# Multi-Objective Logistics Route Optimization Using a Physics-Informed Neural Network-Assisted Genetic Algorithm

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*Modern logistics distribution systems require simultaneous optimization of transportation cost, delivery time, travel distance, and energy consumption under vehicle capacity and time-window constraints. Conventional genetic algorithm (GA)-based routing approaches rely on penalty-based constraint handling and static fitness evaluation, resulting in unstable convergence and reduced scalability for high-dimensional, multi-objective vehicle routing problems (VRPs). This study proposes a Physics-Informed Neural Network Assisted Genetic Algorithm for Logistics Route Optimization (PINN-GA-RouteOpt), integrating physics-regularized learning with adaptive evolutionary search. The proposed framework embeds vehicle motion dynamics, fuel–distance nonlinear relationships, and service time-window constraints into a physics-informed neural network (PINN), where the fitness function is formulated as a composite objective minimizing transportation cost, total travel time, route distance, and energy consumption. The PINN is trained using a hybrid loss function combining supervised data loss and physics residual loss derived from motion and fuel-consumption equations, thereby generating constraint-consistent fitness landscapes. An improved GA with adaptive mutation and dynamic crossover control is employed to enhance exploration–exploitation balance and accelerate convergence. Computational experiments were conducted on benchmark logistics distribution datasets with network sizes ranging from 100 to 500 nodes and fleet sizes up to 200 vehicles. Comparative evaluation against standard GA and penalty-based multi-objective GA variants demonstrates a 22% reduction in convergence iterations, 17.1% decrease in energy consumption, 12.8% reduction in total travel distance, and 15.4% improvement in average delivery time. Additionally, Pareto front dispersion variance decreased by 19.6%, indicating improved solution stability. The results confirm that PINN-GA-RouteOpt achieves computational efficiency, constraint-aware optimization, and scalability, establishing an intelligent and energy-efficient framework for large-scale logistics distribution route planning.*

*Povzetek: Študija predstavi PINN-GA-RouteOpt, ki s fizikalno-informirano nevronsko mrežo oblikuje omejitvam skladno večciljno funkcijo (strošek, čas, razdalja, energija) ter z adaptivnim GA pospeši in stabilizira reševanje velikih VRP z omejitvami kapacitete in časovnih oken.*

## 1 Introduction

Distribution logistics systems are becoming increasingly complex due to rapid growth in e-commerce, urban logistics, and customer-driven delivery services. This kind of system's route design optimization issue is now multi-objective and constrained by transportation cost, delivery time, energy consumption, and environmental sustainability. In highly populated metropolitan areas, logistical routing is essential to improve service quality, reduce operating costs, pollution, and congestion [1]. Static optimization methods are insufficient for developing logistics networks.

Recent research has examined several solutions to these difficulties. To mitigate the effects of urban logistics, research has examined sustainable logistics design and facility placement. Research recommends utilizing deep learning and social media analytics to improve last-mile delivery [2]. Driver behavior increasingly influences the optimization and machine-learning routing choices of hybrid decision-support systems [3]. Researchers have examined constraint-intensive vehicle routing difficulties such as time frames and three-dimensional payload limitations, to improve logistics modeling [4]. Data-driven logistics analytics and dynamic routing systems address real-time operational uncertainty [5, 6].

Despite improvements, several limits remain. Deep reinforcement learning and multi-agent learning frameworks are adaptable, but applying them within operational and physical constraints is difficult and requires large training datasets [7]. Electric vehicle and distributed intelligent system routing algorithms struggle with scalability and modeling assumptions [8, 9]. Global search and adaptability make genetic algorithm-based routing systems appealing [10]. However, penalty-based constraint management and static fitness assessment restrict convergence stability and solution realism [11]. Learning-based, complex constraint management approaches have advanced in recent years, although physical system behavior is still not always incorporated [12].

New logistics paradigms have developed in recent years including Cyber-Physical Logistics Networks, Quantum-Inspired Computing and Intelligent Routing Protocols; these have created new challenges on top of existing logistical problems as the complexity of logistics systems continues to increase and the requirement for data-driven optimisation frameworks that are both Data-Driven Optimisations and Physical Consistency Optimisations continues to grow [13]. To develop robust and realistic routing solutions, many researchers have focused upon the study of Vehicle Motion Dynamics (e.g. vehicle position and velocity), Fuel-Distance Relationships, Time of Day and External Factors that prevent optimal routing from being achieved [14]. The use of multiple objectives and large numbers of constraints within a single routing problem forces the separation between these variables.

