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Artificial Intelligence for sustainable logistics: Reducing carbon emissions and fuel consumption through route optimization

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Abstract

The world logistics industry is coming under pressure to shift its operations to greener practices as environmental awareness and regulatory pressure on these environmental practices rise. Artificial Intelligence (AI) in the direction of an optimal route can help, in particular, find ways of transport logistics in which the savings in carbon emission and an increase in the actual fuel quality can be significantly reduced. The paper examines how AI-based optimization methods could be implemented in logistics networks and play a role in sustainability. With the help of the latest achievements in machine learning, ant colony optimization, and smart logistics with the support of IoT devices, the authors investigate AI technologies' role in minimizing fuel consumption and emissions following the principle of real-time adaptive routing. An extensive literature review provides an analysis of implementation frameworks, primary enablers, and difficulties in the adoption of AI technologies. Its findings suggest that AI-enabled route optimization can produce significant carbon and fuel savings via reductions of up to 15 and 30 percent in specific scenarios with an efficient digital infrastructure and data platforms. Moreover, sustainability benefits are optimized when AI is a part of wider policies in logistics, including green fleet management and reverse logistics. This paper adds to the expanding literature on sustainable logistics and AI and provides strategic suggestions to policymakers and logistics providers willing to decarbonize them via intelligent transportation systems.

Keywords: Artificial Intelligence; Sustainable Logistics; Route Optimization; Carbon Emissions Reduction; Fuel Efficiency; Smart Transportation Systems

1. Introduction

The transport and logistics industry are a central factor in economic growth worldwide since this industry allows the transport of goods, services, and people through vast distances. The industry, nonetheless, has contributed to carbon dioxide (CO2) emission and ecological deterioration of the planet to an extent equaling about 14 percent of the total emission globally. An increasing amount of urbanization and electronic commerce both means that logistic networks are becoming more complicated and therefore pushes the burden on the transportation system to become more efficient and sustainable in terms of the environment [4]; [12].

Artificial Intelligence (AI) has become a force of destabilization and allowance in the hunt of sustainability in logistics. Using data-driven intelligence, machine learning technologies, and sophisticated optimization tools, AI solutions have proven to have great potential in improving transport efficiency, reducing the amount of wasted energy, and lowering carbon emissions [17]. Among the most promising ones is route optimization, or dynamic generation of the most efficient routes used by transportation cars concerning real-time information like traffic conditions, weather conditions, fuel efficiency, etc.

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Combinations of ant colony optimization [6], genetic algorithms, and neural networks are used in Google Maps, maps.me, and arc2.aiAI-driven route optimization systems to identify optimal fuel-saving routes that reduce the idle time and distances covered by cars [9];[20]. With its help, logistics providers can realize considerable reductions in greenhouse gas emissions, expenses, and delivery times, which are the most crucial aims of the emerging concept of Sustainable Logistics 4.0 [17].

Green logistics strategy is a priority for governments, businesses, and other stakeholders in the global sector. The pressure to improve the environmental friendliness of logistics activity only increases with such initiatives as carbon tax policy [25], emissions-trading scheme [7], and green finance [10]. In this context, AI cannot be treated as a tool of efficiency but rather a global climate goal strategy. Therefore, it is necessary to comprehend the relationship between AI-powered streamlining and sustainability achievements in logistics to implement innovation and proper environmental management.

1.1. Problem Statement

Even after being aware of the possible benefit of AI technologies in decreasing the environmental impact, the logistics sector is still experiencing many difficulties in enabling its scale. The lack of unified digital infrastructure, the scarcity of access to real-time information, the aversion to technology implementation, and weak policy frameworks tend to slow down the effective implementation of AI-based solutions in a logistic network [1];[3].

In addition, even though large logistics firms are currently approaching the use of route optimization systems in developed territories, the implementation level in the context of small-to-medium businesses (SMEs) and less developed economies is still minimal. The advantages brought about by these systems, like reduced fuel consumption and clean-up emissions, usually are not maximized because of technical expertise, low capacity to finance, and lack of clarity of the returns obtained. Moreover, the broader sustainability goals and their indicators, including reverse logistics, life-cycle emissions, or socio-environmental externalities, might not be considered in the AI systems [18].

