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Research Article

A Systematic Mapping Study On Multi-Algorithm Methods For Optimizing Transportation Systems

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Abstract: The integration of multi-algorithm methods has emerged as a transformative approach in addressing complex challenges within modern transportation systems. This study presents a systematic mapping review to explore the application, effectiveness, and potential advancements of multi-algorithm techniques across diverse transportation domains, including road, rail, air, and maritime transport. By synthesizing findings from 23 selected studies, this research identifies key algorithmic paradigms, such as machine learning (ML), genetic algorithms (GA), optimization models and hybrid frameworks, and their functional roles in enhancing decision making, resource allocation, and system efficiency. The analysis reveals that multi-algorithm systems offer significant advantages in managing uncertainty, processing large-scale datasets, and generating high-probability solutions for real-time operations. In particular, ML algorithms demonstrate robust capabilities in predictive maintenance and demand forecasting, while GA-based approaches excel in dynamic environments such as traffic signal optimization and UAV path planning. Despite these advances, critical challenges persist, including the need for high-quality data, scalable algorithm design, and seamless integration with existing infrastructure. Furthermore, certain promising methods such as the whale optimization algorithm (WOA) and graph neural networks (GNN) remain underutilized, highlighting opportunities for future exploration. This study underscores the necessity for interdisciplinary collaboration and methodological innovation to overcome deployment barriers and enhance the sustainability of intelligent transportation systems (ITS). Ultimately, multi-algorithm approaches have substantial potential to drive the evolution of transportation networks toward greater efficiency, resilience, and adaptability in an increasingly complex and dynamic mobility landscape.

Keywords: Genetic Algorithms, Intelligent Transportation Systems (ITS), Machine learning, Multi-Algorithm methods, Optimization Models

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1 Introduction

The increasing complexity and dynamism of modern transportation systems have driven the need for advanced computational approaches capable of handling multifaceted challenges [1]. Among these, multi-algorithm methods, which integrate multiple computational techniques such as machine learning (ML), genetic algorithms (GA), optimization models, and hybrid frameworks, have emerged as powerful tools for improving decision-making, resource allocation, and system efficiency [2]. Over the past decades, algorithmic applications in transportation have evolved from simple heuristic rules to sophisticated, data-driven models that support both operational and strategic functions [3]. These methods enable practitioners to decompose complex problems into manageable components, allowing for more effective modeling of traffic patterns, route planning, demand forecasting, and real-time monitoring [4].

This growing reliance on algorithmic systems is not merely a technological shift but a paradigm change in how transportation networks are designed and managed [5]. The integration of soft and hard computing techniques has enhanced the ability to model uncertainty, process large-scale datasets, and generate high-probability solutions for critical decision points [6]. Despite this progress, there remains a lack of comprehensive synthesis that maps the diversity and scope of multi-algorithm applications across different domains of transportation. This gap limits our understanding of which methods are most effective in specific contexts, where research efforts are concentrated, and which areas remain underexplored.

To address this gap, this study presents a systematic mapping review of multi-algorithm applications in transportation systems. Specifically, it aims to: 1) Identify and categorize the types of multi-algorithm methods currently used in transportation, 2) map their application areas, including road, rail, air, and maritime transport, 3) highlight key methodological strengths, limitations, and emerging trends, and 4) identify research gaps and suggest directions for future studies. This study adopts a systematic mapping approach to provide a level of classification and synthesis of multi-algorithm applications in transportation systems. Unlike systematic reviews that focus on evaluating the effectiveness of interventions, systematic mapping studies are particularly useful for identifying research trends, gaps, and opportunities for future work, making them well suited for emerging and multidisciplinary domains such as intelligent transportation systems [7].

2 Research Method

This study adopted a systematic mapping approach to explore the application of multi-algorithm methods in transportation systems. The methodology was designed to ensure transparency, reproducibility, and rigor in identifying, selecting, and analyzing relevant studies.

2.1 Developing protocol

The literature search was conducted using Google Scholar, employing the keyword: "multi-algorithm in transportation systems". While Google Scholar provides broad access to academic publications, it is acknowledged that this database has limitations in terms of indexing comprehensiveness compared to specialized databases such as IEEE Xplore, Scopus, or Web of Science.

To enhance reliability and reduce selection bias, two examiners were involved throughout the process.

(a) Examiner 1 performed the initial screening and extraction based on the established protocol.

(b) Examiner 2 independently reviewed and validated the selected articles, removing those that did not meet the inclusion criteria.

The inclusion criteria were defined as follows:

(a) Studies involving multi-algorithm approaches (not single-algorithm),

(b) Focused on transportation systems (road, rail, air, maritime),

(c) Published in English.

The exclusion criteria included:

(a) Review papers,

(b) Conference proceedings,

(c) Dissertations,

(d) Non-transportation studies,

(e) Articles are not accessible in full text.

(f) Books

All journal citations supporting the arguments in the introduction and initial theoretical framework sections were not included in the extraction activities to maintain the scope. Moreover, all the articles selected were reverified by the second examiner.

2.2 Literature Screening and Selection Process

The journal articles were checked one after the other, page by page, up to the last on the Google Scholar database. Those selected were focused on transportation systems developed using multiple algorithms. To improve clarity and align with standard reporting practices, the article selection process followed a PRISMA diagram [8].