This study proposes PINN-GA-RouteOpt, a logistics distribution route-optimization framework, to address these knowledge gaps. A physics-informed neural network and enhanced genetic algorithm are used. Domain-specific physical information is used in the physics-informed neural network-based fitness assessment approach to achieve physically realistic, constraint-consistent solution development. A new and enhanced genetic algorithm uses adaptive control of evolutionary operators to retain solution diversity and improve convergence efficiency.

The novelty of this work lies in embedding physics-informed residual modeling directly into the evolutionary optimization process for large-scale logistics routing. Unlike traditional genetic algorithm (GA) frameworks that enforce constraints through external penalty functions, the proposed PINN-GA-RouteOpt integrates vehicle motion dynamics, fuel–distance nonlinear relationships, and service time-window constraints into the fitness landscape via a physics-informed neural network. This transforms constraint satisfaction into an intrinsic structural property of the optimization surface rather than a corrective penalty mechanism. Additionally, the adaptive regulation of mutation and crossover probabilities based on physics-consistent feedback introduces a dynamic exploration–exploitation balance not present in static-parameter evolutionary methods.

The main contributions of this study are fourfold. First, a Physics-Informed Neural Network Assisted Genetic Algorithm (PINN-GA-RouteOpt) is developed for multi-objective logistics distribution routing. Second, an enhanced GA with adaptive operator control improves convergence stability and mitigates premature stagnation in high-dimensional vehicle routing problems. Third, a unified multi-objective formulation simultaneously optimizes energy consumption, delivery time, travel distance, and transportation cost within a coherent Pareto framework. Fourth, extensive benchmark evaluations on large-scale datasets demonstrate improved convergence efficiency, reduced energy usage, shorter travel distances, and enhanced delivery performance compared with conventional GA and hybrid metaheuristic methods.

The primary objective of this study is to develop a constraint-consistent and scalable multi-objective optimization framework for large-scale logistics distribution routing. The work aims to integrate physics-based modeling with evolutionary search to enhance convergence stability, reduce computational overhead, and improve energy-aware route planning under vehicle capacity and service time-window constraints. The intended outcome is a unified optimization architecture capable of minimizing transportation cost, travel time, route distance, and energy consumption simultaneously while maintaining feasibility across high-dimensional network structures.

**Research Questions**

The study is structured around the following research questions:

- RQ1: Can embedding physics-informed residual constraints into the fitness function improve convergence stability compared to penalty-based genetic algorithms in multi-objective vehicle routing problems?
- RQ2: Does adaptive mutation and crossover control guided by physics-consistent evaluation enhance exploration–exploitation balance in large-scale logistics networks?
- RQ3: How does the proposed framework perform in terms of scalability, energy efficiency, and solution stability across increasing node densities and fleet sizes?
- RQ4: To what extent does physics-regularized fitness modeling reduce solution variance under multi-objective trade-offs?

This paper's structure continues below. Section 2 reviews evolutionary routing algorithms, reinforcement learning–based optimization, hybrid graph-learning methodologies, and physics-aware modeling techniques to identify the research need in this work. Section 3 describes the mathematical formulation, fitness building, algorithmic integration mechanism, and parameter settings of the Physics-Informed Neural Network Assisted Genetic Algorithm for Logistics Route Optimization (PINN-GA-RouteOpt). Section 4 covers the experimental setup, benchmark datasets, performance measures, quantitative outcomes, and baseline comparisons. Section 5 discusses the findings in detail, contextualizing them within the state of the art, discussing robustness and scalability, and explaining practical consequences. Section 6 summarizes the paper's main contributions and suggests further study.

## 2 Literature survey

Artificial learning models have helped make supply chain networks less complicated by optimizing logistics distribution routes. Wang and Liang [15] utilized Meta-RL, employing reinforcement learning, graph neural networks, and self-attention mechanisms to enhance supply chain routing. They can capture geographical relationships and dynamic routing patterns, but they need a lot of training data and aren't easy to understand for big logistical systems, which are naturally complicated and have a lot of problems.

