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AI-DRIVEN OPTIMIZATION IN CARGO TRANSPORTATION: ENHANCING EFFICIENCY THROUGH INTELLIGENT ALGORITHMS

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Urban transportation networks face increasing congestion due to rising passenger and freight mobility demands. This study integrates a Genetic Algorithm (GA) with MATSim to optimize departure times and routes, minimizing total travel time and distance. The optimization occurs in two phases: departure time adjustment to reduce peak-hour congestion and route selection for improved network efficiency. Results show that GA optimization reduces congestion and enhances traffic flow. The approach demonstrates the potential of AI-driven transport planning to improve urban mobility and logistics. Future work will integrate real-time traffic data for dynamic optimization.

These findings underscore the potential of AI-based techniques in urban mobility planning and freight logistics, offering a scalable and adaptive solution to traffic congestion problems.

Keywords: Agent-based simulation, Genetic Algorithm, Urban traffic optimization, MATSim, Freight logistics, AI-driven mobility.

1. Introduction

Efficient freight transportation is an important component of modern urban mobility, with direct implications for economic performance, environmental sustainability, and quality of life. As cities experience increasing congestion due to growing demand for mobility, optimizing transportation networks becomes essential for reducing travel times, minimizing fuel consumption, and improving overall system efficiency.

Urban transportation networks worldwide face increasing congestion due to rising passenger and freight mobility demands. Major urban areas, from large cities in Europe and North America to rapidly growing metropolises in Asia and South America, have been testing various strategies to mitigate freight-related bottlenecks. For instance, London's congestion charge policy and New York City's off-hour delivery initiatives demonstrate how demand management can effectively reduce peak-hour traffic. Meanwhile, cities like Singapore and Tokyo heavily

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invest in intelligent transportation systems and advanced modeling techniques to coordinate passenger and freight flows in real time.

Despite these global efforts, congestion remains a critical issue for many local administrations, resulting in excessive travel times, elevated fuel consumption, and negative environmental impacts. Traditional traffic management strategies, such as static scheduling and pre-defined routing, often fail to adapt to the fluctuating demand and real-time congestion patterns in both passenger transport and freight logistics, prompting the need for more adaptive and data-driven methods [1].

Building on this international context, our study integrates a Genetic Algorithm (GA) with the Multi-Agent Transport Simulation (MATSim) framework to optimize departure times and routes, aiming to minimize total travel time and overall distance. The specific focus is on an urban network in Romania, but the broader methodological lessons are transferable to other urban areas facing similar freight and passenger transport challenges.

Agent-based transport simulation models, such as MATSim (Multi-Agent Transport Simulation), have gained widespread use in transportation research due to their ability to model individual decision-making processes within a complex transportation network. These models provide valuable insights into traffic dynamics by simulating interactions between passenger and freight agents, allowing researchers to analyze the effects of policy interventions, infrastructure changes, and optimization strategies [2].

In recent years, Artificial Intelligence (AI) techniques have been increasingly employed to improve transportation efficiency. Among these, Genetic Algorithms (GAs) have shown significant promise for optimizing travel schedules and route assignments. GAs are inspired by natural selection and evolutionary principles, enabling iterative refinement of solutions by selecting, mutating, and recombining potential travel plans. Research has demonstrated that GAs can effectively reduce congestion and improve travel efficiency by optimizing departure times and routes in urban networks [3], [4], [5].

Several studies have explored the application of AI-driven optimization in transportation systems. For instance, adaptive traffic control models based on reinforcement learning have been used to dynamically adjust traffic signals in response to changing conditions [5], while metaheuristic algorithms, such as Simulated Annealing and Ant Colony Optimization, have been applied to optimize vehicle routing problems and freight delivery schedules [6], [7].