2.3 Data Extraction and Synthesis

Data were extracted systematically from each selected article, focusing on the following elements:

(a) Study objectives,

(b) Multi-algorithm methods applied,

(c) Transportation domain addressed,

(d) Problem solved in the system,

(e) Implementation strategy of the algorithms.

These data were compiled into Table 1 to provide a comprehensive overview of the applications and outcomes of multi-algorithm methods across various transportation contexts.

2.4 Reporting & Dissemination

The findings were synthesized to highlight key trends, methodological strengths, and research gaps. Emphasis was placed on categorizing the types of algorithms used, their functional roles (classification, optimization, signal processing, route planning), and the specific challenges they addressed within transportation systems. Additionally, the results were interpreted in light of current technological advancements and future directions for integrating multi-algorithm systems in intelligent transportation frameworks.

3 Results

3.1 Initial Theoretical Framework

The rapid evolution of transportation systems has been significantly influenced by the integration of multi-algorithm approaches, which combine various computational techniques to address complex and dynamic challenges. These methods—encompassing machine learning (ML), genetic algorithms (GA), optimization algorithms, and hybrid models are designed to support decision-making, optimize resource allocation, and enhance operational efficiency under uncertain conditions [9]. Multi-algorithm systems represent a paradigm shift in transportation, offering not only solutions to current problems but also opening new avenues for innovation. Unlike conventional tools that often struggle with multifactorial issues, these systems integrate soft and hard computing techniques to provide adaptive, high-quality, and reliable outcomes. For instance, ML algorithms are increasingly used for predictive maintenance and demand forecasting, while optimization algorithms play a crucial role in route planning and traffic management [10]. Moreover, the synergy between different algorithmic approaches allows for better handling of large-scale data, real-time processing, and uncertainty modeling, key factors in modern intelligent transportation systems (ITS) [11]. The application of deep learning further enhances capabilities in traffic monitoring, incident detection, and autonomous vehicle navigation. This theoretical framework underscores the transformative potential of multi-algorithm systems in redefining how transportation networks are planned, managed, and optimized [12].

Multi-algorithm systems can be used to harness different potentialities of algorithms for decision support, resource optimization, and the smooth operation of the system [13]. This theoretical framework outlines the transformative potential of multi-algorithm systems in addressing contemporary transportation challenges and enabling innovative solutions. Transportation systems are commonly seen as integrated networks of infrastructure, vehicles, and communication systems, facilitating the continuous movement of people and goods. However, traditional methods may be inadequate in handling complex, multi-dimensional transportation challenges [14]. It leads to the introduction of multi-algorithm systems that integrate methods such as machine learning (ML), genetics, and optimization algorithms. The integration of these methods aims to produce adaptive, high-quality solutions capable of responding to dynamic conditions with accuracy and reliability [15].

Some of the primary advantages of multi-algorithm systems are associated with the determination of effective solutions to different issues related to transport. For instance, ML can be utilized for predictive maintenance and demand forecasting, while optimization algorithms can aid in route optimization and traffic management [16]. The concerted effort to integrate these methods leads to significant enhancement of the system's performance and user satisfaction. The ability of ML algorithms to analyze large datasets and identify patterns and predict trends is crucial for statistical analysis of traffic congestion, optimizing public transport schedules and locations, and enhancing demand forecasting models [17]. Moreover, intelligent transportation systems (ITS) such as the real-time data application of GPS and social media can predict traffic conditions and also provide alternate road options [18]. The integration of ML into ITS enables the system to be always in a learning mode to ensure more accuracy in prediction. The inclusion of technologies such as deep learning, which can deal with complex data, can also assist in the process of enhancing traffic monitoring and incident detection capabilities [19]. It is necessary because predictive maintenance ensures that vehicles and infrastructure are both reliable and safe. The application of ML algorithms to analyze the maintenance and sensor data can assist in predicting failures and scheduling proactive maintenance.

Genetic algorithms (GAs), commonly referred to as optimization algorithms, imitate natural cycle methods developed with a different purpose for natural selection and evolution using route planning and scheduling actions [20]. The combination of GAs with ML and heuristic methods in the multi-algorithm framework was reported to have increased augmented performance [21]. Moreover, the phases of selection, crossover, and mutation previously explained can lead to the development of a GA each time to improve the population of trial solutions [22]. The method is most suitable for fast-changing situations due to the system's continuous adaptation ability and its ability to develop solutions.

The traffic signal timing optimized in urban traffic management, as used by GAs, can lead to better conditions for the effective utilization of the road [23]. GAs and sensors can be combined to gather data on vehicle flow, waiting time, and congestion. The data can be subsequently used as input in the model that generates and evaluates each possible scenario and selects the most appropriate to be implemented [24]. For efficient resource allocation in transportation, optimization algorithms are considered important due to the ability to solve the task of balancing multiple objectives, such as cost minimization and service quality maximization [25].

In the logistics department, optimization algorithms can be used to plan routes, design cargo transportation, and redistribute machines according to the needs of a particular place based on real traffic and demand data from radios and other sources [26]. A logistics company can select some optimization algorithms and machine learning methods for fleet management to ensure efficient and reliable deliveries despite any possible problem [27]. Moreover, the transportation industry has experienced tremendous cost-saving benefits through the introduction of multi-algorithm systems. However, the application of high-quality data, robust algorithm development, and the construction of a scalable real-time system require some solutions [28].