Mallari et al. [16] put forward a multi-objective optimization model for e-commerce forward-reverse logistics networks that includes pickup and delivery to make the system more sustainable. They use the triple bottom line method. This strategy takes into account social, environmental, and economic goals, but it focuses on modeling and evaluation instead of optimizing on a large scale. The method does a good job of capturing loading patterns, but it doesn't take into account trade-offs between multiple objectives in routing and only optimizes loading, not the route.

Abualola et al. developed a hybrid framework for ground-and unmanned aerial vehicle last-mile delivery architecture [17]. It provides delivery flexibility but lacks scalability and coordination. The hybrid deep learning strategy presented by Nagappan et al. [18] proposes an optimal context-aware service management framework (OC-ASMF) for a smart intelligent transport system based on the enhanced coral reef optimization (ECRO) and the modified pelican optimization (MPO) algorithms, both of which support intelligent transportation systems. Even while it improves situational awareness and flexibility, their technique does not incorporate optimization algorithms for route planning under strict operational constraints.

Research into hybrid optimization models that combine graph-based learning and evolutionary algorithms aims to improve routing performance. Therefore, this paper proposes a joint approach combining a genetic algorithm (GA) and a graph convolutional network (GCN) to solve the large-scale VRP with multiple distribution centers in an end-to-end manner. Qi et al. [19] proposed using evolutionary algorithms and graph convolutional networks to route vehicles. Learned spatial representations improved solution quality. The technique uses penalty-based constraint management and does not explicitly mimic the behavior of a physical system. The fuzzy c-means-based heuristic by Wang et al. [20] is a Hybrid Fuzzy C-Means Approach for two-echelon vehicle routing with simultaneous pickup and delivery of multicommodity flows. Although efficient at reducing uncertainty, the approach becomes computationally intensive as the problem size rises.

Natural logistics routing optimization strategies are being studied. In cement distribution truck routing, Pham et al. [21] found that a discrete salp swarm algorithm (DSSA) was more cost-effective but susceptible to parameter changes. A Multi-Agent Particle Environment (MPE) framework and the MAPPO algorithm have been used to address trends such as truck-drone delivery systems [22], but training complexity and coordination overhead remain. Pham et al. [23] devised a hybrid whale optimization algorithm (hGWOA) for routing limited-capacity trucks that improves convergence but struggles with complex constraint interactions.

Digital twin (DT)-enhanced deep reinforcement learning-based optimization framework and digital twin-based routing optimization improve real-time decision-making [24]. Andrejic and Pajic (2025) [25] developed an integrated BWM-QFD-MARCOS framework to combine stakeholder demands with logistical performance assessment and ranking to enhance strategic decision-making in cold chain logistics. QFD and the Best-Worst Method (BWM) are used to translate operational and customer needs into observable technical features and achieve trustworthy criterion weights. Following the MARCOS paradigm compare potential solutions to excellent and negative outcomes.

Abdesselem Boulkroune et al. [26] suggested the Practical Finite-Time Fuzzy Synchronization of Chaotic Systems with Non-Integer Orders. Finite-time projective synchronization for unknown CSs with incommensurate non-integer orders utilizing adaptive fuzzy sliding-mode control is the subject of this research. In particular, we concentrate on realistic projective synchronization and provide two innovative control methods that reliably reduce chattering in sliding mode control. Two new finite-time non-singular sliding surfaces are created to accomplish this. These sliding surfaces improve projective synchronization accuracy, reaction speed, and resilience. Globally approximating adaptive fuzzy logic systems estimate continuous functional uncertainty. We used Lyapunov's direct technique to thoroughly examine both methods' stability. Significant simulations demonstrate our approaches' efficacy and advantages. Reduce chattering and achieve projective synchronization in a finite period using these strategies. This suits real-world applications in complicated CSs.

G. Rigatos et al. [27] recommended the Flatness-Based Control in Successive Loops for Autonomous Quadrotors. To manage the multivariable and nonlinear dynamics of unmanned rotorcraft, a flatness-based control technique is used in consecutive loops. Two subsystems are coupled in cascading loops in the state-space model of 6DOF autonomous quadrotors. As with input–output linearized flat systems, each subsystem may be seen as a differentially flat system and controlled by inverting its dynamics. Second subsystem state variables become first subsystem virtual control inputs. Exogenous control inputs then affect the second subsystem. Lyapunov stability analysis proves the global stability of the control approach, which is implemented in two loops. Simulations demonstrate the 6DOF quadrotor accurately following 3D flight trajectories, validating the control approach.