As a researcher, this connection between AI-based route optimization and sustainability performance has not been thoroughly discussed in an integrated system. Although numerous studies investigate optimization algorithms or eco-friendly transport behaviors singularly, little research has been conducted on the systematic implication of intelligent routing technology in the direct benefits of carbon emissions and fuel savings [19]; [16]. This body of research that lacks unity prevents decision-makers from creating evidence-based and scalable strategies regarding AI-based sustainable logistics.

1.2. Research Objectives

The current study will examine how Artificial Intelligence can enhance the sustainability of logistics operations, specifically concerning route optimization. In particular, this research will aim at achieving the following objectives

- To understand how fuel consumption and carbon emissions in logistics systems can be reduced due to the use of artificial intelligence in route optimization.
- To examine current technologies, algorithms, and tools used in intelligent routing in sustainable logistics.
- The goal is to establish important enablers and constraints to integrating AI in green logistics and implementation approaches in varying organizational and geographical contexts.
- To create a theoretical framework to understand the connection between using AI-based decision-making and the environmental performance of logistics.

Through these objectives, the study aims to contribute to theory and provide some practical application to logistics providers, technological developers, policymakers, and those who promote sustainability. The results will guide policies to harmonize the use of AI in logistics and its overall climate action, operational improvement, and technological repair.

2. Literature Review

The intersection of artificial intelligence (AI) and sustainable logistics has become a pivotal field of study and industrial development, with worldwide attempts to decarbonize the transport system. The current literature review addresses three dimensions of broad theme areas that are as follows: (1) AI use cases in logistics, (2) route optimization methods and tools, and (3) sustainabilityware in logistics operations (especially keener on fuel consumption and carbon emission).

2.1. Artificial Intelligence in Logistics and Transportation

Introducing AI in logistics has recently acquired momentum during the past ten years. AI can also process a vast quantity of dynamic data and be used in decision-making, which in the past was being done manually or following the rules [14]. Logistics Inventory management, demand forecasting, autonomous vehicle routing, and innovative warehousing are fields of application of AI in logistics. One of them, intelligent transportation systems (ITS) supported by AI, is critical in route optimization, shorter delivery times, and better environmental performance [2]; [8].

Artificial intelligence, especially neural networks, deep learning, and reinforcement learning, is being deployed to develop adaptive routing models. These algorithms would use past and real-time data to calculate the most optimal routes in different situations of operational properties [13]. Also, explainable and risk-averse models of AI are becoming more focused on providing reliable results in logistics [23].