3.2 Extraction Results

3.2.1 Extractions

The selection process implemented through the established protocol by the first examiner showed that 30 transportation systems articles used multi-algorithm analysis. The second examiner conducted a further in-depth study and removed one review journal, five proceedings, and one dissertation, as shown in Figure 1 of the following PRISMA report. After applying exclusion criteria, including review journals, proceedings, and non-transportation studies, 23 articles were retained for final analysis in Table 1.

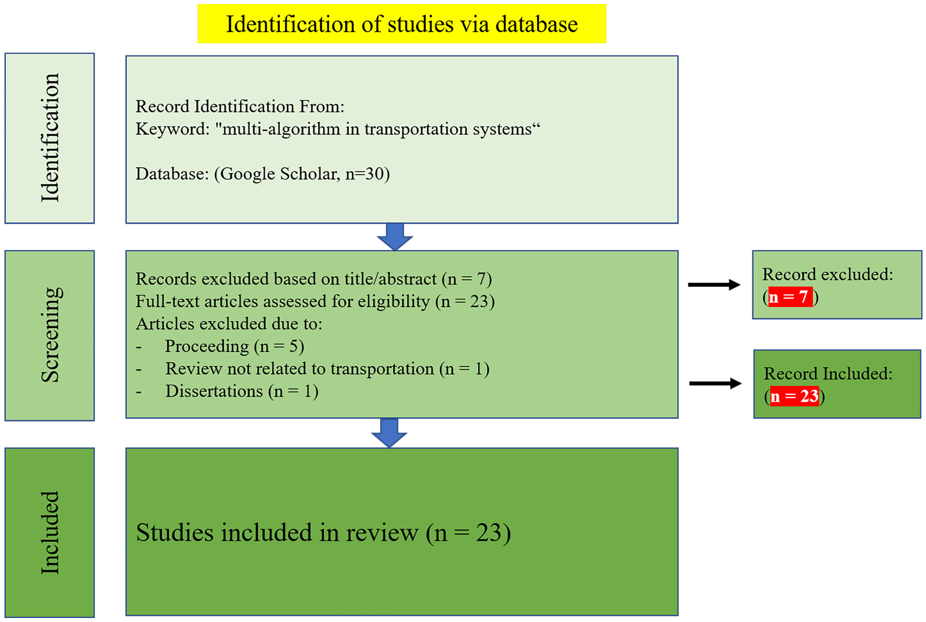

Figure 1: Prisma Report.

Table 1: Extracting Articles

Objectives	Multi-algorithm Use	Problem Solved in the Part of the System	How it Works
Manage incident detection systems [29]	Multi-sensor, multi-site algorithms	Incident detection and traffic management	Combines data from multiple sensors and locations for analysis.
Estimate origin-destination matrices [30]	Disaggregate trip generation, distribution, mode choice models	Traffic demand modeling	Analyzes individual travel behavior for accurate transportation demand modeling.
Improve flight risk identification accuracy [31]	SVM, neural network, fuzzy algorithm	Flight operation risk identification in air traffic management	Classifies risks, predicts issues, and handles uncertainties in operations.
Optimize energy consumption [32]	Differential evolution (DE) variants	Energy consumption optimization in sea-rail intermodal transportation	Optimizes routes and schedules to minimize energy consumption efficiently.

Objectives	Multi-algorithm Use	Problem Solved in the Part of the System	How it Works
Classify traffic congestion [33]	Object detectors, machine learning, deep learning	Traffic flow classification, monitoring systems	Detects, analyzes, and classifies traffic patterns for real-time monitoring.
Improve flight safety under thunderstorms [34]	Ant colony algorithm, artificial potential field	Aircraft conflict avoidance during thunderstorms, flight route planning	Finds optimal flight paths, avoiding conflicts and hazardous areas.
Develop an IoV system with augmented reality [35]	Hough transform, Kalman filter, Sobel edge, SVM	Lane departure, collision detection, IoV Internet of Vehicles, driver assistance	Detects lanes, filters noise, identifies edges, classifies risks accurately.
Optimize multimodal container transport [36]	Multi-objective decision-making	Container sea-land multimodal transport	Balances cost, time, and emissions for optimal transport routes.
Improve pedestrian trajectory tracking [37]	Track-before-detection, Markov transition matrix	Pedestrian detection and tracking, autonomous urban driving	Predicts and tracks pedestrian movement for safer autonomous driving.
Design an autonomous hybrid refueling station [38]	Information gap decision theory (IGDT)	Autonomous hybrid refueling stations	Manages uncertainty in resource allocation for optimal refueling strategies.
Develop a vision system for UAV tracking [39]	Peripheral and central vision cameras	UAV detect-and-avoid, threat classification, small unmanned aircraft systems	Wide detection and detailed focus for identifying and avoiding threats.
Plan rapid container delivery by rail [40]	Mixed programming, genetic algorithm	Intermodal transportation planning, rail transportation	Combines optimization techniques to improve rail transport efficiency.
Predict maritime vessel trajectory [41]	K-Nearest Neighbor (KNN)	Ship location prediction, maritime transportation	Predicts ship positions using nearest data points for accuracy.

