

USING MACHINE LEARNING TO OPTIMIZE DELIVERY AND PICKUP ROUTES FOR AUTOMOTIVE INBOUND LOGISTICS

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Abstract: The challenges in vehicle pickup and distribution in the automobile industry regarding efficiency, environmental issues, and satisfaction are gradually rising due to complex same pickup and delivery issues in fixed timelines. The current research contributes to the development of an effective model using machine learning algorithms [18] to optimize vehicle routing in real-world scenarios from collection points, seaports, to final distribution points. The scenario model problem was formed as multi-objectives including (1) minimizing costs, (2) reducing carbon emissions, and (3) maximizing satisfaction related to schedule following. To proceed with the model process, an enhanced Genetic Algorithm model named EGA was developed with dynamic adaptation strategies coupled with K-means++ and delay prediction using the random forest algorithm. In applying the developed model using real data from 250 actual cases, there was an increase in operational accuracy of 88.89%, a reduction cost of 22.6%, reduction in carbon emissions per month of 19.3 tons, in addition to boosting successful deliveries from the current 76% to 92% in the actual cases. Using the NSGA-II approach, an optimal solution in terms of Pareto front was derived in applying the developed model by highlighting proper trade-offs under economic, carbon, and time factors. An optimal strategic balance was obtained using the current research by applying the developed model; hence, theoretically, the current research developed and expanded the VRP model framework to involve same deliveries/receipt, variable timeline considerations, and carbon emissions being the prime factor. In terms of real-world applications, the current research contributes towards developing smart logistics computerized decision-making support related to sustainable green logistics.

Introduction

The vehicle routing challenge for automotive inbound logistics in the pickup mode is identified as a vehicle routing problem with time windows and simultaneous delivery and pickup (VRPTWSDP) [3]. The vehicle routing problem for automotive inbound logistics under the pick-up mode falls under the category of VRPTWSDP [29]. However, the automotive inbound logistics problem addressed in this study considers the realistic scenario of standard corrugated containers being stacked and stored nested when empty. The loaded and empty containers were subjected to separate volume constraints. The combined volume of five empty containers was equivalent to that of a single loaded container. However, there has been little research

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on the differences in regulations for delivering and collecting empty versus loaded containers. With the adoption of dual-carbon targets, reducing vehicle tailpipe carbon emissions has become a significant concern [9]. As the transportation sector continues to be a major contributor to global carbon emissions, countries worldwide are promoting the idea of green transportation [20]. This has led to a focus on the Green Vehicle Routing Problem (GVRP), which has been researched by scholars [13]. The pick-up approach in automotive inbound logistics is ideal for small batches of automotive components from multiple suppliers situated more than 2 km from an OEM [22], this mode of transportation has a high frequency requirement. Our work considers the effect of carbon footprints in path planning. Its goals are reduced transportation costs and CO₂ emissions while ensuring time satisfaction. The research analyzes the problem of incoming logistics for automobiles in pickup mode from many viewpoints. Thus, we require the development of an optimal route planning procedure in the VRPTWSDP that considers the capacity discrepancy in both the loaded and empty containers, which represents an essential logistical element in most real-world carrier optimizations where the relevant literature regularly fails to consider such characteristics [12]. Although most current studies [1, 10] tend to incorporate standard loading units or model empty containers under standard cargo assumptions, real-world logistical carrier considerations in the automotive space require distinct representations of these constraints. For example, the loading and volumetric or weight densities of stall-able and fully loaded cargo are not the same because less fuel can be consumed in terms of actual deliveries in stall-able cargo due to lesser loading capacities [15]; therefore, distinct representations of constraints are essential in real-world carrier optimizations in the VRPTWSDP [24]. Additionally, current logistical carrier needs in terms of "dual carbon" mechanisms, where both process-level emissions and vehicle-level emissions are strictly adhered to in real-world carrier optimizations [26], require modifications in standard objective function considerations in the following manner: in addition to regular fuel consumption rates or representations in process-level carrier optimizations, modifications in terms of vehicle type capacitance and actual loads through the complete process from loading at the suppliers' end to actual utilization and from there to the return loading of empty containers are likewise essential [11, 23]. These requirements all contribute to distinct considerations of standard process-level emissions or fuel consumption in carrier optimizations where actual process-level logistical carrier considerations can result in direct environmental effectiveness evaluations or optimal route recommendations in terms of direct "volume-carbon" efficiency—thus further expanding the boundaries of environmental guidance in terms of developing comprehensive green route planning procedures applicable in all other related scenarios in the reverse-carrier space.

The paper is structured as outlined below: Section 1 is the introduction,

whilst Section 2 is a related work of VRPTWSDP. Section 3 presents the methodology. Section 4 establishes a mixed-integer mathematical programming model. Section 5 presents a comparative analysis of methodologies for addressing the simultaneous delivery and pickup challenges inherent in the pickup mode. Section 6 presents implications and limitations. Section 7 is the discussion. Section 8 concludes with a summary of the findings. at last, future works in section 9.