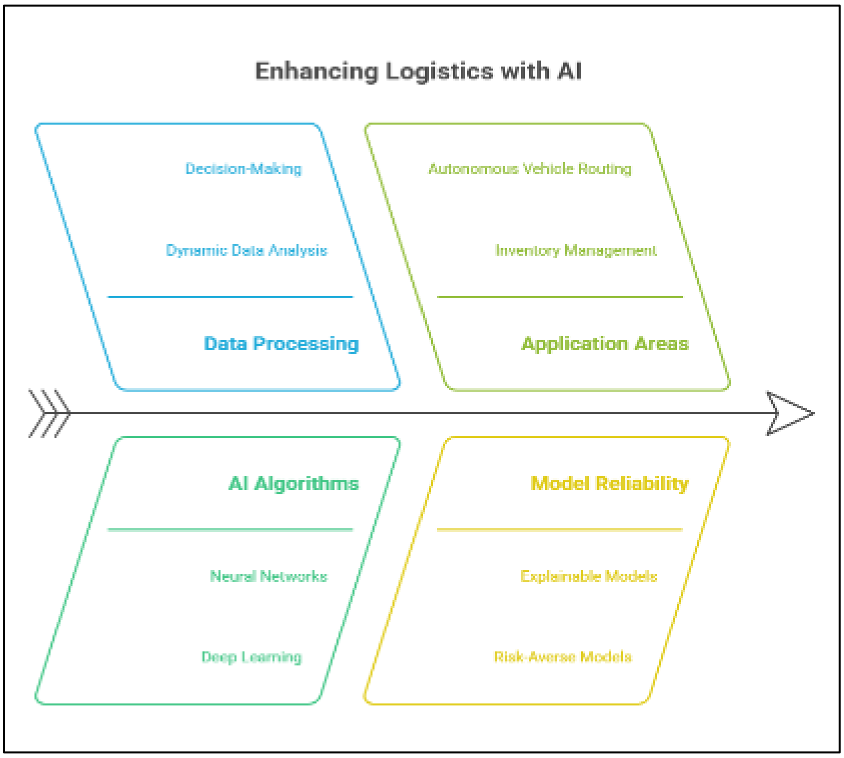

Figure 1 Artificial Intelligence in Logistics and Transportation

2.2. Route Optimization Techniques and Intelligent Algorithms

The priority of AI in sustainable logistics is route optimization. Methods like ant colony optimization (ACO), genetic algorithms, dynamic programming, and metaheuristic techniques have demonstrated great success when applied to vehicle routing problems (VRPs) [6]; [8]. For example, ACO simulates the nature of ants in determining the best routes to food and has been applied in optimising energy-efficient logistics routes over complicated networks.

Contemporary methods integrate the Internet of Things (IoT), edge, and adaptive learning to establish real-time responsive routing systems. [16] have created an innovative textile waste collection project that uses IoT-based dynamic route planning to minimize costs and emissions. In the same way, [20] established the possibility of optimizing a bus route evaluation model with multi-source data.

Furthermore, hybrid solutions that find a compromise between the classical heuristics approach and AI are becoming popular due to their best-of-both-worlds characteristics to balance the computation speed and constraints in the real world in terms of delivery time, vehicle capacity and rush hour traffic [17]. The models are also helpful in last-mile logistics, where real-time responsiveness is a significant factor in fuel consumption.

2.3. Sustainable Logistics and Environmental Performance

The concept of sustainability in logistics can be defined as reducing harmful environmental, economic, and social effects of the transportation system. Carbon emissions and fuel consumption are the most examined environmental performance indicators since they directly affect climate change [3]; [7].

The sustainability of AI-enhanced route optimization involves minimalizing vehicle mileage, reducing wasted time, and eliminating unwanted detouring. Analysis indicates that intelligent routing can reduce fuel consumption and emission rates by 10-30 percent, depending on the degree of maturity and state of data provided [11]; [21]. Moreover, according to some researchers, [5] and [22], fuel efficiency can be boosted further once route optimization is combined with advanced vehicle technologies and fuel properties optimization.

Reverse logistics and green fleet plans are also part of sustainable logistics frames and, therefore, are made easier with the assistance of AI in planning and usage [12]; [18]. Specifically, [25] note that the combination of logistics planning by AI and controls in the environmental field, including a carbon tax, allows the reasonable development of an ecosystem where environmental changes can be achieved materially. In addition, according to [15], digitalization improves the efficiency of fossil fuels through increased consumption transparency and easy regulation.

Other studies warn that AI sustainability might not be an effective project unless quality data is available, systems can be linked, and sectors are connected [1]; [4]. These enablers are critical, as without them, AI's potential in sustainable logistics may go unexpressed.

2.4. Summary of AI Techniques in Logistics Optimization

To summarize the variety of AI applications referred to by various works reviewed in the previous studies, this subsection provides the table that summarizes the commonly used AI methods in route optimization, their logistic implications, sustainability potential, and the sources. In this table, an outline of both possible algorithmic and measurable environmental capabilities is shown in a quick-reference format.

Table 1 Overview of AI Techniques for Route Optimization in Logistics

AI Technique	Application in Logistics	Sustainability Contribution	Reference(s)
Ant Colony Optimization (ACO)	Dynamic vehicle routing and transmission line planning	Reduces mileage and fuel usage through optimal path-finding	[6]; [9].
Neural Networks	Learning from historical traffic and delivery data	Predicts fuel-efficient routes and improves delivery accuracy	[2]; [13].
Reinforcement Learning	Adaptive decision-making for real-time routing	Reduces idle time and emissions through continuous learning	[8]; [20]
Hybrid Metaheuristics	Combines genetic algorithms and heuristics for multi-objective routing	Optimizes fuel and cost trade-offs in last-mile delivery	[17]; [16]
IoT-Enabled Optimization	Sensor-based dynamic routing for waste and public transport logistics	Enhances real-time emission tracking and route efficiency	[16]; [20]
Data-Driven Simulation	Scenario modeling using big data for emissions forecasting	Supports low-emission route planning and carbon benchmarking	[7]; [3]

3. Methods

3.1. Research Design

The research design of this study is descriptive-analytical, based on an intersection of literature synthesis, comparison modeling, and scenario-based approaches. The methodology framework relies on the existing literature on optimization research and AI implementation models in logistics [16]; [17]. It is proposed that the effect of various AI algorithms on fuel consumption and carbon emissions in different operating conditions be examined using simulation-based modeling in the data.

