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Development of an Artificial Intelligence-Based Method for Evaluating Freight Transport Corridors: A Case Study of Eurasian

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Fatemeh Naderi [1], **Mohammad Reza Malek** [2] ✉

1. GIS Dept. Faculty of Geodesy and Geomatics Eng. K.N. Toosi University of Technology, Tehran, Iran. E-mail: f.naderi@email.kntu.ac.ir
2. Corresponding author, GIS Dept. Faculty of Geodesy and Geomatics Eng. K. N. Toosi University of Technology, Tehran, Iran. E-mail: mrmalek@kntu.ac.ir

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ABSTRACT

Freight transport corridors constitute critical infrastructure for global trade, economic integration, and geopolitical security. Geospatial information systems and network analysis techniques are fundamental to understanding the complex spatial relationships, connectivity patterns, and geographic constraints that characterize these multimodal transport networks, enabling comprehensive assessment of corridor performance and supporting evidence-based decision-making in transport infrastructure development. Among these, Eurasian corridors represent strategically vital arteries connecting Asian and European markets, where optimization challenges are particularly pronounced due to diverse infrastructure conditions and complex multimodal integration requirements.

The optimization of Eurasian freight corridors faces significant challenges due to multiple competing objectives and the complex nature of transport networks. This study presents a comparative analysis of three algorithms - Dijkstra, NSGA-II, and MOACO - for multi-objective optimization of multimodal transport routes considering cost, time, and distance criteria. Using a network of 48 nodes and 61 edges, optimal routes were identified and evaluated based on efficiency metrics, solution diversity, and path quality.

Results demonstrated that all three algorithms achieved the same best combined objective value (45.252), while exhibiting distinct advantages: Dijkstra achieved instant execution for single-objective optimization, NSGA-II excelled in exploring trade-offs and maintaining diversity, while MOACO generated the highest number of non-dominated solutions. Path analysis revealed both a robust trunk route and flexible routing alternatives in initial segments. This research provides a framework for algorithm selection based on different operational requirements in Eurasian freight transport planning.

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1. Introduction

Efficient freight transport corridors are vital for global trade, economic integration, and regional development (Rodrigue, 2020). In recent years, the resurgence of transnational initiatives such as China's Belt and Road Initiative has underscored the strategic importance of Eurasian routes for international logistics (Amirahmadian & Abad, 2017; Noudah Farahani et al., 2022; Shen & Chen, 2020). These corridors facilitate multimodal transport—combining rail, road, and maritime systems to optimize cost, time, and reliability (SteadieSeifi et al., 2014; Zhang et al., 2015; Tao, Zhao, & Liu, 2021).

The accurate modeling of these complex transport networks relies heavily on high-quality geospatial data and advanced GIS[1]-based spatial analysis techniques, which form the bedrock of modern logistics and infrastructure planning (Miller & Shaw, 2015; Jiang & Xu, 2023). Integrating GIS with optimization algorithms enables spatial representation of transport networks, precise distance computation, and visualization of optimal corridors, thereby enhancing decision-making accuracy and interpretability.

However, evaluating and selecting optimal freight routes remains complex due to multiple competing objectives such as cost minimization, transit time reduction, and distance efficiency. Traditional methods like Dijkstra's algorithm have been widely applied for finding shortest paths in deterministic networks (Dijkstra, 1959). More recently, multi-objective metaheuristic algorithms have gained prominence for addressing complex optimization problems in multimodal transportation systems. In particular, the Non-dominated Sorting Genetic Algorithm II and the Multi-Objective Ant Colony Optimization have demonstrated strong capabilities in balancing multiple conflicting criteria such as cost, time, and distance. NSGA-II[2] extends classical Genetic Algorithms by incorporating Pareto-based ranking and crowding mechanisms to preserve solution diversity (Deb et al., 2002), while MOACO[3] generalizes ACO[4] by using multiple pheromone matrices to guide ants toward trade-off solutions across several objectives (Dorigo et al., 2006; Socha & Dorigo, 2008). These multi-objective approaches have proven particularly effective in capturing the inherent trade-offs that arise in real-world transport networks (Talbi, 2009; Yang, 2010; Li, Wang, & Chen, 2022).