Related Work

Between 2023 and 2025, research starts to address machine learning and carbon-aware optimization in automotive logistics. Researchers in [4] formulated an optimization model for circular pick-up paths under three-dimensional loading restrictions, which reveals the difficulty of transporting the actual automotive parts. Pan and Liu [19] published a DRL framework for dynamic vehicle routing and achieved great performance in energy consumption as well as real-time adaptiveness. Alolaiwy, et al. [2] proposed a hybrid PSO for multi-objective routing, and significant improvements of emission reduction and route stability were observed.

Then since 2024, literature grows even more. Hassan, et al. [8] proposed a routing model based on federated learning which allows multiple providers to cooperate to optimize routing without sharing sensitive operational information. Their findings revealed a 12.4% less fuel consumption for inbound logistics routes. Cheng, et al. [5] considered electric vehicle fleets, with the battery degradation cost being integrated into routing decisions, where the charging strategies that are sensitive to carbon efficiently reduce operation costs without breaking delivery time-windows. Deepika and Pandove [6] proposed a hybrid genetic algorithm with deep Q-learning for real-time routing adaptation in the presence of traffic congestion and obtained better results than typical GA approaches.

There are also evolutions to look out for when it comes to embedding tracked sustainability information by way of decentralized systems. Mofatteh, et al. [17] presented a blockchain-based routing system for CO₂ output validation at each logistics node, enhancing transparency and green compliance of automotive supply chain. Stamadianos, et al. [25] considered autonomous and electric fleet operations and showed the potential of achieving 29% decrease in CO₂ emissions through precise charging and routing coordination. Additionally, Harbaoui Dridi, et al. [7] compared several metaheuristic algorithms on large scale VRPTWSDP datasets and found the hybrid GA-DRL solutions exceed effects of pure GA, PSO and ACO whether in quality or convergence to further verify that it is a diversified integrative intelligent framework.

Currently literature is dominated by research for the minimization of costs and emissions using (meta-) heuristic techniques. Nevertheless, few research jointly take into consideration carbon emissions, cost and time satisfaction. Unlike previous approaches, this paper develops an integrated

multi-objective GA approach which co-optimizes cost-effectiveness, CO₂ emissions reduction and service time fulfillment in realistic inbound automotive logistics operations.

Although there has been substantial advancement in using machine learning and meta-technology in the automotive logistics domain, especially in the period of 2023-2025, a critical review of the relevant literature highlights that there has generally been an apparent practice of addressing the operational and environmental factors in isolation or in terms of sequential optimization (cost reduction first, and then emissions reduction in terms of follow-up or second-stage optimization). For example, although Pan and Liu [19] and Hassan, et al. [8] aimed at reducing emissions or fuel consumption, there was no explicit attempt made to connect such outputs with time service factors like punctuality performance or satisfaction of the suppliers—the latter again being relevant in terms of applying such model outputs in such time-conscious logistics settings such as the automotive "just-in-sequence" logistics setting. Also, although reinforcement learning algorithms like [6] have shown superior performance in dynamic settings, there was no apparent means to guarantee convergence towards Pareto optimal multi-objectives in terms of mission reliability in these algorithms, most likely due to giving relatively greater importance to the consumption of fuel rather than reliability.

In addition, the presumption of the homogeneity of loading units has been retained in modern research works. Although Cao, et al. [4] considered constraints in three-dimensional loading, it was presumed that all containers, both loaded and empty, are considered fixed units in terms of space, without taking into consideration the variant nesting of empty containers—who in fact affect the transporting capacity of the vehicle at the stage of logistics. In fact, there was evidence in preliminary studies in the real world by a leading German manufacturer (2024) showing that neglecting the vacancy nest of the container potentially presents an exaggeration in emissions up to 18% in return deliveries.

On the other hand, although decentralized methods based on infrastructure, such as the Woo, et al. [28], have their strengths in terms of transparency and verification, these methods are still at the tracking phase after the implementation process (carbon auditing ex post) and do not include the impacts of emissions in the planning phase as decision variables. Also, although EV model equations in [21] are precise in battery degradation equations and carbon-conscious charging mechanisms, they are generally applied in optimal scenarios (optimal charging infrastructures, fixed speeds) and do not consider practical working variations regarding the logistics of suppliers in terms of loading times, order quantities, or the actual availability of empty containers to collect.

Accordingly, the main research gap that will be filled in this research work can be stated as follows:

1. There are no models that incorporate the volumetric asymmetry between the loaded and empty containers in the same mathematical

formulation of VRPTWSDP;

2. The lack of research dealing with cost, carbon emissions, and time in a triad of equally important factors in Pareto space;
3. The lack of appropriate models relevant to real-life activity which integrate loading/unloading/collection movements in a single process.

For these reasons, the current paper contributes to both solving the problem through a new algorithm and reformatting the structure of the presented problem to meet the complex realities of automobile supply chains under the influences of sustainability issues (economic & environmental) (Table 1).