Objectives	Multi-algorithm Use	Problem Solved in the Part of the System	How it Works
Optimize route planning for HAS [42]	Genetic algorithm, greedy strategy	Multi-mission-point route planning, heavy-duty semi-rigid airship	Optimizes flight paths efficiently by combining evolutionary and heuristic methods.
Detect railway intrusion [43]	Dynamic intrusion region, lightweight neural network	Intrusion detection in complex railway environments, railway safety systems	Adapts detection zones, uses neural networks for accurate monitoring.
Predict electric vehicle driving range [44]	Linear regression, ensemble stacked generalization	Driving range prediction, electric vehicles	Combines models for precise electric vehicle range estimation.
Improve UAV trajectory planning for logistics [45]	Ant colony optimization, deep Q-network	UAV path planning, energy efficiency, flight safety, intelligent logistics	Finds efficient, safe routes for UAVs using bio-inspired techniques.
Assess flood hazard on infrastructure [46]	InSAR coherence, RGB composition, SVM	Flood detection and monitoring, transportation infrastructure	Analyzes satellite images for accurate flood detection and monitoring.
Improve localization and tracking [47]	PF, MM, AMPC	Localization and tracking under non-Gaussian noises, auto vehicle systems	Filters noise, predicts states, and controls movement in vehicles.
Reliable logistics delivery system [48]	Trajectory optimization, resource scheduling	UAV and land vehicle collaboration for logistics	Plans efficient routes and allocates resources for coordinated deliveries.
Enhance traffic signal control [49]	Graph neural networks, deep reinforcement learning	Management of traffic signal control at intersections	Analyzes traffic patterns, optimizes signal timings for flow efficiency.
Efficient workload assignment [50]	K-means, evolutionary, hybrid evolutionary ensemble	Workload balancing in last-mile delivery, last-mile urban package delivery	Clusters deliveries, optimizes routes, balances workload efficiently.

Objectives	Multi-algorithm Use	Problem Solved in the Part of the System	How it Works
Optimize urban distribution routes [51]	Whale optimization, hybrid multi-phase heuristic	Scheduling and packing for electric meters, urban distribution logistics	Optimizes schedules and packing to enhance urban delivery efficiency.

Table 1 provides detailed information on several study objectives, the use of multi-algorithm methods, solutions to specific problems in transportation systems, and the precise strategy employed to apply these algorithms. For each entry, a notable aspect of the transportation difficulties was the sophistication in applying algorithmic solutions. Some of the methods included the integration of sensors in multi-sensor, multi-site algorithms for incident detection. It was observed that using more than one data source enhanced the performance and accuracy of the system while speeding up the response time. A similar example was the management of traffic using SVM, neural networks, and fuzzy algorithms to classify risks and predict potential issues to improve flight risk. The purpose was to minimize doubts in areas of high risk. Moreover, GAs, which were optimization methods developed based on evolution and natural selection, have become popular choices for minimizing congestion and road safety issues [21]. In the multi-algorithm execution, GAs were combined with ML and heuristic methods to achieve the highest performance. The method was confirmed to be population-based and applied through selection, crossover, and mutation operations [20]. It was found to be effective in constantly changing conditions requiring the discovery and adaptation of several solutions. In urban traffic management, GAs were used to set the optimal traffic signal timings to keep flow interference minimized and consequently improve traffic operation [23]. It was achieved by using traffic sensors and cameras to connect the vehicle flow and the block lines, which were processed in the GA model to provide the ideal signal timing scenario for the adoption of the most suitable [24].

The efficient use of optimization algorithms is fundamental for the proper allocation of resources in transportation systems by minimizing costs and maximizing the quality of services [25]. It is evident in the application in logistics to plan routes, schedule deliveries, and dynamically allocate vehicles, incorporating data on real-life traffic and demand [24] [25] [26]. Several logistics companies have combined optimization algorithms and ML models as a fleet management method to ensure efficient and reliable delivery even during aggravated unexpected circumstances [27]. These multi-algorithm systems can improve efficiency, dependability, and sustainability in transport management [28]. However, some of the main challenges are good-quality data requirements, reliable algorithm design, and the ability to set up real-time systems in Cale.

Figure 2 provides a comprehensive overview of the different components that constitute the modern transportation system. It is divided into four primary categories, including infrastructure, which encompasses five branches of knowledge, while each of vehicles, management systems, and technological innovations has 4 [52]. The infrastructure part includes roads, rail tracks, airports, maritime transport, ports, and urban public transport. It focuses on the significance of modal containerized transport and hybrid refueling stations known as multimodal transport through the utilization of the rail-water system, along with green energy-based refueling points. The vehicle part discusses all types, such as road vehicles, railway locomotives, airplanes, and boats, with a focus on quick delivery by rail and green transportation. The entire traffic management sector is based on planning traffic light synchronization, communication transmission, air traffic handling, and usage of port systems. It also includes methods to address raw materials distribution, sea-rail unification, incident management, the use of UAVs, congestion reduction, trip creation, and vehicle route selection. The latest advancements in the field of automation, IoT connectivity, environmentally friendly technologies, and advanced materials were used to configure trajectory prediction, electric vehicle driving, and overall transportation safety and efficiency.