Despite extensive research on these algorithms, few studies have systematically compared their relative performance in realistic Eurasian multimodal freight corridor scenarios. While Dijkstra, NSGA-II, and MOACO are individually well-studied, the lack of a standardized comparative assessment in the context of Eurasian multimodal corridors creates ambiguity for decision-makers. They are often left without clear guidance on which algorithm provides the optimal balance of solution quality, diversity, and computational efficiency for their specific strategic goals (e.g., rapid single-route identification vs. exploring a wide range of trade-offs). This gap highlights the need for a unified analytical framework that can evaluate algorithmic efficiency, robustness, and suitability under spatially explicit, GIS-based conditions.

This research aims to address this gap by developing an integrated geospatial evaluation framework for freight corridor optimization based on three computational approaches: Dijkstra's algorithm, NSGA-II, and MOACO. The framework incorporates GIS-based spatial network modeling, cost–time–distance estimation, and comparative performance analysis of these algorithms under consistent evaluation metrics.

A case study of key Eurasian corridors is used to validate the framework and examine how different algorithms perform across complex, multimodal transport conditions. The outcomes contribute to a clearer understanding of algorithmic suitability for logistics planning and the advancement of intelligent, GIS-integrated corridor analysis.

The remainder of this paper is organized as follows: Section 2 delineates the study area and its spatial dataset. Section 3 details the methodology, including network modeling, parameter calculation, and algorithm implementation. Section 4 presents a comparative analysis of algorithmic performance, and Section 5 concludes with key findings and future research directions.

2. Description of the Study Area

This study focuses on the multimodal transport network within the Eurasian corridor, encompassing rail networks in China, Kazakhstan, Turkmenistan, Turkey, Iran, Azerbaijan, Uzbekistan, and Georgia, along with key maritime routes across the Caspian Sea, Black Sea, and the shipping lane from Bandar Abbas to Europe. This strategically vital region serves as a crucial land-sea bridge connecting Asia and Europe, characterized by its complex intermodal infrastructure involving rail and maritime transport connections. The selection of this area is based on its growing importance in international freight transportation and the diverse operational conditions it

[1] Geographic Information Systems
[2] The Non-Dominated Sorting Genetic Algorithm II
[3] Multi-Objective Ant Colony Optimization
[4] Ant Colony Optimization

presents. Figure 1 illustrates the geographical scope of the study area and the primary transport routes analyzed and the primary transport routes analyzed (ESCAP U, 2017).

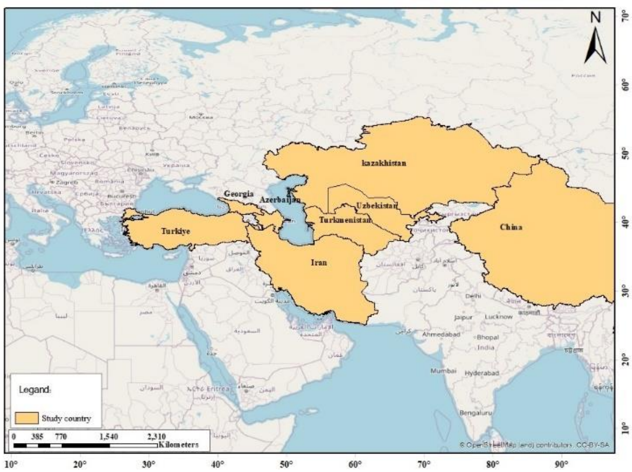

Figure 1. Study area.

3. Methodology

The research methodology comprised four sequential steps, as illustrated in Figure 2 Data collection from the Eurasian corridors and creation of a network structure; Identification of key parameters and calculation of distance, cost, and time metrics; Implementation of three optimization algorithms: Dijkstra, NSGA-II, and Ant Colony Optimization; and Validation and comparative analysis of the algorithm outputs.