There are three phases in the research design, namely

- Identification of those AI-based optimization algorithms that apply to logistics.
- A comparative study of parameters of route optimization and sustainability indicators.
- The approximate environmental impact based on modeled outputs based on assumptions of real-world logistics data.
- Such an organized approach offers a transferable foundation to assess the contribution of AI to sustainable logistics activities.

3.2. Data Sources and Simulation Assumptions

The process of the study is not primary field studies; the secondary data used by the authors of the study is based on peer-reviewed studies (e.g., [6]; [11] and industry reports with which simulated cases of route optimization are performed. The modeling framework considers the following variables: average route distance, fuel used per kilometer, carbon emission factor per liter of fuel, frequency of delivery, and coefficients of traffic delay.

The model presupposes a medium-duty delivery truck with internal combustion engines that operates in mixed urban and suburban flights. The given emissions values are grounded on the average worldwide values (2.68 kg CO_2 per liter of diesel fuel). The estimate of fuel consumption relies on the baseline and optimized routing conditions.

3.3. Optimization Algorithms

3.3.1. The analysis chose three primary AI optimization methods

- Ant Colony Optimization (ACO) modeled after [6]is more appropriate when dynamic network routing is used.
- Neural Networks (NNs) - Neural Networks learned using historical delivery and traffic data with predictive purposes on planning routes [2].
- Hybrid Genetic Algorithms (HGAs) The representative algorithms in Hybrid Genetic Algorithms (HGAs) use both metaheuristics tuning and classic VRP models [17].

All methods were evaluated in three logistics settings, including normal routing, predictive routing, where learning returns are provided, and hybrid routing, which has elements of environmental limitations.

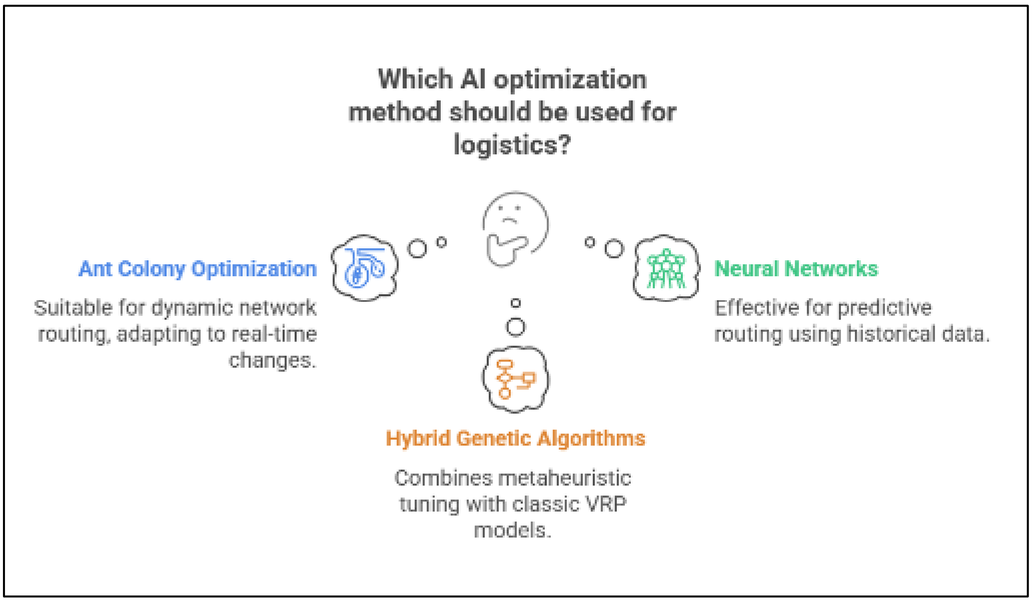

Figure 2 Optimization Algorithms

3.4. Comparative Parameters and Modeling Framework

For the comparison to be relevant, the performance of each algorithm is compared in terms of fuel savings, carbon emissions reduction, efficiency of the routes (in km), and estimated delivery time difference. The following table describes the table parameters and performance measures considered in the simulation.