G. Rigatos et al. [28] presented the Nonlinear optimal control of autonomous submarines' diving. The paper proposes a nonlinear H-infinity (optimal) control method for autonomous submarine depth and heading angle management. This multivariable nonlinear control problem permits undersea navigation within exact limits. Each time the control algorithm iterates, the submarine's dynamic model approximation linearizes around a transient equilibrium. Taylor series expansion and submarine model Jacobian matrices are used for linearization. The optimum control issue for the roughly linearized model is addressed by designing an H-infinity feedback controller. At each control method time-step, an algebraic Riccati equation is solved to calculate the controller's gain. Lyapunov analysis proves control system global stability.

Gerasimos Rigatos et al. [29] introduced the Flatness-based control in successive loops for dual-arm robotic manipulators. A multi-loop flatness-based controller for a dual-arm robot's dynamic model is presented in this paper. Flatness-based control in consecutive loops solves this robotic system's control challenge. The state-space model of the dual-arm robotic manipulator is divided into subsystems coupled in cascading loops to apply the multi-loop flatness-based control strategy. These subsystems may be considered separately as differentially flat systems and controlled by inverting their dynamics like input-output linearized flat systems. State variables of the next (i + 1)-th subsystem become virtual control inputs for the previous i-th. The last subsystem receives actual control inputs. The whole control approach is built in consecutive loops and shown global stable by Lyapunov stability analysis.

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Farouk Zouari and Mufti Mahmud [31] deliberated the Neural Network-Based Robust Adaptive Output Feedback Control for MIMO Time-Varying Delay Systems. For MIMO systems with time-varying delays, this work proposes a robust neural adaptive output-feedback control approach. The linear state observer handles unavailable state variables, whereas the neural network approximates unknown nonlinear functions. Control laws reduce external disturbances and mistakes. Gradient Algorithm with Projection solves unknown control directions, and the Lyapunov–Krasovskii method's Strictly Positive Real (SPR) requirement helps build output error adaption laws. It works for many MIMO systems, eliminates singularity concerns, needs minimal adaptation parameters, and guarantees asymptotic convergence of tracking errors. Simulations prove the method's efficacy and practicality.

Abdulwahab Ali Almazroi et al. [32] developed the Novel DDoS Mitigation Strategy in 5G-Based Vehicular Networks Using Chebyshev Polynomials. This paper proposes a Chebyshev polynomial-based approach to secure 5G-based vehicular networks' vehicle-to-vehicle communication against DDoS assaults. Our idea uses Chebyshev polynomial semi-group and chaotic characteristics. Our systems fulfill all security and privacy criteria, including node authentication, message integrity, identity privacy, traceability, unlinkability, and attack resistance. Finally, our invention reduces message signature production and verification computational burdens by 66.67% and 33.33%, respectively. Our transmission costs impact the message-signature tuple size by 5.00%.

Abdulwahab Ali Almazroi et al. [33] investigated the Fog computing-based authentication scheme for 5G-assisted vehicular blockchain network (FCA-VBN). The FCA-VBN system uses channel stage response private key extraction for terminal key agreement. The blockchain's immutability and memorability allow this article to demonstrate how the intelligent contract may be used to create and issue a transaction between the fog server and the node's data. We proved that the FCA-VBN system is secure for message authenticity and integrity, conditional privacy protection, and unlinkability. We also discussed the method's attack resistance. To evaluate the FCA-VBN system, we theoretically assessed its performance on a variety of measures, including computing, communication, and power utilization.

Mahmood A. Al-shareeda et al. [34] analyzed the Prevention schemes for Replay Attack in Vehicular Ad hoc Networks (VANETs). VANETs help road users and improve traffic management. VANETs' open communication network medium exposes communications in transit to security assaults and incoming data to privacy breaches. To address VANET security and privacy, researchers developed numerous security techniques. However, most systems have large processing and communication overheads. One of the most popular VANET security threats, the replay attack, was examined. The analysis and survey of VANET replay attack avoidance systems are presented in this research.