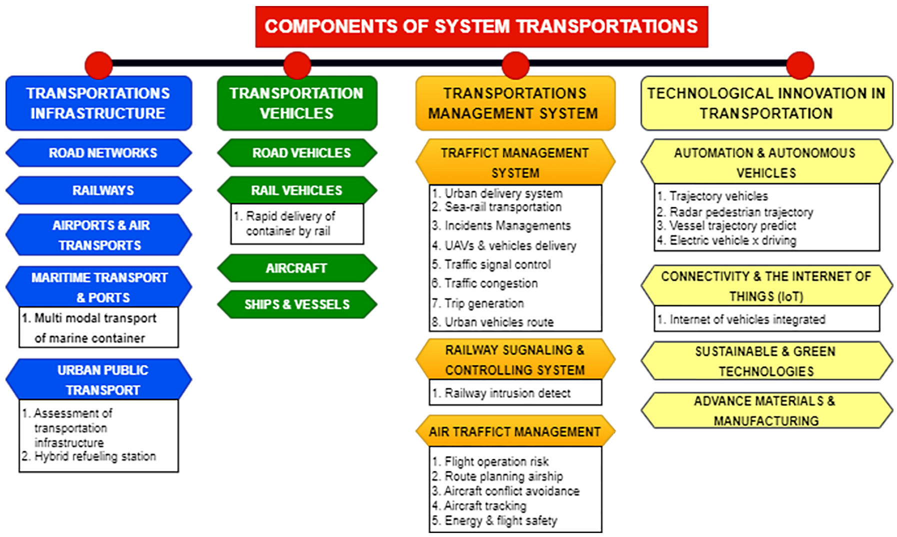

Figure 2: Part of the problems solved in the transportation system.

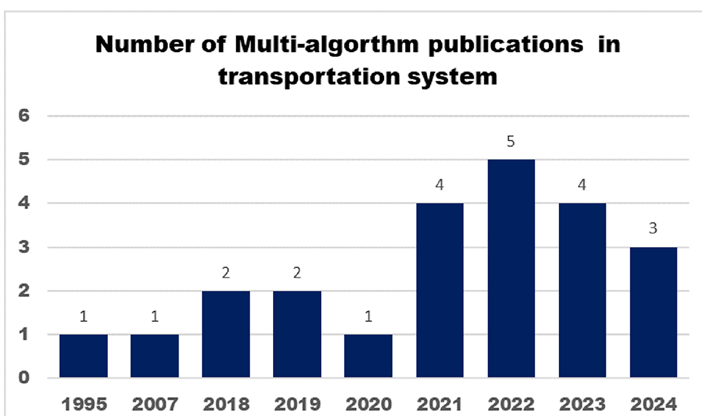

Figure 3: Journal Publication Frequency Identified Year (Google Scholar Version).

Figure 3 shows the small number of publications related to multi-algorithms in the transportation system from 1995 to 2024, and a significant trend in study interest is identified over the years. Between 1995 and 2007, a modest level of publications was observed, with only one recorded in each year. The interest picked up in 2018 and 2019, as observed in the increase to 2 publications in both years. After a slight dip in 2020, the number surged in 2021 to 4 and peaked in 2022 with 5, indicating a growing focus on multi-algorithm methods in transportation studies. There was also a slight decline in 2023 and 2024, with 4 and 3 publications, respectively. However, the overall trend suggests a sustained and significant interest in leveraging multi-algorithm methods to address complex problems in the transportation sector. This trend shows the continuous recognition of the value provided by multi-algorithm methods in optimizing and enhancing transportation systems. Figure 3 also illustrates a steady increase in publications related to multi-algorithm applications in transportation since 2018, peaking in 2022 with five publications. However, this growth has slowed slightly in recent years, suggesting either the maturation of the field or the need for more diverse methodological exploration.

Table 2: Summary of the Category Function of the Multi-algorithms

Category	**Algorithm**
Classification and Pattern Recognition	SVM, Neural Network, Object Detectors, Machine Learning, Deep Learning, Lightweight Neural Network, KNN, Linear Regression, Ensemble Stacked Generalization, Graph Neural Networks, Deep Reinforcement Learning
Optimization and Decision Making	DE, Multi-objective Decision-making, Genetic Algorithm, Greedy Strategy, Mixed Programming, Ant Colony Algorithm, Whale Optimization Algorithm (WOA), Hybrid Multi-phase Heuristic, Ant Colony Optimization, Deep Q-Network, IGDT, Multi-weight Probability
Signal Processing and Filtering	Hough Transform, Kalman Filter, Sobel Edge, InSAR Coherence, RGB, Composition, Track-before-detection, Markov Transition Matrix, PF, MM, AMPC
Transportation and Route Planning	Disaggregate Trip Generation, Distribution, Mode Choice Models, Trajectory Optimization, Resource Scheduling, Multi-sensor, Multi-site Algorithms, Ant Colony Algorithm, Artificial Potential Field, SLAM, Lane Detection and Tracking, Peripheral Vision Camera, Central Vision Camera, Dynamic Intrusion Region, Mixed Programming, Genetic Algorithm

3.2.2 Critical Synthesis and Comparative Insights

From the extracted studies, several key patterns emerged regarding the use of multi-algorithm methods across different domains:

(a) Classification and Pattern Recognition: Algorithms such as Support Vector Machines (SVM), Neural Networks, Deep Learning, and KNN have been widely applied in traffic congestion classification, flight risk identification, maritime trajectory prediction, and pedestrian tracking. These methods excel at extracting meaningful insights from noisy or complex datasets, particularly in real-time monitoring scenarios.