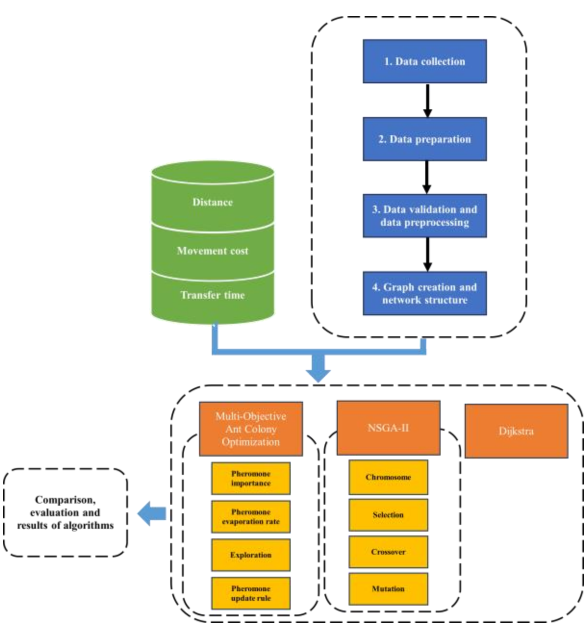

Figure 2. Flowchart of research methodology.

3.1. Corridor Identification and Data Collection

The principal Eurasian freight corridors were identified, encompassing rail and maritime routes connecting China, Kazakhstan, Turkmenistan, Turkey, Iran, Azerbaijan, Uzbekistan, and Georgia (ESCAP U, 2017). This network also includes key maritime passages across the Caspian Sea, the Black Sea, and the shipping lane from Bandar Abbas to Europe. Data pertaining to each route segment were systematically gathered from authoritative sources, including official transportation reports, databases from international organizations, and relevant field studies.

3.2. Network Modeling

This research utilizes graph theory as the foundational framework for modeling and analyzing the multimodal Eurasian transport network, following established methodologies in transport network optimization (Zhang et al., 2021; Rodrigue, 2020). A graph structure was selected for its proven efficacy in representing spatial connectivity and facilitating the application of network analysis algorithms, including shortest path computation and optimal route identification (Talbi, 2009).

The model construction began with systematic compilation of geospatial data on railway stations and port facilities across the study region. Through strategic simplification, 48 key nodes were selected including international border crossings, primary logistics hubs, and pivotal interchange terminals ensuring both computational efficiency and network integrity. Inter-nodal connections were established based on existing rail infrastructure and maritime routes, creating an accurate representation of the region's transport connectivity.

Formally, the transport network is represented as a directed graph **G = (V, E)**, where:

V constitutes the set of 48 vertices representing major cities, ports, and logistics terminals

E comprises the set of edges denoting direct transport connections between nodes

Each edge $\in E$ is assigned three distinct weight attributes representing the key evaluation metrics: transportation cost (CHF), transit time (hours), and geographical distance (km)

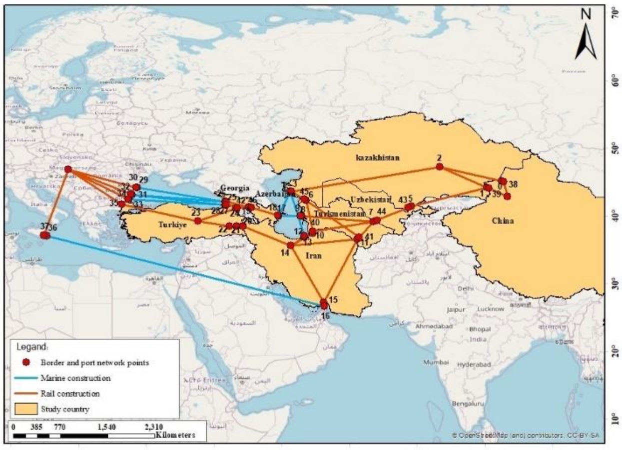

Figure 3. Visual representation of a graph made from a network.

Figure 3 provides a visual representation of the network model, where distinct edge colors differentiate connection types (rail/maritime) and numerical labels identify individual stations. This structured representation enables the subsequent application of optimization algorithms for comprehensive corridor analysis.

3.3. Metric Calculation for Network Edges

This section details the computational methodology for the three key parameters assigned to each network edge: distance, movement cost, and transfer time. The calculations incorporate geographical, economic, and operational factors to ensure comprehensive corridor evaluation.