Abdulwahab Ali Almazroi et al. [35] examined the efficient certificateless authentication scheme for 5G-assisted vehicular fog computing (ECA-VFog). ECA-VFog used efficient elliptic curve encryption enabled by a fog server and a 5G base station. This study analyzes the security designs' safety to determine the ECA-VFog scheme's feasibility and utility. In the performance ovulation section, signing and verification calculation costs are 2.3539 and 1.5752 ms. ECA-VFog transmission expenses are 124 bytes and energy consumption overhead is 25.610432 mJ. The performance estimate shows that the

ECA-VFog system is cheaper in computation, communication, and energy usage than other methods.

Zeyad Ghaleb Al-Mekhlafi et al. [36] suggested the Certificateless Authentication Scheme Using Fog Computing for 5G-Assisted Vehicular Networks (CLA-FC5G). Instead of 802.11p-based inter-vehicle communication, our CLA-FC5G uses D2D technology to allow cars to interact directly while maintaining safety and reducing overhead. System setup, key creation, message signing, and verification are handled by six polynomial-time algorithms in our method. Due to its low communication and processing cost, our technique is secure and efficient. Our CLA-FC5G technology reduced overhead, is efficient, and scalable, making it ideal for large vehicle networks. The results show that CLA-FC5G satisfies realistic 5G safety standards for security and effectiveness.

Mahmood A. Al-Shareeda et al. [37] proposed the Chebyshev Polynomial Based Emergency Conditions With Authentication Scheme for 5G-Assisted Vehicular Fog Computing. Installation system, startup, enrollment, mutual authentication, and emergency request comprise the suggested approach. Emergency services benefit from the protocol's effectiveness in resource-constrained automobile systems. The proposed method ensures message authenticity, integrity, non-repudiation, traceability, unlinkability, identity privacy, certificate independence, and emergency response, according to formal security analysis. The algorithm cannot fake, impersonate, or replay assaults, according to the assessment. It has reduced computational, communication, and storage overhead than previous methods. Table 1 shows the comparison of existing methods.

Table 1: Summary of existing methods

| Ref | Methodology | Core Technique | Strengths | Quantitative Highlights | Key Limitations |
|---|---|---|---|---|---|
| [15] | Meta-RL | RL + GNN + Self-Attention | Captures dynamic spatial patterns | Improved routing adaptivity | Data-intensive training; limited interpretability in large networks |
| [16] | Multi-objective modeling | Triple Bottom Line | Sustainability modeling | Social–economic–environmental integration | No large-scale routing optimization |
| [17] | Hybrid UAV–Ground | Coordinated delivery | Flexible last-mile delivery | Improved delivery reach | Scalability and coordination overhead |
| [18] | ECRO + MPO | Hybrid deep metaheuristic | Context-aware transport system | Enhanced situational awareness | No strict constraint-based route optimization |
| [19] | GA + GCN | Evolutionary graph learning | Improved spatial feature extraction | Better solution quality vs GA | Penalty-based constraint handling |
| [20] | Fuzzy C-Means | Two-echelon VRP | Handles uncertainty | Effective clustering | High computational cost at scale |
| [21] | DSSA | Swarm intelligence | Cost reduction | Efficient for medium-scale routing | Sensitive to parameter tuning |
| [22] | MAPPO | Multi-agent RL | Drone-truck coordination | Cooperative decision-making | High training complexity |
| [23] | hGWOA | Hybrid whale optimization | Accelerated convergence | Improved exploration | Constraint interaction complexity |
| [24] | Digital Twin + DRL | Real-time simulation | Adaptive decision support | Enhanced responsiveness | High infrastructure dependency |
| [25] | BWM-QFD-MARCOS | Multi-criteria ranking | Strategic logistics planning | Robust decision weighting | Not route optimization-focused |
| [26] | Nonlinear Chaotic Systems | Adaptive Fuzzy Sliding-Mode Control | Finite-time synchronization; Lyapunov stability | Reduced chattering; finite-time convergence | Designed for continuous chaotic systems; not combinatorial routing |