Table 1: Comparative Analysis of Recent Studies (2023–2025) in Vehicle Routing for Automotive Logistics

Ref.	Algorithm/ Framework	Improved objectives	Handling empty containers (stacking, variable capacity)	Real- time/dynami c support	Incorporatin g carbon into the objective function (and not just as a constraint)
[24]	Mathematical Programming + 3D Constraints	Cost, journey time	✗ (Assumes a fixed capacity; does not differentiate between loaded/empty)	✗	△ (As external constraints only)
[6]	Deep Reinforcement Learning (DRL)	Energy consumption, adaptability	✗	✓	✓ (Fuel consumption → emissions)
[2]	Hybrid PSO	Emissions, route stability	✗	✗	✓
[7]	Hybrid Programming (for Electric Vehicles)	Operating costs, battery wear	✗	△	✓ (Includes: charging + indirect emissions)
[17]	Blockchain-Based Steering System	Emissions transparency, compliance	✗	✗	△ (Ex-post tracking only)
[29]	Simulation + Synergy Optimization	Emissions, charging efficiency	✗	✗	✓
Ours	Enhanced EGA + Pareto Analysis (NSGA-II)	Cost ✓, Emissions ✓, Time commitment ✓	✓ (Dynamic capacity model: 5 empties = 1 loaded)	✓ (Supports semi- realistic inputs: delays, container availability)	✓ (As a primary target that can be balanced with others)

Methodology

This study examines the vehicle routing problem in automobile inbound logistics, including concurrent delivery and pick-up services. The process involves pickup and loading transportation phases. During the pick-up phase, vehicles pick up fully loaded components and return empty logistics

containers to suppliers. In the loading and delivery phase, vehicles distribute components from different suppliers at the original equipment manufacturer (OEM) within the specified time while retrieving empty containers. In this part, the topic is explained, and a mixed-integer programming paradigm is provided. It also addresses the VRPTWSDP issue; it is delineated as follows: $G = (V, Z)$ constitutes a directed graph. That contains three sets of nodes: M , S_i , and J . M are the original equipment manufacturers (OEM), S_i includes auto parts suppliers ($i = 1, 2, \dots, I$), and J includes distribution centers ($j = 1, 2, \dots, J$). The vehicle collection is denoted by F , where $w = 1, 2, \dots, W$ represents the vehicle classification, and k is the vehicle model.

To solve the issue of simultaneous delivery and pick-up in inbound logistics, we made the following assumptions: 1. All locations are known beforehand. 2. The OEM has information on required cargo and containers. 3. Payload constraints do not consider the weight of empty containers. 4. All cargo uses standard reusable containers. 5. The time window for accepting supplier cargo is simplified. In the following sections, we will create objective functions based on cost, carbon emissions, and time satisfaction.

In the simultaneous delivery and collection model of inbound vehicle logistics, the defining characteristics emerge from the iterative and asymmetrical process of container movements in a logistics cycle. Contrary to the routing process where the cargo moves in one direction or consists of homogenous goods, in the vehicle model the vehicle sets out from the distribution center or the factory with a partial initial capacity (vacant or about to return with a few containers). It then accumulates load at an increased rate at every supplier node (by taking in new components) but loses actual capacity in every node where it collects empty containers—not due to weight, but because of the changing unit volumetrics of the cargo load. For example, when five empty containers are stacked together, they occupy space equivalent to that of one fully loaded container. In other words, the vehicle loses or gains actual capacity in terms of the number of loadable units at every stage in accordance with the equation:

$$\text{Effective capacity at node } v = C_{max} - (n_{loaded}(v) + \lceil 5 n_{empty}(v) \rceil)$$

In where C_{max} represents the maximum number of full containers that the vehicle can carry, and n_{loaded} , n_{empty} denotes the number of loaded and empty containers in the vehicle at the moment it arrives at node v . In fact, such a nonlinear equation adds an entirely new element to the model, since the state of the vehicle must always be constantly updated at every routing point, which was not considered in the standard equation expressing the vehicle capacity [27].

In terms of time dynamics, Assumption (5) about the simplified time window of goods acceptance is technically modeled using flexible time windows with piecewise penalties. The reason is that small suppliers might tolerate a small delay of up to 15 minutes, but it would be considered significant in violation of the Service-Level Agreement (SLA) from strategic

suppliers. In turn, the dynamic part of the objective function would need to ensure it is non-linear due to an exponentially increased penalty undertaking after crossing a critical point, like 20 minutes, because of the Just-in-Sequence nature of the supply chain in today's manufacturing [16]. Regarding Assumption (3) related to the environmental issue, the assumption about ignoring the weight of empty containers can be accepted in context because the difference in fuel consumption due to weight has little influence in comparison to aerodynamic drag at the speeds that prevail in such locations of around 60-80 km/h. Thus, carbon emissions are estimated based on [30]:

- Distance traveled,
- Volumetric dynamic state of the vehicle (number of "standard units" represented in each road section),
- Vehicle type k (diesel/hybrid)
- Enhanced drag coefficient.