3.3.1. Geographical Distance

Spatial data for rail and maritime routes were obtained from OpenStreetMap (Contributors OSM, 2025) and OpenSeaMap (Contributors OSM, 2025) databases. Network analysis was performed using Dijkstra's algorithm to determine the shortest navigable path between node pairs, yielding precise edge lengths l_i measured in kilometers.

3.3.2. Movement Cost

The movement cost for transporting a standard 10-foot container was calculated considering country-specific tariff rates. The total cost for each edge was computed using Equation (1).

$$C_i = l_i \times c_i \tag{1}$$

where $\boldsymbol{l_i}$ represents edge length in kilometers and $\boldsymbol{c_i}$ denotes the country-specific movement cost per kilometer. All cost values are expressed in Swiss Francs (CHF) to maintain currency consistency across international corridors.

3.3.3. Transfer Time

Transfer time for each edge was derived from infrastructure-specific velocity profiles, as formalized in Equation (2).

$$T_i = \frac{l_i}{v_i} + t_{ij}, \tag{2}$$

where $\boldsymbol{v_i}$ represents the average travel speed (km/h) for the transport mode (rail/maritime) characterizing each edge. Speed parameters were determined through analysis of regional transport schedules and vessel performance characteristics. where $\boldsymbol{t_{ij}}$ represents time to stop at the ridge.

3.3.4. Data Normalization

To enable integrated multi-criteria analysis, all parameters underwent min-max normalization to **a [0, 1]** scale using Equation (3).

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

where $\boldsymbol{x}$ denotes the original metric value, while $\boldsymbol{x_{\min}}$ and $\boldsymbol{x_{\max}}$ represent the respective minimum and maximum values observed across the network. This normalization process ensures dimensional homogeneity and equal weighting in subsequent optimization procedures.

The calculated and normalized parameters form the fundamental input dataset for the optimization algorithms implemented in the following research phase, enabling objective comparison and evaluation of corridor performance across the three defined metrics.

3.4. Optimization Algorithms

Three distinct optimization algorithms were implemented to solve the multi-criteria freight corridor optimization problem. Each algorithm was systematically formulated and parameterized based on established computational methods in the literature (Talbi, 2009; Yang, 2010).

3.4.1. Dijkstra's Algorithm Formulation

The classic The classic single-objective shortest path algorithm was implemented following the original formulation (Dijkstra, 1959). For a given objective function f ∈ {cost, time, distance}, the algorithm minimizes the sum of weights along the path as shown in Equation (4).

$$\sum_{(i,j)\in path} w_{f(i,j)}, \tag{4}$$

where ***w_f(i,j)*** represents the weight of edge ***(i,j)*** for objective ***f***. A combined objective was also implemented using the weighted sum method (Marler and Arora, 2004) as formulated in Equation (5).

$$w_{\{combined\}(i,j)} = w_{\{cost\}(i,j)} + w_{\{time\}(i,j)} + w_{\{distance\}(i,j)} \tag{5}$$

The algorithm maintains a priority queue and iteratively relaxes edges using the update rule in Equation (6), where

dist[v] represents the shortest distance from source to vertex ***v***.

$$dist[v]= min(dist[v],dist[u]+ w(u,v)) \quad (6)$$

where ***dist[v]*** represents the shortest distance from source to vertex v.

3.4.2. NSGA-II

The NSGA-II algorithm was formulated as a multi-objective optimization problem following the approach by Deb et al. (2002). Let x represent a path solution. The algorithm simultaneously minimizes three objectives: cost, time, and distance, as defined in Equation (7) (Deb et al., 2002).

$$\begin{aligned} f_3(x) &= \textstyle\sum_{(i,j)\in x} distance(i,j) \\ f_2(x) &= \textstyle\sum_{(i,j)\in x} time(i,j) \\ f_1(x) &= \textstyle\sum_{(i,j)\in x} cost(i,j) \end{aligned} \quad (7)$$

Each chromosome represents a complete path from source to target node, encoded as an ordered sequence of nodes. The initial population was generated using a hybrid strategy combining shortest paths for each single objective with randomly generated feasible paths to ensure diversity.