Table 2 Comparative Parameters for Route Optimization Simulation

Parameter	Description	Baseline Value	Optimized Value (AI-Driven)	Reference(s)
Route Distance (km)	The average length of the delivery route	120 km	100 km	Share & Hasnat (2021); Ebid et al. (2024)
Fuel Consumption (liters)	Liters used per delivery cycle	40 L	32 L	Jang et al. (2022); Srivastava et al. (2023)
Carbon Emissions (kg CO_2)	Based on the diesel emission factor (2.68 kg CO_2 per liter)	107.2 kg	85.76 kg	Szybist et al. (2021); Guo et al. (2022)
Delivery Time (minutes)	Estimated time, including traffic and stops	210 mins	180 mins	Shi et al. (2021); Martikkala et al. (2023)
Algorithm Convergence Time	Time required to reach an optimal solution in simulation	Not applicable	< 10 seconds	Chen et al. (2020); Heyken Soares et al. (2019)

3.5. Evaluation Criteria

The following are the criteria through which the simulation outputs are assessed

- Decrease The percentage of carbon smoke and fuel consumed.
- Optimization Efficiency, which is the reduction of routes per liter spared.
- Environmental Payback, which is CO 2 avoided emissions over standard routing.
- Performance of Algorithms, which are pegged on the convergence time and adaptability.

The metrics were normalized in three runs to make them statistically relevant.

4. Results

4.1. Overview of Simulation Outcomes

The simulation compared how three motor vehicles of the same height can be designed with an embedded AI-based route optimization model as Ant Colony Optimization (ACO), Neural Networks (NN), and Hybrid Genetic Algorithm (HGA) to reduce carbon emission and fuel consumption during the logistics activities. A comparison was made between each model and an existing baseline, which signifies a conventional process of routing that has not been conducted with AI assistance.

The results have demonstrated that the three AI methods significantly positively impacted sustainability. Optimized scenarios resulted in shorter routes and fuel consumption, thus reducing carbon. Of the methods tested, Hybrid Genetic Algorithms produced the best performance in all the indicators measured, and Neural Networks and ACO are close behind.

4.2. Comparative Analysis of Optimization Techniques

The implementation of each model was achieved through four performance indicators

- Distance of route and on-time delivery,
- The amount of fuel used to cover the routes,
- Emission of carbon when utilizing fuel,
- Percent changes of the initial baseline.

All techniques recorded a quantifiable improvement in such areas, and this provides feasible outcomes of interest to logistics companies aiming to adopt AI-driven solutions.

Table 3 Estimated Reduction in Fuel Consumption and Carbon Emissions by AI Model

Metric	Baseline (No AI)	ACO	Neural Network	Hybrid Genetic Algorithm (HGA)
Route Distance (km)	120	105	102	98
Fuel Consumption (liters)	40	33.5	32.1	30.8
Carbon Emissions (kg CO_2)	107.2	89.78	85.23	82.54
Reduction in Fuel (%)	–	16.3%	19.75%	23.0%
Reduction in CO_2 Emissions (%)	–	16.2%	20.5%	23.0%
Estimated Delivery Time (minutes)	210	185	175	170

4.3. Fuel Consumption Reduction

The amount of fuel consumed per route dropped continuously throughout all AI-powered approaches. The ACO model generated an average reduction of 6.5 liters per delivery route or a 16.3 percent improvement. The neural network model beat ACO by 19.75 percent, whereas the highest efficiency was realized in the HGA due to savings of up to 9.2 liters, or 23 percent of the baseline consumption. Such decreases are based chiefly on improved path selection, minimized inactivity, and a responsive approach to real-time priorities.