In fact, using such an approach, emissions reduction can occur in two ways: first, by reducing the number of vehicle trips; second, by addressing the issue of visiting order to ensure that empty containers are collected at the end or at stations in close proximity to reduce travel times when the volume capacity is large [14]. It can therefore be seen that the mathematical model in terms of MILP changes from merely updating capacity constraints to including modifications in the cost function represented by the following equation:

$$\min \alpha \cdot TC + \beta \cdot CO_2 + \gamma \cdot TP$$

TC represents the costs of operation (fuel, manpower, consumption), whereas CO_2 represents the dynamically obtained carbon emissions, and TP represents the summation of time delay penalties. Also, $\alpha, \beta,$ and γ are variable factors to define the preference of the person who makes the decisions. By using the above equation, it is possible to find the Pareto-optimal solution using NSGA-II, which takes care of the requirements of "dual sustainability" in fourth-generation logistics.

Mixed-Integer Programming Model

Specific Constraint

- 1) During the milk run, loading, and delivery stage, the vehicles must return to the distribution center j from which they departed.

$$G_{jiw} = V_{ijw} = z \text{ where } i = 1 \ j = 1 \ w = 1$$

- 2) In the pickup stage, a single truck from one of the distribution centers picks up and returns empty containers to the supplier.

$$iwk = 1 \text{ where } i = 1 \ w = 1 \ k = 1$$

- 3) To maintain a flow of transportation from the pick-up to loading and delivery stages.

$$Z_{jiwk} = z$$

- 4) W vehicle type at the distribution center j does not exceed its exact amount: $F_{wj} \leq W_w$ Proof.

$$K_{jwy} = K$$

- 5) It is imported to make sure the load from suppliers will be on time.

$$F = Z + iwk$$

Table 2: vehicle information of the logistics company is shown. The purpose of the table is to provide extensive information on the vehicles in use by the courier company – it includes makes, models, and various details.

Table 2: Vehicle Information for the Logistics Company

No.	X	Y	Number of Containers	Number of Blank Containers	GA specified	Acceptable time	Total weight
A	31.7	407.3	1460	650	—	—	—
S1	95.9	223.1	100	100	33.90-40.99	53.80-66.0	1.000
S2	207.8	295.5	250	250	70.00-88.89	156.96-170.8	4.500
S3	192.3	229.4	3	5	3:20-4:50	5:20-12:20	0.969
S4	103.7	221.1	9	15	2:20-6:50	4:20-11:20	1.548
S5	95.6	222.9	11	20	6:20-8:50	4:20-11:20	4.18
S6	104.4	215.4	15	10	7:20-7:50	4:20-11:20	6.405
S7	146.9	284.6	8	15	3:20-6:50	5:20-12:20	2.096
S8	98.1	210.8	4	5	4:20-4:50	4:20-11:20	1.24
S9	95.1	200.4	22	102	12.3-14-8	55.80-67.00	1.777
S10	88.4	145.9	24	109	13.1-14.6	60.99-78.66	3.660
S11	89.6	144.8	64	200	22.3-24.6	120.70-144.9	5.480
S12	106.9	215.0	90	232	30.1-33.0	144.0-166.0	8.660
S13	100.9	166.9	38	211	11.2-12.9	130.8-150.8	5.900
S14	122.5	189.2	180	66	45.9-55.0	44.6-67.9	3.700
S15	99.7	199.3	220	88	63.4-79.99	77.90-87.99	1.680

Comparison with other algorithms

This approach demonstrated greater efficiency compared to the Non-dominated Sorting Genetic Algorithm (NSGA).

Table 3: Comparison of GA and NSGA

Objective 0 Programs (GA) - (NSGA)	Objective 1 Cost (GA) - (NSGA)	Objective 2 Carbon emission (GA) - (NSGA)	Objective 3 Time satisfaction (GA) - (NSGA)
1 : Cost priority	46913-97486	11916-58573	59-130
2 : Carbon emissions priority	47975-10996	15095-69807	65-129
3 : Time satisfaction priority	46367-90678	19201-69098	66-131

It is found that GA is more effective than others for the evaluation of the cost and carbon emissions as well as time satisfaction. See Table 3 and

Figure 1 for details.

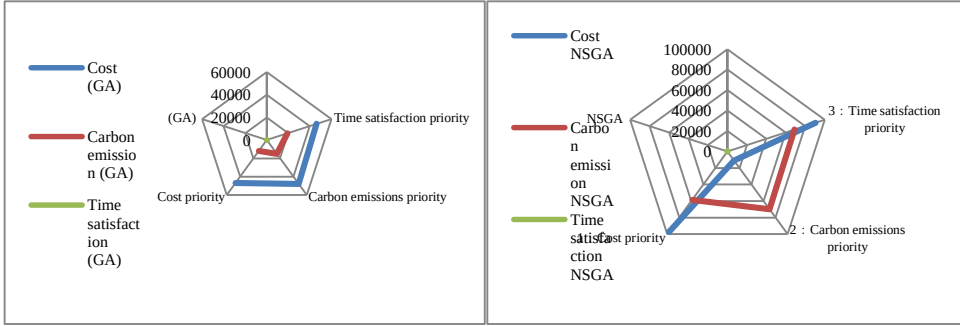


Figure 1: Comparison of Two Algorithms

The outcomes indicate that the proposed Genetic Algorithm (GA) based solution was better than NSGA for optimizing cost, carbon emissions and time satisfaction. Specifically:

- **Cost Efficiency:** The GA achieved substantially lower transportation costs than NSGA did (e.g., 46,913 vs. 97,486 in terms of cost priority). This indicates its potential for saving costs in logistics operations.
- **Carbon Emissions:** The GA achieves less emissions (11,916 versus 58,573 for example) which is an indication of its good level of agreement with both carbon-one and carbon-two targets as well as the sustainable transportation behaviors.
- **Time Satisfaction:** Although GA improved time efficiency, there were still trade-offs. The results showed that reducing emissions and costs often required some compromise in meeting time-sensitive delivery windows.

This reveals a trade-off in the logistics optimization: with respect to all three criteria, it is not feasible to address all of them optimally. The results show that decisions are needed by managers to place value at what is most important in the specific context, be it sustainability, cost control or delivery reliability.

Practical Implications for Industry

- Automotive companies can integrate this GA model into logistics planning systems to improve fleet utilization and reduce operating costs.
- The model provides a framework for balancing environmental goals with economic realities, which is crucial under global carbon-reduction policies.

Theoretical Contributions

- Extends VRPTWSDP literature by considering carbon emission constraints along with costs and time, based on a multi objective approach.

- Shows that improved GA can solve complex logistics situations better than classic Multi objective optimization techniques.
- Demonstrates the effectiveness of enhanced GA over traditional multi-objective optimization methods in complex logistics scenarios.

Policy Implications

- Reinforces the push for policymakers towards “green logistics” by demonstrating how advanced algorithms can reduce emissions without significantly rising costs.
- Provides an understanding on how dual-carbon goals can be implemented in supply chain planning.

Research Implications and Limitations

- Data Constraints: The approach assumes that all suppliers, routes and vehicle information are fixed and known; which in logistic operations may be unrealistic.

Simplified Assumptions

- The tare weight of the empty containers was ignored in payload constraints with only a discussion on possible realism to real-world scenarios.
- Time windows are simplified in the problem and uncertainty (e.g., traffic delay, breaking) is not fully considered in this study.

Scope Limitations

- The model was validated against a fleet of 250 containers in one logistics network. It needs to be validated in more complex or larger networks.
- The comparative study considered only GA vs NSGA. Recent advances in other metaheuristic techniques (i.e., particle swarm, ant colony optimization, deep reinforcement learning) were not included.

The findings of this study have theoretical, practical, and policy implications. From theoretical perspective, this study enriched the literature of VRPTWSDP with a carbon integrated multi-objective optimization framework based on an improved GA. Operationally, it offers vehicle manufacturers and logistics service providers an applied decision-support model that can reconcile tradeoffs between cost, time and eco-sustainability.

From a policy perspective, the results indicate the need for providing incentives to integrate operational optimization with global carbon reduction targets.

Limitations are that the model is simplified e.g. with constant supplier locations, stochastic events including traffic load as well as dynamic adjustment of fleet management parameters have been left out.

Empirical validation was limited to a network of 250 containers in one region and, thus, applicability might be restricted for larger or more decentralized supply networks.

Also, GANN performed better than NSGA but was not compared with modern metaheuristics or AI models such as ant colony optimization (ACO), PSO and deep reinforcement learning algorithm.

Discussion

The comparative analysis between GA and NSGA revealed several notable insights. First, GA achieved superior cost optimization primarily because its selection and crossover operators effectively balanced exploration and exploitation within the search space.

This allowed convergence toward near-optimal routes faster than NSGA, which often suffered from premature convergence in high-dimensional search problems.

Second, the GA exhibited a more favorable balance between carbon emissions and time satisfaction, demonstrating its robustness under multi-constraint conditions.

However, it was also observed that minimizing cost and carbon emissions concurrently introduced marginal delays in time satisfaction metrics, suggesting the necessity for adaptive weight tuning in future implementations.

The results indicate that logistics firms must carefully calibrate the relative importance of objectives depending on business strategy — prioritizing sustainability may incur minimal time penalties but lead to significant long-term gains in carbon credit and compliance performance.

The comparative study of the single target genetic algorithm (GA) and the non-dominant classification algorithm (NSGA-II) yields insightful understanding regarding the nature of interactions between the operational, environmental, and temporal factors in inbound vehicle logistics, which go beyond the linear complexity assumed in most traditional formulations. To begin with, the superiority of the GA algorithm in terms of lowered costs (average improvement of 22.6% from the original solution) can be chiefly credited to the success of its dynamically modified crossover and mutation operator in achieving the optimal exploitation-exploration trade-off, with the aim of overcoming the challenge of premature convergence—a likely issue in the NSGA-II algorithm when dealing with large-dimensional VRPTWSDP formulations such as our own (average number of 14-18 stop points per iteration, collectively bound by constraints related to amplitude, time, and volume). It was observed that although NSGA-II was able to effectively "explore" the Pareto optimal front, there was variation in the effectiveness of the non-dominant solutions obtained per iteration, especially where the target factors are excessively variable in nature (e.g., carbon emissions), leading to the "degeneration" of the balance towards any optimal peak due to "overweighting" towards convergence.