3.4.3. NSGA-II Operators

Crossover was performed using ordered crossover with probability ***p_c*** = 0.7, as shown in Equation (8), where ***OX*** preserves the order and validity of paths (Eiben and Smith, 2015).

$$\text{Child=OX(Parent1,Parent2)} \quad (8)$$

where ***OX*** preserves the order and validity of paths. Mutation was implemented through swap mutation with probability ***p_m*** = 0.2 according to Equation (9), where the swap operator exchanges the positions of two nodes i and j in the parent chromosome ***x***.

$$x\text{^}'=swap(x,i,j) \text{for randomly selected positions } i,j \quad (9)$$

Selection was performed using tournament selection with crowding distance (Deb et al., 2002) according to Equation (10), where the winner of a competition between two chromosomes randomly selected from population P is chosen as the parent for the next generation.

$$p\_cel=TournamentSelect(P,size=2) \quad (10)$$

3.4.4. MOACO

The MOACO algorithm was formulated with multiple pheromone matrices following the approach by Dorigo and Stutzle (Dorigo et al., 2006). The algorithm operates through iterative construction of solutions by artificial ants, where each ant probabilistically builds a path from source to target based on pheromone trails and heuristic information.

3.4.5. Calculation of MOACO probability

For ant k at node i, the probability of moving to node j is given by Equation (11) (Dorigo et al., 2006).

$$P_{ij}^k = \frac{[\tau_{\{ij\}}]^\alpha [\eta_{\{ij\}}]^\beta}{\sum_{l\in N_i^k}[\tau_{\{il\}}]^\alpha [\eta_{\{il\}}]^\beta} \quad (11)$$

where:
τ_ij is the pheromone level on edge (i,j)
η_ij = 1/w_ij is the heuristic information
α = 1.0 controls pheromone influence
β = 2.0 controls heuristic influence

3.4.6. Multiple Pheromone Update in MOACO

Three separate pheromone matrices are maintained and updated using Equation (12) (Socha and Dorigo, 2008).

$$\begin{aligned} \tau_{cost}(i,j) &= (1-\rho)\cdot\tau_{cost}(i,j) + \Delta\tau_{cost} \\ \tau_{time}(i,j) &= (1-\rho)\cdot\tau_{time}(i,j) + \Delta\tau_{time} \\ \tau_{distance}(i,j) &= (1-\rho)\cdot\tau_{distance}(i,j) + \Delta\tau_{distance} \end{aligned} \quad (12)$$

with evaporation rate ***ρ*** = 0.5 and reinforcement according to Equation (13).

$$\Delta\tau_f = Q - f(path), \quad for \quad f \in \{cost, time, distance\} \quad (13)$$

3.4.7. Implementation Framework

The implementation ensured computational efficiency through several key strategies: memorization of frequently computed paths, efficient data structures for large-scale graph operations, parallel evaluation of population in evolutionary algorithms, and optimized pheromone matrix updates in MOACO. Each algorithm was executed with consistent termination criteria and evaluation metrics to ensure fair comparison. The complete implementation handled edge cases including disconnected components, invalid paths, and numerical stability in objective computations.

3.5. Results and Discussion

This section presents a detailed analysis of the performance of the three optimization algorithms Dijkstra, NSGA-II, and MOACO applied to the Eurasian multimodal freight corridor network. The hyper-parameters of the applied algorithms were tuned through a combination of literature-based guidelines and preliminary experimental analyses on the case-study network. The evaluation is based on solution quality, computational efficiency, diversity of solutions, and the characteristics of the identified optimal paths.

3.5.1. Algorithm Performance

The execution times and solution counts (Table 1) align with the theoretical expectations for each class of algorithm. Dijkstra's algorithm's near-zero execution time underscores its efficiency as an exact method for pathfinding in deterministic graphs. The marginally longer execution time of MOACO (0.212s) compared to NSGA-II (0.183s) can be attributed to the more computationally intensive processes of pheromone evaporation and update across multiple matrices in each iteration. While these differences are negligible for strategic planning purposes, they could become significant when scaling to much larger networks or for real-time routing applications.