More recent approaches combine deep reinforcement learning with multi-agent systems to further enhance network-wide efficiency[8], [9]. Finally, multi-criteria and multi-objective techniques, which integrate fuel consumption, time constraints, and carbon emissions, underscore the growing importance of sustainability factors in freight operations [10], [11]. However, many of these approaches focus on either passenger transport or freight logistics in isolation, whereas an integrated optimization framework addressing both components simultaneously remains relatively underexplored.

Traditional transportation planning approaches often rely on static scheduling and pre-defined routes, which fail to adapt to real-time traffic conditions and evolving congestion patterns. This limitation has prompted the integration of artificial intelligence (AI) techniques into transportation models to improve decision-making processes. One promising approach is the use of Genetic Algorithms (GAs) for optimizing travel schedules and routes, enabling adaptive, data-driven improvements to urban logistics.

This study employs an AI-based optimization framework within MATSim (Multi-Agent Transport Simulation) to enhance freight and passenger transportation. The objective is to reduce travel time and congestion by dynamically adjusting departure times and travel routes. The proposed approach utilizes a Genetic Algorithm (GA) to iteratively improve transportation plans, leveraging data from simulation results to refine decision-making at each step.

The optimization process consists of two sequential steps:

a) Departure Time Optimization – adjusting departure schedules to distribute travel demand more evenly throughout the day;
b) Route Optimization – identifying alternative paths to minimize congestion and travel distance.

The simulation model was developed using an agent-based approach, representing the behavior of individual travelers and freight operators. The transportation network is based on real road network and urban areas in Romania. The population dataset includes 1,000 agents, of which 800 are passenger agents following home-to-work commute patterns, while 200 represent freight agents conducting deliveries between depots and customer locations.

This paper is structured as follows: Section 2 details the methodology, outlining the optimization framework and the Genetic Algorithm approach. Section 3 presents results and discussion, evaluating the impact of optimization on congestion and travel time. Finally, Section 4 provides conclusions, summarizing key findings and implications for future research in AI-driven transportation optimization.

2. Methodology

This study proposes an AI-driven approach to optimize cargo logistics, addressing two central objectives: the real-time, large-scale adaptation of routing and scheduling, and the integration of sustainability factors (specifically cost, time, and environmental impact) into a single decision-making framework. The methodology is designed to handle the dynamic nature of freight operations, where sudden disruptions, new orders, and shifting congestion patterns can quickly render static or single-run solutions inadequate.

A key premise of the method is the seamless ingestion and processing of real-time data from multiple sources. Vehicle telemetry, comprising global navigation satellite system (GNSS) coordinates, speed, and fuel consumption, forms the backbone of the operational status. Complementary data arrives from external feeds such as traffic APIs, which provide live congestion updates, incident alerts, and weather forecasts that can affect travel times or route feasibility. Additionally, in-house operational databases supply order information, scheduling windows, and warehouse capacities. These streams are channeled through a message broker that timestamps each data packet and ensures consistency in format, thus enabling quick validation and preprocessing. Once cleaned, the data is stored in a state database (relational or NoSQL, depending on scale) so that the optimization routines can access current information at frequent intervals.

The optimization component rests on a classical multi-objective model that merges cost, time, and sustainability into a single weighted-sum function. Drawing on established work in operations research, the methodology treats cost as a measure of operational expenses, time as the measure of delivery or transit durations, and sustainability as an estimate of carbon emissions. The combined objective function remains flexible through user-defined weights for each metric, allowing stakeholders to prioritize certain criteria over others (for instance, emphasizing lower emissions over minimal transit time, or vice versa). While various multi-objective methods exist, the weighted-sum approach offers simplicity and speed, making it particularly suitable for scenarios requiring frequent recalculations. Each route R is evaluated on:

- Cost (C): Operational costs include fuel, driver wages, and vehicle maintenance per route;
- Time (T): Delivery time, plus any waiting times at distribution centers;
- Sustainability (S): Estimated CO^2 emissions based on vehicle type, distance traveled, and load weight.