(b) Optimization and Decision-Making: Genetic Algorithms (GA), Ant Colony Optimization (ACO), Differential Evolution (DE), and Mixed Programming have shown strong performance in optimizing logistics routes, energy consumption, and signal timing control. GA, in particular, is popular due to its adaptability in dynamic environments, especially in urban traffic signal optimization and UAV path planning.

(c) Signal Processing and Filtering : Techniques like Kalman Filters, Hough Transform, and Sobel Edge Detection are commonly used in vision-based systems for lane detection, collision avoidance, and intrusion monitoring. Their strength lies in noise reduction and accurate feature extraction, essential for autonomous driving and safety-critical applications.

(d) Underutilized Methods: Despite their potential, certain algorithms remain underexplored. Whale Optimization Algorithm (WOA) and Multi-objective Decision-Making frameworks, for example, have only appeared in niche areas such as electric meter distribution and container transport optimization. Similarly, Information Gap Decision Theory (IGDT) has seen limited use in refueling station design despite its value in managing uncertainty.

3.2.3 Domain Specific Performance

Some algorithms demonstrate superior performance in specific domains:

(a) Ant Colony Optimization (ACO): Dominates UAV path planning and air traffic routing, particularly under adverse weather conditions.

(b) Graph Neural Networks (GNN) & Reinforcement Learning (RL): Show promise in intelligent traffic signal control, where they can dynamically adjust timings based on real-time flow data.

(c) KNN & Ensemble Models: Effective in maritime and electric vehicle range prediction, leveraging historical data points for accurate forecasting.

(d) Hybrid Multi-phase Heuristic & WOA: Emerging as viable options for urban delivery logistics involving heterogeneous fleets and three-dimensional packing constraints.

4 Discussion

This study provides a systematic mapping of multi-algorithm methods applied across various domains of transportation systems, highlighting their transformative potential in decision-making, resource allocation, and operational efficiency. While the integration of machine learning (ML), genetic algorithms (GA), optimization techniques, and hybrid models has significantly enhanced system performance, several critical challenges remain.

4.1 Critical Reflection on Methodological Strengths

One of the key strengths of this study lies in its structured categorization of multi-algorithm applications into four major functional areas: classification and pattern recognition, optimization and decision-making, signal processing and filtering, and transportation and route planning (see Table 2). This classification enables a clear understanding of which algorithmic approaches are most effective in specific contexts. For example:

(a) SVM, Neural Networks, and Deep Learning dominate in traffic congestion detection and flight risk identification due to their ability to model complex, nonlinear relationships.

(b) Genetic Algorithms and Ant Colony Optimization are particularly suited for dynamic environments such as UAV path planning and urban traffic signal control, where adaptability is crucial.

(c) Kalman Filters and Hough Transform play essential roles in vision-based systems for lane detection and intrusion monitoring, especially in autonomous vehicles.

The discussion also addresses important limitations inherent to these methods. First, the reliance on high-quality data remains a significant barrier. Inconsistent or noisy datasets can compromise the accuracy of ML predictions and optimization outcomes. Second, scalability remains a challenge, particularly for hybrid models that combine multiple algorithms and require extensive computational resources. Third, real-time implementation remains problematic in large-scale systems, especially when integrating heterogeneous technologies and legacy infrastructure. These observations align with findings from recent studies (e.g., [8], [9], [23]), which emphasize the need for robust, scalable, and adaptive frameworks capable of handling uncertainty and complexity in intelligent transportation systems (ITS).

The multi-algorithm methods integrated into the transportation sector represent a complex and adaptive solution to the new-age traffic systems. The primary aim is to enhance decision-making processes, promote resource allocation, and increase the overall efficiency of the system [8]. It is necessary because the transportation system, including the infrastructure, vehicles, and communication networks, is multifaceted. Therefore, a robust adjustable solution is needed to satisfy the dynamic conditions as well as to ensure efficient, accountable, and reliable results [9]. This comparative study shapes the current field of multi-algorithm-based transportation systems and also shows the technological metamorphosis.

In Table 1, the objectives, multi-algorithm methods applied, specific problems addressed within transportation systems, and application process in the studies reviewed were meticulously documented. For instance, multi-sensor and multi-site algorithms were used for incident detection and enhanced traffic management through the combination of data from different sensors [29]. Similarly, ML algorithms such as SVM, neural networks, and fuzzy were used to improve flight risk identification through adequate classification and prediction of potential issues [31]. The study showed the importance of handling uncertainties in high-stakes environments. Moreover, optimization algorithms such as Differential Evolution (DE) variants were applied to optimize energy consumption in sea-rail intermodal transportation by efficiently improving routes and schedules [32].

