155–1179, 2024.

[17] I. Derpich, C. Duran, R. Carrasco et al., "Pursuing optimization using multimodal transportation systems : A strategic approach to minimizing costs and CO_2 emissions," J. Mar. Sci. Eng., vol. 12, no. 6, p. 976, 2024.

[18] C. Zhao, J. Tang, W. Gao et al., "Many-objective optimization of multi-mode public transportation under carbon emission reduction," Energy, vol. 286, p. 129627, 2024.

[19] H. Zhang, Q. Huang, L. Ma et al., "Sparrow search algorithm with adaptive t-distribution for multi-objective low-carbon multimodal transportation planning problem with fuzzy demand and fuzzy time," Expert Syst. Appl., vol. 238, p. 122042, 2024.

[20] H. Seada and K. Deb, "U-NSGA-III : A unified evolutionary algorithm for single, multiple, and many-objective optimization," COIN Report, no. 2014022, 2014.

[21] D. Li, C. Zhang, X. Shao et al., "A multi-objective TLBO algorithm for balancing two-sided assembly line with multiple constraints," J. Intell. Manuf., vol. 27, pp. 725–739, 2016.

[22] B. Mahdad and K. Srairi, "Optimal power flow improvement using a hybrid teaching-learning-based optimization and pattern search," Int. J. Mod. Educ. Comput. Sci., vol. 10, no. 3, pp. 55–65, 2018.

[23] J.-H. Yi, S. Deb, J. Dong et al., "An improved NSGA-III algorithm with adaptive mutation operator for big data optimization problems," Future Gener. Comput. Syst., vol. 88, pp. 571–585, 2018.

[24] R. V. Rao, et al., "Review of applications of TLBO algorithm and a tutorial for beginners to solve the unconstrained and constrained optimization problems," Decis. Sci. Lett., vol. 5, no. 1, pp. 1–30, 2016.

[25] Q. Liu, X. Liu, J. Wu et al., "An improved NSGA-III algorithm using genetic K-means clustering algorithm," IEEE Access, vol. 7, pp. 185239–185249, 2019.

[26] K. Huang, "Multimodal transportation optimization data," *GitHub Repository*, Dec. 2023. [Online]. Available : https ://github.com/hzjken/multimodal-transportation-optimization. .