We represent the global objective as a function $f(R)$ that balances cost, time, and sustainability:

$$\min f(R) = (wh_C \cdot \mathrm{C} + wh_T \cdot \mathrm{T} + wh_S \cdot \mathrm{S}) \tag{1}$$

where wh_C, wh_T, wh_S are weights reflecting the relative importance of each criterion.

In terms of algorithmic implementation, the study explores a metaheuristic approach (Genetic Algorithms), in order to link solutions to chromosomes, iteratively refining them by means of crossover and mutation to achieve near-optimal configurations in large-scale networks.

To handle the dynamic nature of cargo operations, the methodology relies on a continuous feedback loop. At each time step (or upon specific triggers such as a road closure) the central system retrieves up-to-date data on vehicle positions, traffic conditions, and incoming orders, then executes an optimization run to produce route or scheduling updates. These updates are relayed to dispatch operators or directly to onboard devices, enabling real-time adaptation of logistics activities. Following the dispatch of updated plans, the system immediately enters a monitoring phase, awaiting the next wave of operational data or events. In this manner, the approach ensures that routing and scheduling remain synchronized with evolving ground realities, rather than being constrained by initial assumptions.

To validate the proposed methodology, the study implements an agent-based simulation designed to capture the interplay between freight vehicles and background traffic. The simulator used was the MATSim environment, and it was chosen because it supports real-time data feeds and permits large-scale experiments. The simulated network included urban road segments, distribution centers, and diverse traffic flows (see Fig. 1), with freight vehicles representing a fraction of the total agent population (20%).

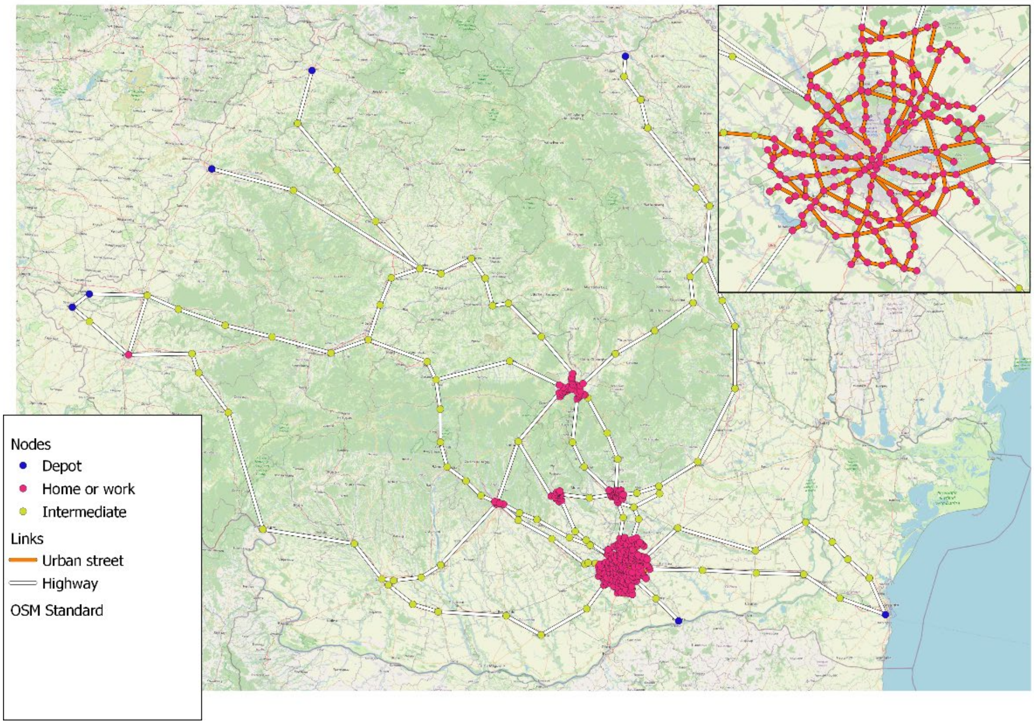

Fig. 1. Overview of the network used for the simulation

The initial simulation setup was based on an agent-based model implemented in MATSim, designed to replicate urban mobility patterns for both freight and passenger transportation. The transportation network consisted of 382 nodes connected through 890 links (445 with duplicated reversed direction counterparts), representing road intersections and connections, respectively. Each link was characterized by attributes such as free speed, capacity, number of lanes, and allowed travel modes.