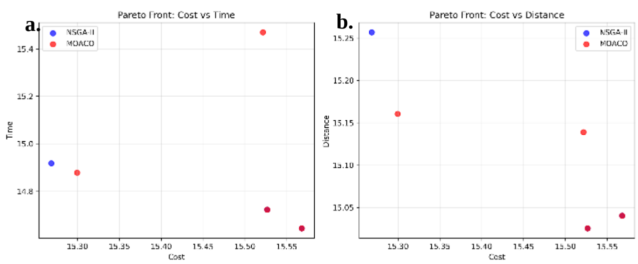

Table 1. Comparative performance metrics of optimization algorithm.

Algorithm	Execution Time (s)	Solutions Found	Best Combined Score	Best Cost	Best Time	Best Distance
Dijkstra	0.0	4	45.252	15.269	14.644	15.025
NSGA-II	0.183	3	45.252	15.269	14.644	15.025
MOACO	0.212	4	45.252	15.300	14.644	15.025

3.5.2. Trade-off Analysis and Solution Diversity

The Pareto fronts (Figure 4) provide a clear visualization of the inherent conflicts between the optimization objectives in the Eurasian network. The negative correlation between cost and time (Figure 4a) confirms that faster routes, often involving better infrastructure or more direct maritime links, incur higher operational costs.

Similarly, the trade-off between cost and distance (Figure 4b) suggests that the most geographically direct paths are not always the cheapest, possibly due to terrain difficulties, border crossing delays, or imbalanced trade flows that affect pricing.

Figure 4. Pareto front comparison for (a) Cost vs. Time and (b) Cost vs. Distance.

The solution diversity, quantified by the cost range (Figure 5), reveals distinct algorithmic behaviors. NSGA-II's crowding distance mechanism successfully promoted a wider spread of solutions along the cost axis. In contrast, MOACO's pheromone reinforcement, while effective in converging to good solutions, may have prematurely concentrated the search, leading to a slightly narrower cost range. This highlights a classic trade-off in metaheuristics: exploration (searching new areas) versus exploitation (refining known good areas).

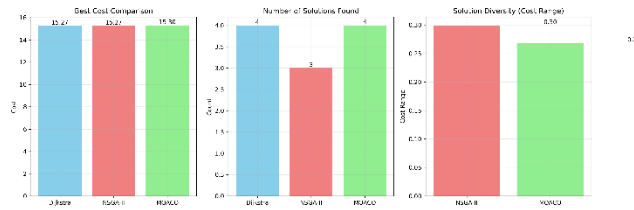

Figure 5. Comparison of solution quantity and cost diversity.

3.5.3. Path Characteristics and Network Robustness

The path analysis (Figure 6) yields critical insights into the network's structure. The consistent emergence of the trunk route (Figure 7) across multiple algorithms and objectives signifies a structurally robust corridor.

This path likely represents a sequence of high-capacity, well-connected hubs and links, making it a reliable backbone for Eurasian freight flow.

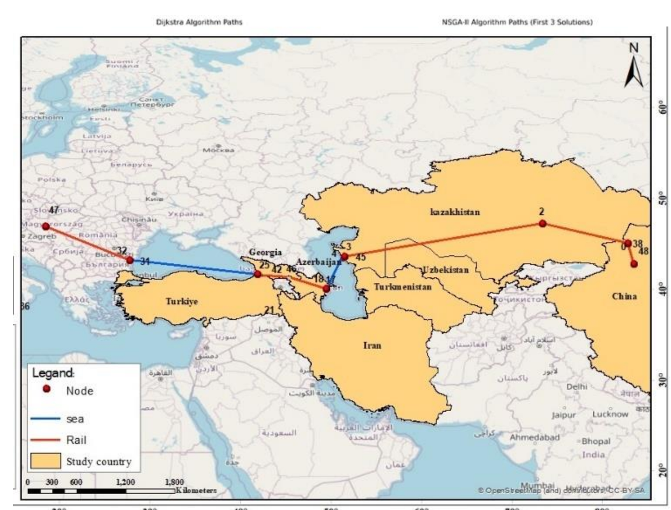

Figure 6. Representative optimal paths identified by the algorithms

Figure 7. The path that is selected as the optimal path in all algorithms.