4.4. Carbon Emission Reductions

Carbon emissions were calculated using a standard emission factor per liter of diesel fuel. All AI models contributed significantly to emission reductions. ACO reduced emissions by 16.2%, Neural Networks by 20.5%, and HGA by 23.0%. These gains are closely aligned with the reductions observed in fuel usage, reinforcing the environmental advantages of intelligent logistics routing.

4.5. Route Efficiency and Time Optimization

Beyond the emission and fuel measures, the three AI models presented efficiency measures in the operations as well. Under ACO, the delivery time was cut by 185 minutes compared to the baseline average of 210 minutes; in contrast, under the Neural Networks model, the delivery time was shortened by 175 minutes and the HGA model by 170 minutes compared to the baseline average of 210 minutes. Such savings can be explained by more intelligent route decision-making, avoiding traffic jams, reducing traffic delays, and improving service and resource consumption efficiency.

4.6. Synthesis of Findings

The findings made it evident that route optimization powered by AI has a highly complex value

- Other significant decreases in the consumption of fuel and greenhouse gas emissions,
- Improvement in efficiency in routes and delivery time,
- Enhancement of agility to change conditions on the road.

All in all, the Hybrid Genetic Algorithm model proved to be the most efficient, which promised the most optimal—in terms of the environment and operating efficiency ratio. These results note the promise of artificial intelligence to become a revolutionary means of attaining goals in sustainable logistics.

5. Discussion

5.1. Interpretation of Results

Simulation findings indicate that avenues that integrate artificial intelligence into route optimization models can have substantial environmental and operational advantages. All three implemented AI methods, which included Ant Colony Optimization (ACO), Neural Networks (NN), and Hybrid Genetic Algorithms (HGA), proved to be more effective when it comes to achieving efficiency in terms of reduction of route length, fuel use, and carbon emissions. The performance of the Hybrid Genetic Algorithm model was the highest in all indicators, and this is attributable to its ability to facilitate a balance in the exploitation and exploration of the solution space, which is much reported in sustainability optimization environments [17].

The decrease in the average fuel consumption is directly converted into cost savings related to operation, where route length and delivery time cuts can be interpreted as a higher responsiveness to dynamic routing constraints. These results corroborate the earlier record that real-time AI decision-making is important for measuring logistical effectiveness [9]; [20]. Also, the reduced emissions performed through optimized routing are consistent with universal needs towards decarbonizing transport infrastructure, as shown in various emission governance papers [25]; [7].

5.2. Integration with Existing Literature

This study's results align with the general work on sustainable logistics and AI utilization. Trained neural networks on traffic and delivery data have been deemed to make route predictability and adaptability higher, and this finding contributes to that of others in earlier studies [2]; [13]. Similarly, the ACO model will continue to apply to constrained and repetitive routing problems like port operations and last-mile logistics [6].

The success of hybrid optimization algorithms, specifically HGAs, is similar to the results of digital transformation research, which emphasizes the significance of metaheuristic and predictive strategies to prevent ineffective logistics performance [17]; [12]. The advantage of these models is the utilization of real-time data to avoid excessive traveling, fuel consumption, and emissions, adjusting the logistics operation to the fundamental principles of circular economy and green supply chain management [18].

Sustainable logistics systems are now revolving around digital technologies such as AI, IoT, and data analytics that allow following precise routes, tracking vehicles, and making sound decisions, which is critical to the transportation industry [16]. The research confirms that route optimization is no longer a simple efficiency strategy but a key part of the world community geared towards decreased transport-related emissions.

5.3. Practical Implications

5.3.1. These outcomes provide a few operational lessons

- To the Logistic Operators: Implementing AI routing tools considerably decreases operating expenses and emissions. Compared to some traditional methods, real-time adaptive systems can better respond to delays and traffic congestion [1].
- To Technology Providers: There is a chance to roll out AI-enabled platforms, including GPS, telemetry, and predictive traffic data, to optimize end-to-end routing. The integration of past and current records will improve the operation of logistics support systems [2]; [8].
- To Policy Makers: The emission reductions observed in this study and the proof thereof should incentivize regulation regarding AI adoption in logistics. The development of carbon pricing instruments, digital infrastructure investments, and subsidies might stimulate greener transportation behavior [25]; [24].
- To urban planners: Urban Planners can incorporate smart city systems with AI-controlled logistics routing to alleviate traffic and enhance air quality. When connected infrastructure, including smart traffic light systems and EV charging networks, is integrated, efficiency will increase [16].