The population dataset included a total of 1,000 agents, out of which 800 were passenger agents and 200 were freight agents. Passenger agents followed a structured home-to-work commute, starting from designated nodes and traveling to work locations assigned to work nodes. In contrast, freight agents operated between depots nodes and home nodes (customer locations), simulating urban freight deliveries. Each agent followed a fixed travel plan, consisting of a sequence of activities (home, work, or freight delivery) connected by legs specifying the mode of transport. The baseline simulation produced detailed travel logs, including departure times, travel times, distances, and congestion levels, which served as input for subsequent optimization. The goal was to analyze congestion patterns and assess the potential benefits of optimizing departure times and routes.

To enhance the efficiency of freight and passenger transportation, we implemented a Genetic Algorithm (GA) to optimize both departure times and routes within a simulated urban network. The primary objective of this optimization process was to minimize overall travel time and total distance traveled, thereby mitigating congestion and improving transportation efficiency.

The optimization process focused on two key areas. First, departure time optimization was implemented to strategically adjust departure schedules and alleviate peak-hour congestion. Second, route optimization was performed to identify alternative paths that would contribute to a reduction in total travel time and lessen the overall congestion impact. Both of these optimization steps were executed in sequential stages, ensuring that the most effective results were achieved.

The GA utilized data extracted from the MATSim simulation output, encompassing several critical datasets. The initial population was derived from the original agent-based travel plans, providing a baseline for optimization. Network data containing details about links, nodes, travel times, and capacity constraints served as an essential component of the optimization process. Additionally, simulation output data, including observed travel times and distances from previous iterations, was used to guide the refinement of departure schedules and route selections.

The optimization process was driven by a fitness function specifically designed to minimize total travel time and distance. The function was formulated as:

$$Fitness = \frac{1}{\sum TT_i + D_i} \tag{2}$$

where:

TT_i represents the travel time for an individual i
D_i denotes the distance traveled by individual i

A lower fitness score indicated a more optimal solution, ensuring that improvements in travel efficiency were systematically rewarded.

The GA followed a structured evolutionary process, incorporating well-established genetic operations. Initially, the first population was created based on the existing MATSim scenario plans. From this population, the most efficient individuals (those with the lowest travel time and shortest distance) were selected for reproduction. Using crossover techniques, these selected individuals were recombined to generate new solutions. Mutation operations were then applied, introducing small random adjustments to departure times and modifications to route selection. Each new population was subsequently evaluated in MATSim, where fitness scores were recalculated. This iterative process was repeated across multiple generations until a stable and optimized solution was reached.

To maximize efficiency, the optimization was conducted in two distinct phases. The first phase adjusted only departure times, keeping routes fixed to evaluate congestion distribution improvements. The second phase incorporated optimized departure times while concurrently optimizing routes. This sequential refinement process allowed for progressive congestion reduction by first efficiently distributing departures and then fine-tuning travel paths to ensure further optimization.

By leveraging GA-driven optimization, the study aimed to achieve multiple benefits. A primary goal was the reduction of congestion during peak hours by efficiently staggering departures. Additionally, the identification of alternative routes contributed to a more balanced network load, ensuring smoother traffic flow. The combination of these improvements led to a significant reduction in overall travel times and a measurable enhancement in transportation efficiency. The following section presents an analysis of the impact of these optimizations on network performance and congestion trends.