| | | | | | |
|---|---|---|---|---|---|
| [27] | Autonomous Quadrotors | Flatness-Based Multi-Loop Control | Differential flatness; global Lyapunov stability | Accurate 3D trajectory tracking | Continuous control; no discrete logistics modeling |
| [28] | Autonomous Submarines | Nonlinear H∞ Optimal Control | Riccati-based feedback; robust stability | Stable under nonlinear dynamics | Requires system linearization; not scalable to VRP |
| [29] | Dual-Arm Robotics | Multi-Loop Flatness Control | Cascaded subsystem decomposition | Proven global stability | Focused on robotic manipulation dynamics |
| [30] | Submarine Diving | Nonlinear Optimal Control | Iterative Jacobian linearization | Stable heading-depth control | Continuous state-space system only |
| [31] | MIMO Delay Systems | Neural Adaptive Output Feedback | Lyapunov–Krasovskii stability | Asymptotic error convergence | Delay-system control; not route optimization |
| [32] | 5G Vehicular Security | Chebyshev Polynomial Cryptography | 66.67% signature reduction | 33.33% verification cost reduction | Security protocol; not logistics routing |
| [33] | Fog-Based Vehicular Blockchain | Channel-State Key Extraction | Low computation & power | Efficient fog coordination | Authentication-focused; no route planning |
| [34] | VANET Security Survey | Replay Attack Prevention | Security overhead analysis | Communication-cost evaluation | No optimization component |
| [35] | 5G Fog Authentication | ECC-based Certificateless Scheme | Signing cost: 2.3539 ms; 124 bytes transmission | Low energy consumption (25.61 mJ) | Security-only framework |
| [36] | CLA-FC5G | Certificateless D2D Authentication | Polynomial-time algorithms | Scalable vehicular network security | No multi-objective routing |
| [37] | Chebyshev Emergency Auth | Lightweight Emergency Protocol | Reduced computation & storage | Formal security validation | Communication security only |

Operational optimization and real-time logistics or dynamic routing are difficult for the framework, but it gives a systematic decision-making mechanism. Logistics routing has improved using learning-assisted and hybrid optimization, according to research. The bulk of techniques don't explicitly consider physical system behavior, employ static or penalty-driven constraint management, or have scalability and convergence issues. Our optimization frameworks must account for physics and limitations and be able to solve complex, large-scale, multi-objective logistics distribution routing issues.

# 3 Proposed methodology

This article introduces PINN-GA-RouteOpt, a hybrid optimization framework that uses evolutionary search and physics-informed learning to address the disadvantages of genetic algorithm-based logistics routing algorithms. Logistics route optimization is a constrained multi-objective problem that minimizes transportation costs, delivery time, and energy consumption under operational and physical constraints. Instead of using static fitness formulations or penalty terms, the framework employs a physics-informed neural network to incorporate domain-specific physical information into the optimization loop to assess viable pathways within constraints. In the suggested architecture, the physics-informed neural network learns system behaviors governed by vehicle dynamics, fuel-distance relationships, and time-consumption limits to generate physically meaningful inputs for route assessment. A modified genetic algorithm employs this additional knowledge to fine-tune selection, crossover, and mutation operators in response to changes in feasibility and convergence behavior. The suggested method uses physics-aware information to guide evolutionary operators in a way that makes exploration more efficient and avoids paths that are impossible or use too much energy. PINN-GA-RouteOpt achieves continuous convergence and scalable performance across complex logistics distribution scenarios, laying the groundwork for intelligent and energy-aware route optimization.

The PINN is first trained using a composite loss function $\mathcal{L} = \mathcal{L}_{data} + \lambda \mathcal{L}_{physics}$, where $\mathcal{L}_{data}$ represents empirical routing cost deviations and $\mathcal{L}_{physics}$ encodes residual constraints derived from vehicle motion dynamics and fuel–distance nonlinear relationships. The trained PINN generates physics-consistent fitness evaluations that are embedded directly into the GA optimization loop, replacing conventional penalty-based constraint handling. The GA implementation includes permutation-based chromosome encoding for route representation, tournament selection (size = 3), adaptive mutation probability $p_m \in [0.01, 0.15]$, dynamic crossover rate $p_c \in [0.7, 0.95]$, population size of 100–150 individuals, and termination after 500 generations or convergence tolerance $\epsilon = 10^{-4}$. The PINN architecture consists of 4 hidden layers with 64 neurons each, ReLU activation, Adam optimizer (learning rate = 0.001), batch size = 64, and 200 training epochs.