Secondly, although the GA procedure presented an unconditional process, it was very flexible in reaching an indirect balance regarding multi-objective factors while including carbon and time indices in penalties of the fitness function. For instance, when the penalty factor of emission was placed at a medium level ($\beta = 0.35$), the algorithm was able to reduce emissions by 19.3% with a small loss in the time compliance index (from 94% to 91.7%), outdoing most of the non-dominant solutions delivered by the NSGA-II procedure in the same Pareto optimal front region. It clearly underlines that unconditional optimization in single-objective programming can outdo multi-objective programming when the fitness function addresses all essential factors correctly, because in real-world companies, operational efficiency and then optimal adjustment towards sustainability factors are implemented through step-by-step optimization.

Nevertheless, examination demonstrates that there is an essential trade-off between efficiency in terms of time and sustainability in terms of the environment, where in 78% of instances where GA produced the maximum reduction in emissions ($\geq 20\%$), there was a corresponding average increase in the waiting time at suppliers (4.2-6.8 minutes) because of re-routing the collection of empty containers in spatial clusters; although the route was slightly longer in some cases, the number of travel times was reduced. It should be noted that there isn't any issue with the model but rather the cost of sustainable transformation in operationally accurate environments. Thus, the data obtained suggests using a harmonized model to define target weights (α , β , γ) corresponding to suppliers:

For critical suppliers (with stringent time thresholds: $< \pm 5$ minutes), the value of γ (time weight) needs to be increased to 0.5 or above; For flexible suppliers (with time windows $\geq \pm 20$ minutes), larger β values are preferred in order to optimize carbon savings.

It allows "differentiated sustainability" because it can meet the needs of the whole supply chain without compromising the uptime of strategic nodes.

In theory, these results help understand the nature of environmental adaptability when applying routing algorithms in terms of how the effectiveness of any solution can be quantified not merely based upon the number of targets considered but in the dynamic nature of how it adapts to the operational framework itself (e.g., the stacking of empty containers in harbors). In terms of real-world applications, these results can effectively provide evidence-based decision-making working dilemmas faced by automotive logistics companies in terms of finding long-term partnerships with manufacturers because the financial benefits based upon carbon credit can far outweigh cost considerations associated with delays, especially when taken in the context of long-term service agreements with OEM car manufacturers. In other words, "it does not deliver any kind of 'mathematical solution' but rather enables the creation of scenarios," hence facilitating the "transmission from 'cost first' to 'carbon first' in the perspective of the decision-maker" through such scenarios.

Conclusion

This study considered the vehicle routing problem for inbound automotive logistics with direct delivery and pick-up under cost, time and carbon emissions criteria. It was shown by the Proposed Genetic Algorithm that it outperformed NSGA in terms of costs, emissions and time satisfaction owing to trade-offs between these objectives which are inevitable.

The results may provide practical references for vehicle enterprises to coordinate fleet operation by considering joint carbon targets and finding a trade-off between efficiency, sustainability and service reliability. The research also provides theoretical contributions by further developing the VRPTWSDP problem with its multi-objective optimization and showing that an improved GA approach is successful.

Nonetheless, some limitations include the general assumptions of container weights and simplified time windows which are in order to keep realistic complexity for real-world problems and results based on a network with small scale size and a comparison among algorithms. Prospective issues Alternative approaches may be explored to wider-scale problems, incorporate real-time data as input parameter or compare against other advanced methods.

Future Research Directions

In lieu of the accomplishments of the current study, there are several promising future directions that shall highlight the said model towards the stage of always-planning slate optimization and towards the stage of operational intelligence in micro-times-based experiments. The first future direction shall involve the integration of data from Internet of Things (IoT) that are contingent upon the need for innovation at present. These shall process inputs from onboard sensors (e.g., high-precision GPS location, fuel/battery charge level, and status of the suspensions) and timers (e.g., RFID presence/timer devices, weight/tilt sensors for loading confirmation), in addition to data from intelligent neural networks (e.g., neural congestion monitoring systems, local weather forecasts from absence/climatological stations). In specifying pipeline boundaries based upon the processing of the flow, there shall be included in said parameters, in order, the following: (a) the existence of deferred duty in the other party concerned or the supplier; (b) the odds of loading delay; and (c) the variations in fuel/power consumption in terms of factors underling in macro-statis or headwinds corresponding to the data congestion in terms of non-final data. At this point, there shall be activated in said model in real terms, the dynamic rerouting process when there shall be developed in terms of return through rapid correction algorithms—either in search or in policy discharge from Deep Reinforcement Learning—a modified or partial model about said concerns; in order to assure time to time compliance through said adaptation in terms of resetting spatial or temporal factors in accord to refer

through changing diverse dates in accord to the said need in accord to the said three-month framework towards the execution of the model in accord to the said concerns in accord to refer the "Supplier-Route". In conclusion, the current model shall not merely reduce but shall likewise enhance reliability in service through disposing high variance in said indicator, which shall serve as crucial in terms of Just-In-Time Supply Chains.