Although data privacy and regulatory considerations are not the principal focus of this study, they remain implicit concerns in any real-world deployment of real-time tracking and automated decision-making. The authors acknowledge the need for compliance with relevant data protection standards and recognize the potential need for anonymization or restricted data access. Similarly, integrating sustainability targets aligns with the broader policy and market trends that push logistics toward greener operations.

This proposed methodology leverages a multi-objective optimization paradigm, enriched by continuous data updates and versatile AI algorithms, to maintain agility in the face of volatile logistics contexts. Its real-time recalculations, structured data pipeline, and emphasis on carbon metrics collectively promise a more responsive and environmentally aware cargo management system. Subsequent sections elaborate on the empirical evaluation, including simulation design, parameter tuning, and performance comparisons against baseline or single-objective approaches.

The configuration files, the outcomes of the MATSim simulation, and the script for the GAs are available at the following link: https://github.com/mapenthusiast/Simulation-Genetic-algorithms.

3. Results and discussion

The initial simulation setup consisted of 1,000 agents, including 800 passenger agents and 200 freight agents. The network contained 382 nodes and 445 links, with each link having a duplicated reverse counterpart. Passenger agents were assigned home and work locations, while freight agents were designated to travel between freight nodes (depots) and customer locations. The demand distribution followed real-world traffic patterns, with peak-hour congestion evident in the initial results.

The first iteration of the simulation showed significant traffic congestion during peak hours, particularly between 07:00 - 09:00 and 16:00 - 18:00. The average travel time was highest during these periods, with some trips taking over 300 minutes. Figure 2 illustrates these congestion trends before optimization.

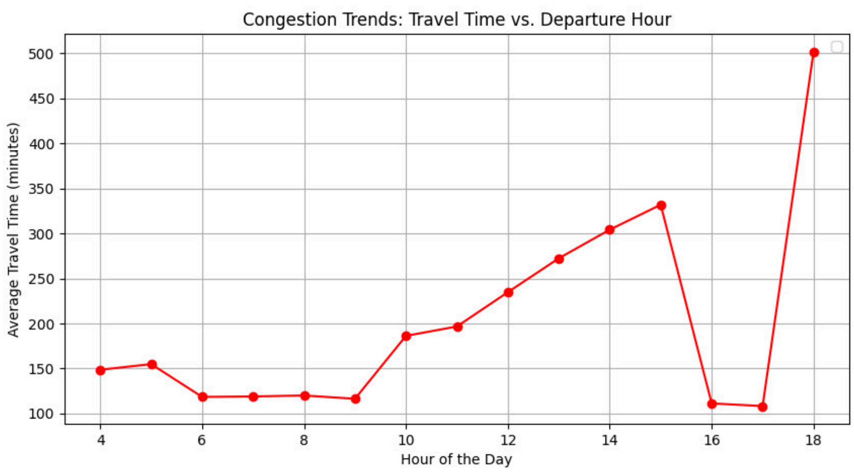

Fig. 2. Congestion trends before the optimization

After applying GA-based departure time optimization, the peak-hour congestion was alleviated as departures were more evenly distributed throughout the day. However, total travel distances remained largely unchanged.

A second optimization phase, where routes were also optimized, further reduced overall travel times. Figure 3 compares the congestion levels before and after both optimization steps.

The optimization process led to significant improvements in travel efficiency, with reductions in both total travel time and congestion levels. By comparing the initial simulation results with the first and second optimization iterations, we observed a more balanced distribution of departures and a noticeable decrease in peak-hour congestion.

The final optimized results show a more balanced utilization of the road network, leading to a smoother traffic flow and an overall improvement in travel efficiency.