5.4. Challenges and Limitations

Nevertheless, even with good outcomes, a number of barriers still exist

- Data Quality and Availability: Availability of real-time, clean data is critical in the context of the performance of AI models. Performance evaluation metrics can be compromised in the case of AI work in environments with low data infrastructure [23].
- Scalability and Real-World Complexity: Simulations demonstrate their benefits; on the other hand, real-life applications should deal with legal, operational, and human issues that reduce efficiency [12].
- Technical Barriers: Neural networks and mix-and-match algorithms require a lot of computing power. This restricts the deployment of such solutions by small and medium logistical players who might not be very technical or have the hardware capacity [14].
- Multi-Objective Routing Trade-Offs: It is possible to optimize the routes for emissions or time only, but this does not necessarily satisfy customer preferences. Next-generation AI systems should be designed with a flexible ratio between competing objectives, including speed of delivery, pricing, and environmental costs [5].

These constraints make it necessary to implement it cautiously, context-dependently, and to further experiment in the field of operation.

5.5. Opportunities for Future Research

5.5.1. This study opens several future research directions

- Electrical vehicle routing and the combination of AI: AI can be applied in electric vehicles to measure battery capacity, highway indemnification, and topography for clean last-mile delivery [21].
- Cooperative AI Models: Exploring how AI can facilitate cooperation across supply-chain partners to minimize standard routing and avoid redundancy will improve network efficiency [12].
- Geographic-Dependent Models: It would be beneficial to encourage researchers to evaluate AI models in developing nations or complicated urban settings with insufficient logistics infrastructure, where logistics inefficiencies are at the highest [19].
- Integration With AI and Green Finance: AI-enabled route optimization may be integrated with green financing programs or carbon credit markets to promote sustainable transportation behaviors [10].

Overall, the conversation validates that AI-powered route optimization is a strategy well on the road to achieving environmental sustainability and efficiency in the logistics industry. With the rapid pace of digitalization, intelligent systems are becoming ever more vital in driving supply chain advancements for the benefit of our planet.

6. Conclusion

The use of artificial intelligence in optimum logistics routes for reducing carbon emissions and fuel—crucial elements of environmentally friendly transportation systems was examined in this study. A simulation-based performance comparison of three well-recognized AI models, i.e., ACO, NN, and HGA, showed that all the AI models achieved much better results than present-day routing in environmental and operational terms.

The Hybrid Genetic Algorithm was found to be superior among the investigated models, resulting in a 23% decrease in both fuel consumption and CO_2 emissions. Neural Networks and ACO also achieved very good performance; the savings were, on average, 16%—20%. These results confirm that AI in creative design and deployment techniques can improve route planning by reducing delays, reacting to current time constraints, and providing better resource solutions.

The review combined the results of empirical findings and literature. Past research proves that AI-based logistics systems contribute to two good environmental practices: delivery fulfillment speed, reliability, and customer satisfaction. Furthermore, the alignment of digital transformation to sustainability objectives is becoming clearer in the logistics space, particularly as global supply chains move to comply with climate adaptation frameworks and regulatory carbon reduction goals.

This study also provides practical implications for logistics companies that must open their doors to intelligent routing systems. The near- and long-term payoff can be equally significant—better cost efficiency today and a positive environmental impact tomorrow. Likewise, technology providers, policymakers, and infrastructure planners are needed to support these changes by building enabling ecosystems—from regulatory benefits and data-sharing platforms to the enabling infrastructure of smart cities that will facilitate connected transport systems.

Still, there are challenges. The scalability of AI in practice arises from—and is bounded by—issues of data quality, computational resources, and the ability to navigate trade-offs between environmental goals and commercial priorities. Overcoming these constraints will depend on multi-stakeholder engagement, continued research, and linking AI with wider sustainability and digitalization agendas.

In conclusion, this study highlights the role of AI in transforming logistics towards a low-carbon future. ADL and intelligent route planning form one of the pillars of climate-resilient transport planning. While environmental and operational constraints bind industries, the findings of this research can be argued to be a strong advocacy for the extensive deployment of AI technologies to provide sustainable operations in logistics.

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