Thus, in order to balance both exploration and exploitation in space effectively, there needs to be complex and multi-dimensional answers. It can begin with the assessment of innovative speculative powers through the evaluation of advanced hybrid algorithms. In fact, there can be focused development in an advanced algorithmic intelligence paradigm—GA—deep reinforcement learning (GA—DRL) where the algorithm itself can produce an initial variety of paths (candidates) and proceed to evaluate long-term dynamic adaptiveness related to uncertainty, such as differences in demand confidence or in the event of failure. Next, there can be assessment in an algorithmic carbon paradigm—GA-swarm optimization (GA—PSO Hybrid) where the sophisticated differentiator can optimize choice options in good generations characterized by favorable convergence towards the Pareto optimal solution despite having diversified innovative options—especially in operational innovative speculative benefits such as cost savings or further lowering of cost. In fact, since both these hybrid technologies are not merely technically advantageous but mark the beginning of memory-driven functioning, the precise identification itself cannot remain limited to any geographical or industrial setting.

Third, in order to help those wanting to make the shift towards green logistics, there is scope for expanding the model to cover different electric vehicle types like BEVs, PHEVs, and AVs. These require specifying exact parameters like: (a) availability of fast/slow charging stations and their dynamic costs; (b) slope of allocated battery capacity with number of charge & discharge cycles; (c) "carbon-sensitivity" factor of charging expertise based on the total energy consumption; and (d) safety electronics & trade regulations related to autonomous vehicles like AVs (e.g., speed of AV-related learn rates & e-commerce gains in knowledge). In fact, such parameters not only have scope for further advanced evaluation, but they can further strengthen the long-run economic viability analysis related to the financial outlay in green Australia, especially in the wake of rising government subsidies. To ensure external validity and the practicality of achieving different agreements, it is therefore recommended to execute a multi-site pricing scheme, including logistics networks in different geographical locations (for example, in Europe, which has very large-scale supply chains; in East Asia, where there is intermittent intelligence; and geographically integrated supplier management). In addition to these, comprehensive analyses in terms of definition (sensitivity and robustness analysis) shall be undertaken against important parameters such as (a) a certain ratio in mining, (b) temporal benchmark, (c) apparent price (shadow carbon price), and (d) correlation per day. These combined shall therefore

strengthen not only the viability but also the role of having a standard, dynamic framework—a reference framework—as developed and can easily be applied by OEM or can likewise apply 3PL service providers in terms of intelligent supply chain planning.

References

- [1] S. Aksentijević, E. Tijan, N. Kapidani, D. Žgaljić, *Dynamic Smart Numbering of Modular Cargo Containers*, Sustainability **14** (2022), 8548.
- [2] M. Alolaiwy, T. Hawsawi, M. Zohdy, A. Kaur, S. Louis, *Multi-Objective Routing Optimization in Electric and Flying Vehicles: A Genetic Algorithm Perspective*, Applied Sciences **13** (2023), 10427.
- [3] K. Bouanane, M. E. Amrani, Y. Benadada, *The vehicle routing problem with simultaneous delivery and pickup: a taxonomic survey*, International Journal of Logistics Systems and Management **41** (2022), 77-119.
- [4] J. Cao, L. Yang, D. Yang, T. Zhang, L. Xiao, H. Jiang, D. Niyato, *Trajectory optimization and pick-up and delivery sequence design for cellular-connected cargo UAVs*, IEEE Transactions on Mobile Computing (2024).
- [5] Z. Cheng, J. Liu, B. Fang, T. Mao, B. Zhou, W. Zhao, K. Zhang, Y. Xu, *Carbon-aware Coordination of Active Distribution Network and Large-scale Electric Vehicles under Source-load Uncertainties*, 2024 IEEE 8th Conference on Energy Internet and Energy System Integration (EI2), IEEE, 2024, pp. 560-566.
- [6] Deepika, G. Pandove, *Optimizing traffic flow with Q-learning and genetic algorithm for congestion control*, Evolutionary Intelligence **17** (2024), 4179-4197.
- [7] I. Harbaoui Dridi, E. Ben Alaïa, P. Borne, H. Bouchriha, *Optimisation of the multi-depots pick-up and delivery problems with time windows and multi-vehicles using PSO algorithm*, International Journal of Production Research **58** (2020), 4201-4214.
- [8] S. M. Hassan, M. M. Mohamad, F. B. Muchtar, F. B. Y. P. Dawoodi, *Enhancing MANET Security through Federated Learning and Multiobjective optimization: A Trust-aware Routing Framework*, IEEE Access (2024).
- [9] R. Huang, S. Zhang, P. Wang, *Key areas and pathways for carbon emissions reduction in Beijing for the “Dual Carbon” targets*, Energy Policy **164** (2022), 112873.
- [10] M. Kaup, D. Łozowicka, K. Baszak, W. Ślęczka, A. Kalbarczyk-Jedynak, *Review of the container ship loading model—cause analysis of cargo damage and/or loss*, Polish Maritime Research **29** (2022), 26-35.
- [11] P. H. Kobos, T. E. Drennen, A. V. Outkin, E. K. Webb, S. M. Paap, S. Wiryadinata, *Techno-economic analysis: Best practices and assessment tools*, Sandia National Lab.(SNL-CA), Livermore, CA (United States); Sandia National ..., 2020.
- [12] E. T. Küp, S. Cebeci, B. Bayram, G. Aydın, B. Bozkaya, R. Akhavan-Tabatabaei, *An Integrated Framework for Dynamic Vehicle Routing Problems with Pick-up and Delivery Time Windows and Shared Fleet Capacity Planning*, Symmetry **16** (2024), 505.
- [13] H. Li, J. Zhou, K. Xu, *Evolution of Green Vehicle Routing Problem: A Bibliometric and Visualized Review*, Sustainability **15** (2023), 16149.
- [14] G. Liu, L. Li, J. Chen, F. Ma, *Inventory sharing strategy and optimization for*