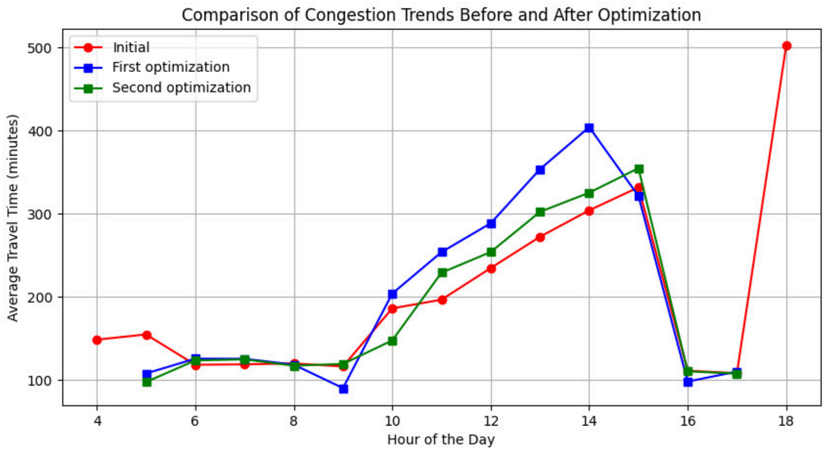

Fig. 3. Congestion levels before and after both optimization steps

Future Research Directions. While our GA-based approach shows promise in reducing congestion and improving efficiency, several avenues remain for further investigation. One potential direction is integrating live sensor data to enable real-time re-routing in response to incidents and changing traffic patterns. Additionally, exploring multi-modal solutions, such as combining roadway transport with rail or waterways, could further reduce congestion in densely populated urban corridors. Another significant research avenue is developing robust cost-benefit analyses to evaluate the long-term social, economic, and environmental impacts of AI-driven transportation policies. Finally, advanced machine-learning techniques, such as reinforcement learning or hybrid metaheuristics, may help refine optimization algorithms for even larger and more complex urban environments.

4. Conclusions

This study demonstrated the effectiveness of a Genetic Algorithm (GA)-based optimization approach in improving urban transportation efficiency by adjusting both departure times and routes for freight and passenger agents. The results confirmed that the optimization process successfully reduced total travel time and alleviated congestion, leading to a more balanced distribution of traffic across the network.

By implementing a two-stage optimization, where departure times were first adjusted and then used as input for optimizing routes, the model gradually improved traffic conditions. The second optimization iteration further refined route selection, distributing vehicle loads more effectively and mitigating peak-hour congestion. The comparison between the initial simulation and the optimized scenarios revealed a significant reduction in travel time, particularly during peak hours. Freight movement efficiency also improved, ensuring more predictable delivery times and reducing unnecessary delays. Moreover, congestion patterns shifted as a result of the optimization process, smoothing out extreme bottlenecks and contributing to a more stable traffic flow.

Overall, the GA-driven approach provided a scalable and adaptable method for optimizing transportation networks. The results suggest that such an approach has the potential for real-world applications in urban logistics and infrastructure planning. Future research could focus on integrating multi-modal transport solutions and incorporating real-time traffic data to enhance the adaptability and responsiveness of the optimization framework.

From a managerial standpoint, logistics operators, public transportation planners, and city administrators can leverage these findings to inform scheduling policies and optimize fleet utilization. More predictable and shorter delivery windows can reduce operating costs and fuel consumption, benefitting transport companies in terms of both efficiency and sustainability. Urban policy-makers can also use insights from these optimizations to shape regulations, for instance, incentivizing off-peak deliveries or implementing congestion pricing, thereby distributing traffic more evenly. For local communities, reduced congestion translates to shorter commute times, lower emissions, and less noise pollution, ultimately improving quality of life. By fostering collaboration between governments, logistics providers, and citizens, GA-driven transport solutions can serve as a strategic blueprint for sustainable urban growth.

Future work could extend this approach by incorporating real-time data, multi-modal transport systems, and advanced AI techniques to further refine optimization strategies.

List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
CO^2	Carbon Dioxide
GA	Genetic Algorithm
GNSS	Global Navigation Satellite System
MA	Multi Agent

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