Figure 2 provides a comprehensive overview of the different components that constitute a modern transportation system. The multi-algorithm methods integrated were also classified into four primary categories, including infrastructure, vehicles, management systems, and technological innovations. Each category emphasized different aspects of transportation, such as the importance of multimodal container transport, rapid delivery by rail, urban delivery systems, and advancements in automation and autonomous vehicles. This integrated method was used to develop a seamless, efficient, and sustainable transportation network [52]. The synergy between the components and the multi-algorithm methods adopted enhanced the responsiveness and accuracy of the system.

Figure 3 shows the publication frequency of relevant articles from 1995 to 2024, and a continuous increase in interest is identified. The data showed a growing focus on multi-algorithm methods that peaked in 2022 with five publications. This trend further shows the continuous recognition of the value provided by multi-algorithm methods in optimizing and enhancing transportation systems. Despite slight fluctuations, it also indicates the sustained interest in leveraging the methods to solve the complex problems in the sector. Therefore, multi-algorithm methods were observed to be evolving and important in driving innovation and efficiency in transportation [8]. Among the four main categories of transportation systems, nine branches of science were identified that have not been touched by multi-algorithm studies based on the Google Scholar platform version, as seen in Figure 2. This finding reveals a potential work gap, indicating that comprehensive and systemic transportation performance remains suboptimal and unevenly distributed.

The extraction results presented in Table 2 show that the transportation system is a complex and dynamic network requiring advanced algorithms to guarantee efficiency, safety, and reliability. Moreover, SVM, Neural Networks, and Deep Learning were found to be the main algorithms in the Classification and Pattern Recognition category. It could be due to the assistance provided by the transportation system to detect and analyze sets of data with great precision. The results showed that the key areas focused on were traffic congestion reduction, vehicle detection, and driver analytics. The algorithms recognize patterns and forecast the future, thereby aiding the development of smarter and more responsive transportation systems.

In the Optimization and Decision-Making category, algorithms such as Genetic, DE, and Multi-objective Decision-making were found to be important. The trend could be due to the ability of the algorithms to optimize different aspects of transportation, from route planning to resource allocation, ensuring that operations are conducted most efficiently. It was considered important in making informed decisions that balanced multiple objectives, such as the minimization of travel time while reducing fuel consumption and emissions. The most important algorithms in the Signal Processing and Filtering category were the Hough Transform, Kalman Filter, and InSAR Coherence. It was associated with the role of refining and filtering the raw data collected from different sensors to eliminate noise and enhance clarity for accurate interpretation and analysis. The capability was particularly important in applications such as image processing for traffic monitoring and sensor data analysis for vehicle navigation.

In the Transportation and Route Planning, Slam, Trajectory Optimization, and Resource Scheduling algorithms were observed to be unavoidable. It was based on the application for routing and route optimization in combination with different modes of transportation. The process was considered important to ensure that cargo and passengers reached their preferred destinations efficiently. Furthermore, the algorithms were also responsible for resource scheduling in different platforms, such as vehicles and personnel, to maximize productivity and minimize delays. Ant Colony Optimization and Artificial Potential Field were also applied to the pathfinding and navigation systems to enhance the efficiency of the transportation networks further.

The gradual integration and application of algorithms in the transportation system demonstrates a commitment to modern technology and a problem-solving approach that leads to the sector's complete improvement. The results showed that multiple algorithms related to classification and pattern recognition, optimization and decision-making, signal processing and filtering, as well as transportation and route planning algorithms were used to modify conditions, fulfill diverse demands, and ensure efficient work. The entire process was beneficial to the transportation system and also ensured sustainability and user satisfaction. It is possible because multi-algorithms ensure reliable, faster, and environmentally friendly transportation to all relevant parties.

4.2 Areas of Underutilization and Research Gaps

Despite the growing interest in multi-algorithm systems, certain promising methods remain underexplored. For instance:

(a) Whale Optimization Algorithm (WOA) and Multi-objective Decision-Making have shown potential in logistics distribution and multimodal container transport but are rarely adopted outside niche applications.

(b) Information Gap Decision Theory (IGDT) offers a robust framework for managing uncertainty in refueling station design but has been scarcely explored in the transportation domain.

(c) Graph Neural Networks (GNN) and Deep Reinforcement Learning (DRL) are gaining traction in traffic signal control but lack widespread application beyond experimental settings.

Moreover, there is limited research on the integration of generative AI and deep learning for demand forecasting and fleet scheduling in last-mile delivery systems. Similarly, while some studies have addressed rural and intermodal transport systems, these areas remain relatively understudied compared to urban mobility solutions. To highlight these gaps, we propose the following Research Gap and Emerging Opportunities in Table 3.