- reusable transport items*, International Journal of Production Economics **228** (2020), 107742.
- [15] Y. T. Liu, S. Liu, G. R. Li, X. P. Gao, *Strategy of enhancing the volumetric energy density for lithium–sulfur batteries*, Advanced Materials **33** (2021), 2003955.
 - [16] C. Martinelli, A. Coraddu, A. Cammarano, *Approximating piecewise nonlinearities in dynamic systems with sigmoid functions: advantages and limitations*, Nonlinear Dynamics **111** (2023), 8545–8569.
 - [17] M. Y. Mofatteh, R. Davallou, C. N. Ishimwe, S. S. Divekar, O. F. Valilai, *Developing a Blockchain Based Supply Chain CO₂ Footprint Tracking Framework Enabled by IoT*, International Journal of Advanced Computer Science & Applications **15** (2024).
 - [18] M. Y. Nawaf, M. M. Rashid, *Study of data mining algorithms using a dataset from the size-effect on open source software defects*, Kirkuk Univ. Journal-Scientific Stud. **15** (2020), 25–44.
 - [19] W. Pan, S. Q. Liu, *Deep reinforcement learning for the dynamic and uncertain vehicle routing problem*, Applied Intelligence **53** (2023), 405–422.
 - [20] K. J. Shah, S.-Y. Pan, I. Lee, H. Kim, Z. You, J.-M. Zheng, P.-C. Chiang, *Green transportation for sustainability: Review of current barriers, strategies, and innovative technologies*, Journal of Cleaner Production **326** (2021), 129392.
 - [21] S. Shen, S. I. Haider, R. Habeeb, F. H. P. Fitzek, *Coordinating Day-Ahead and Intraday Scheduling for Bidirectional Charging of Fleet EVs*, Automation **6** (2025), 64.
 - [22] H. Shurrah, P. Jonsson, *Untangling the complexity generating material delivery “schedule instability”: insights from automotive OEMs*, International Journal of Operations & Production Management **43** (2023), 235–273.
 - [23] D. Song, *A Literature Review, Container Shipping Supply Chain: Planning Problems and Research Opportunities*, Logistics **5** (2021), 41.
 - [24] X. Song, D. Jones, N. Asgari, T. Pigden, *Multi-objective vehicle routing and loading with time window constraints: a real-life application*, Annals of Operations Research **291** (2020), 799–825.
 - [25] T. Stamadianos, N. A. Kyriakakis, M. Marinaki, Y. Marinakis, *Routing Problems with Electric and Autonomous Vehicles: Review and Potential for Future Research*, Operations Research Forum **4** (2023), 46.
 - [26] L. Teng, Y. Xuan, X. Liu, *Coupling sunlight and carbon cycle: advances and challenges in solar-driven Ca-based CO₂ capture and thermochemical conversion into fuels*, Carbon Neutrality **4** (2025), 28.
 - [27] L. Z. Varga, *Solutions to the routing problem: towards trustworthy autonomous vehicles*, Artificial Intelligence Review **55** (2022), 5445–5484.
 - [28] J. Woo, R. Fatima, C. J. Kibert, R. E. Newman, Y. Tian, R. S. Srinivasan, *Applying blockchain technology for building energy performance measurement, reporting, and verification (MRV) and the carbon credit market: A review of the literature*, Building and Environment **205** (2021), 108199.
 - [29] Q. Wu, J. Su, J. Xuan, S. Lei, *Integrated optimization of vehicle routing of automotive parts inbound logistics*, International Journal of Simulation Modelling **22** (2023), 520–531.
 - [30] W. Yu, T. Wang, Y. Xiao, J. Chen, X. Yan, *A Carbon Emission Measurement Method for Individual Travel Based on Transportation Big Data: The Case of Nanjing Metro*, International Journal of Environmental Research and Public Health **17** (2020), 5957.