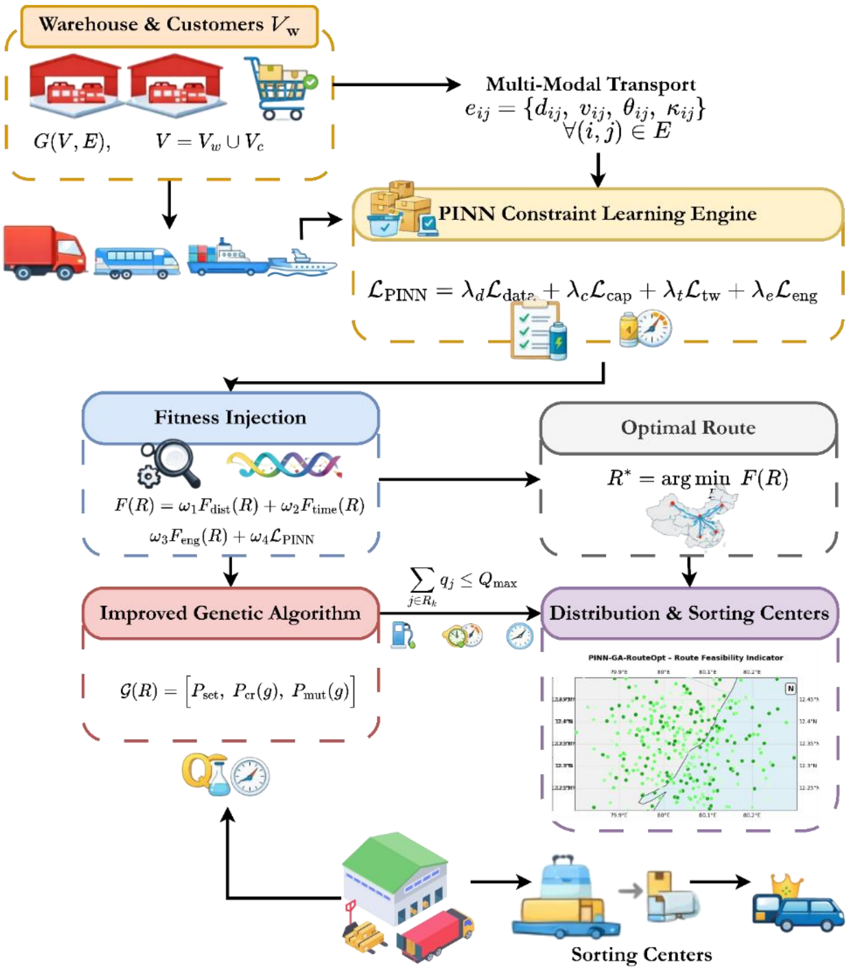


Figure 1: Proposed diagram

The proposed PINN-GA-RouteOpt optimizes multimodal logistics delivery routes using physical-constraint learning and evolutionary search, as shown in Figure 1. This creates viable and efficient delivery routes. Receiving and delivering items to customers starts the logistics network graph. These edges show probable transit links depending on distance, speed, road or route quality, and mode of conveyance. To accurately illustrate multi-modal logistics operations, we clearly show trucks, buses, trains, ships, and airplanes.

This network feature enables the PINN Constraint Learning Engine to incorporate domain-specific physical and operational constraints into the optimization. A composite physics-informed loss considers data integrity, transportation capacity, delivery time, and energy use. Instead of focusing solely on distance optimization, the PINN accounts for logistical constraints to ensure physically viable, operationally optimal routes.

A multi-objective fitness function is utilized to evaluate each route R after injecting the learnt constraint information. This function considers distance, trip time, energy use, and PINN penalty. This fitness-augmented assessment repeatedly builds the route population using adaptive selection operators to lead the enhanced genetic algorithm. By leveraging feasibility awareness, the evolutionary algorithm may enhance performance by rejecting or penalizing evolutionary paths that exceed capacity or time constraints.