Table 3: Summary of Research Gaps and Emerging Opportunities

Area	**Underutilized Methods**	**Key Challenges**	**Potential Applications**
Logistics & Distribution	Whale Optimization Algorithm, Multi-objective Decision-Making	Scalability, Dynamic Demand	Urban Electric Meter Delivery, Multimodal Container Transport
Infrastructure Planning	IGDT, Robust Optimization	Uncertainty in Resource Allocation	Hybrid Refueling Stations, Flood Hazard Assessment
Autonomous Systems	GNN, DRL	Real-time Adaptation, Safety Constraints	Intelligent Traffic Signal Control, UAV Navigation
Rural & Intermodal Transport	Heuristic Search, Hybrid Models	Data Scarcity, Limited Infrastructure	Last-mile Connectivity, Sea-Rail Integration
Demand Forecasting & Fleet Management	Generative AI, Ensemble Learning	Volatility, Spatiotemporal Complexity	Ride-sharing, Predictive Maintenance

The study provides a comprehensive overview of the application of multi-algorithm methods in transportation, but several limitations were observed. First, the rapid pace of technological advancements shows that some of the methods discussed can quickly become outdated as new algorithms and technologies are introduced. Second, the review primarily focuses on studies published, potentially overlooking valuable insights from industry practices and unpublished ones. Third, the diversity of transportation systems across different regions can limit the generalizability of the results. The implementation of multi-algorithm systems also requires high-quality data, which can be challenging to obtain consistently. Lastly, the study shows the potential benefits of these systems, but practical challenges in real-world deployment, such as scalability and integration with existing infrastructure, need to be further considered.

To overcome these limitations, future research can enhance the literature review's thoroughness by incorporating more databases and sources beyond Google Scholar. An example of these databases might be IEEE Xplore, Scopus, and Web of Science. Moreover, there is the potential to incorporate a wider range of viewpoints by including conference proceedings, books, and dissertations. Additionally, applying a more systematic approach that encompasses a variety of publication types and includes grey literature might be a way to enhance the outcomes of the study and yield a more complete exploration of multi-algorithm methods in transportation systems.

4.3 Future Directions

Given the current state of research, future studies should focus on three main areas:

(a) Data Quality and Integration: Developing strategies for collecting, cleaning, and integrating high-quality, real-time data from diverse sources is essential for improving algorithmic reliability.

(b) Algorithm Robustness and Adaptability: Enhancing the resilience of multi-algorithm systems to dynamic changes, uncertainties, and edge cases will be crucial for deployment in safety-critical applications.

(c) Scalable and Real-Time Architectures: Designing lightweight, distributed computing frameworks that support real-time execution of complex algorithms is necessary to enable large-scale adoption.

Furthermore, interdisciplinary collaboration between computer scientists, transportation engineers, and policy makers will be vital in addressing practical deployment challenges and ensuring ethical considerations are integrated into algorithmic design.

5 Conclusion

This systematic mapping study highlights the transformative role of multi-algorithm methods in reshaping modern transportation systems. By integrating diverse computational techniques, such as machine learning, genetic algorithms, optimization models, and hybrid frameworks, these approaches have significantly enhanced decision-making, resource allocation, and operational efficiency across various domains of transportation.

Key Findings:
From the analysis of 23 selected studies, several critical insights emerged:

1. Multi-algorithm systems improve system performance by combining strengths from different algorithmic paradigms. For instance:
   (a) Machine learning algorithms like SVM, Neural Networks, and Deep Learning are highly effective in classification and pattern recognition, particularly in traffic congestion detection and maritime trajectory prediction.
   (b) Optimization algorithms such as Genetic Algorithms (GA), Differential Evolution (DE), and Ant Colony Optimization (ACO) excel in route planning, energy optimization, and logistics scheduling.
   (c) Hybrid models that integrate heuristic search with reinforcement learning or deep learning demonstrate superior adaptability in dynamic environments, including UAV path planning and intelligent traffic signal control.
2. Domain-specific advantages were observed:
   (a) In urban mobility, GA-based traffic signal timing optimization has shown measurable improvements in reducing congestion and travel time.
   (b) In logistics and distribution, Whale Optimization and Multi-phase Heuristic methods are promising for urban electric meter delivery and 3D packing problems.

   (c) In autonomous systems, lightweight neural networks combined with Kalman filters enhance safety through real-time intrusion detection and lane departure monitoring.

3. Critical success factors include:
   (a) The availability of high-quality, real-time data to train and validate models.
   (b) Scalable and robust algorithm design capable of handling uncertainty and edge cases.
   (c) Integration capabilities with existing infrastructure and multimodal transport systems.

Limitations and Future Directions:

1. Despite their benefits, the implementation of multi-algorithm systems still faces challenges:
   (a) Data quality and interoperability issues limit the generalizability of some models.
   (b) Real-time deployment remains difficult due to computational complexity and hardware constraints.
   (c) Certain promising methods, such as Graph Neural Networks (GNN), Information Gap Decision Theory (IGDT), and Whale Optimization, remain underutilized despite showing potential in niche applications.
2. Future research should focus on:
   (a) Developing data-efficient algorithms that can operate with limited or noisy datasets.
   (b) Exploring generative AI and federated learning for decentralized and privacy-preserving transportation systems.
   (c) Creating interoperable frameworks that allow seamless integration of multi-algorithm models into heterogeneous transport infrastructures.

Moreover, interdisciplinary collaboration between transportation engineers, data scientists, and policy-makers will be essential to ensure that these technologies are not only technically sound but also ethically and socially responsible. In conclusion, multi-algorithm methods hold significant promise for advancing intelligent transportation systems. With continued innovation and targeted research efforts, they can play a central role in achieving more efficient, sustainable, and resilient mobility solutions for the future.

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