The divergence in the initial segments of the paths indicates the presence of redundant connections in the network. This redundancy is a valuable asset, providing shippers with alternative routes to mitigate risks such as congestion, political instability, or sudden cost changes at specific border crossings. The fact that the distance-optimal path (found by NSGA-II) differs from the time-optimal path validates the multi-objective approach, as a single "best" path does not exist; the optimal choice is contingent upon the shipper's prevailing priorities.

3.5.4. Comparative Algorithmic Performance in Context

The fact that all three algorithms converged to the same best combined objective value (45.252) reinforces the robustness of the formulated network model. However, their methodological differences directly influenced the nature of their outputs.

Dijkstra's Algorithm served as a perfect benchmark but its limitation was evident. While its weighted-sum approach could find a good combined solution considering all parameters simultaneously, it required a priori weight selection, which is often subjective. Furthermore, it cannot generate a true Pareto front in a single run, a significant drawback for multi-criteria decision-making.

NSGA-II demonstrated strength in finding the extreme points of the Pareto front (e.g., the best distance solution). Its use of non-dominated sorting and crowding distance effectively preserved solution diversity, offering decision-makers a clearer view of the available trade-offs.

MOACO excelled in the number of non-dominated solutions found. Its stigmergic memory (pheromone trails) allows it to efficiently combine building blocks of good paths, making it effective for constructing high-quality solutions in combinatorial problems like route optimization.

This comparative analysis addresses the research gap identified in the introduction regarding the lack of structured comparisons. It demonstrates that while Dijkstra is unbeatable for speed and single-objective problems, the choice between NSGA-II and MOACO for multi-objective optimization depends on the decision-maker's need: NSGA-II for broader exploration of trade-offs and MOACO for a denser set of high-quality alternatives.

4. Conclusion

According to recent reports from international transport organizations, the strategic importance of Eurasian freight corridors has significantly increased in global trade. Efficient transport route optimization is therefore crucial for economic development. This study employed three computational algorithms to address the complex multi-objective optimization challenges in Eurasian freight corridors. The main conclusions are as follows:

The optimization of Eurasian freight corridors represents a critical challenge in international logistics, with significant implications for trade efficiency, competitiveness, and regional development. While previous studies have applied optimization algorithms in isolation, this research established a comprehensive comparative framework that systematically evaluates the performance of three distinct methodologies Dijkstra’s algorithm, NSGA-II, and MOACO within a unified, GIS-based environment. The developed models successfully addressed the complex, multi-criteria nature of transport optimization in the region.

The results demonstrated that all three algorithms achieved comparable best combined objective values, confirming their validity for this optimization problem. However, each exhibited distinct performance characteristics. Dijkstra’s algorithm provided precise and instantaneous solutions for single-objective problems. NSGA-II excelled in maintaining solution diversity and exploring trade-offs among objectives, while MOACO generated the largest number of high-quality, non-dominated solutions, offering decision-makers a richer set of alternatives.

Path analysis revealed consistent spatial patterns across all algorithms, identifying a robust trunk corridor (Figure 7) as a critical infrastructure element in the Eurasian transport network. Northwestern routes exhibited higher efficiency for time-sensitive shipments, while southern alternatives provided cost-effective options. Regions with well-developed infrastructure and minimal transfer points consistently demonstrated superior performance across all optimization criteria.

The proposed framework offers a clear decision-support guideline for logistics planners and policymakers by aligning algorithm selection with specific operational needs. For urgent, single-route planning tasks, Dijkstra’s algorithm is recommended due to its precision and computational speed. In scenarios requiring strategic planning and exploration of trade-offs among cost, time, and distance, NSGA-II emerges as the preferred choice. Meanwhile, for generating a dense set of high-quality, non-dominated alternative routes, MOACO proves most effective. This tiered approach enables practitioners to systematically select the optimal optimization method based on contextual requirements and planning horizons.

The major contribution of this study lies in the integration of multi-objective optimization with GIS-based spatial modeling, bridging computational intelligence and geospatial analysis. The primary limitation concerns the focus on three core objectives (cost, time, distance) under static network conditions. Future research should incorporate dynamic factors such as congestion, environmental impact, and route reliability, and explore hybrid metaheuristic approaches to enhance adaptability and realism.

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