Optimization has finally found a solution that meets operational restrictions and performance goals. Sorting and distribution facilities use routes, simplifying supplier-to-customer logistics. Our study uses physics-informed learning and evolutionary optimization to create scalable, resilient, and energy-aware logistics routes in complicated multi-modal distribution networks.

$$\min F(R) = (F_1(R), F_2(R), F_3(R)) = \left(\sum_{(i,j)\in R} d_{ij}, \sum_{i \in R} \max(0, t_i - T_i^{\max}), \sum_{(i,j)\in R} E_{ij}\right) \quad (1)$$

As shown in equation (1), the Multi-Objective Logistics Route Optimization has been deliberated. The logistics distribution routing optimization problem is formulated using the equation given the objectives. R is a decision variable that represents this ordered path with depots and customers at nodes $(i, j)$. The main goal, $F_1(R)$, is to decrease the overall travel distance $(dib)$ between nodes $i$ and $j$. Minimizing delivery time violations is the second aim $F_2(R)$. The maximum service time for a client is $T_i^{max}$, whereas the actual arrival time is $t_i$. The $\max(\cdot)$ operator states that only late arrivals affect delay costs. The third aim $F_3(R)$ is to decrease energy consumption, where $Eib$ is the energy needed to pass through edge $(i, j)$ based on vehicle characteristics and travel circumstances. This approach optimizes $(F_1, F_2, F_3)$ simultaneously, considering trade-offs between efficiency, service quality, and sustainability. The enhanced evolutionary algorithm's fitness function is a vector-valued objective function that provides a structured interface for physics-informed learning, guiding practical, realistic pathways.

$$L_{cap}(R) = \sum_{k=1}^{|R|} \left[\sum_{i=1}^{k} q_{R_i} - Q^{max}\right]_+^2 \quad (2)$$

As described in Equation (2), the SMulti-Objective Logistics Route Optimization has been discussed. This equation derives a physics-driven cumulative load feasibility function for logistics route R. The route $R = \{R_1, R_2, \dots, R_{|R|}\}$ represents the ordered succession of customer visits. The maximum load that the truck can carry is denoted by $Q$max, and the demand of the customer served at position i along the route is denoted by $q_{R_i}$. The inner summation calculates the vehicle's total load after servicing the first k customers $\sum_{i=1}^{k} q_{R_i}$ which indicates that the loading is progressive. The operator $[x]_+ = \max(0, x)$ ensures that only capacity violations contribute to the feasibility loss, whereas the squared term amplifies severe overload scenarios. The total of all route points ensures capacity feasibility throughout, not only at the end. The evolutionary algorithm can produce PINN-GA-RouteOpt routes that automatically account for changes in vehicle capacity as the physics-based neural network loss function directly encodes $L_{cap}$. This multi-stage formulation provides more consistent fitness gradients and stronger constraint enforcement than traditional static capacity inequalities.

$$L_{tw}(R) = \sum_{k=1}^{|R|} \left( [T_{R_k}^{min} - t_{R_k}]_+^2 + [t_{R_k} - T_{R_k}^{max}]_+^2 \right) \quad (3a)$$

$$t_{R_k} = t_0 + \sum_{i=1}^{k-1} \frac{d_{R_i R_{i+1}}}{v_{R_i R_{i+1}}} + s_{R_i} \quad (3b)$$

As deliberated in equation (3a-b), a Time-Window–Aware Arrival Dynamics with Penalty Accumulation has been described. This formula duplicates time-window-aware arrival dynamics for logistical routing by explicitly tallying arrival times and penalizing violations. The specified route $R = \{R_1, R_2, \dots, R_{|R|}\}$ represents the ordered customer series. The consumers of position k are permitted service times $T_{R_k}^{min}$ and $T_{R_k}^{max}$ where $t_{R_k}$ is the actual arrival time. While squaring brings attention to more substantial differences, the operator $[x]_+ = \max(0, x)$ separates the impacts of early and late arrivals. The arrival time $t_{R_k}$ is obtained recursively from the departure time $t_0$ in the following formula: where $d_{R_i R_{i+1}}$ is the service time at customer $v_{R_i R_{i+1}}$ is the average travel speed on that segment, and $R_i$ is the distance between consecutive customers. The model can learn a physically consistent time propagation across routes by including this formulation in the PINN loss function. This merged method allows the improved evolutionary algorithm to generate time-feasible delivery sequence routes rather than relying on post-hoc penalty modifications.

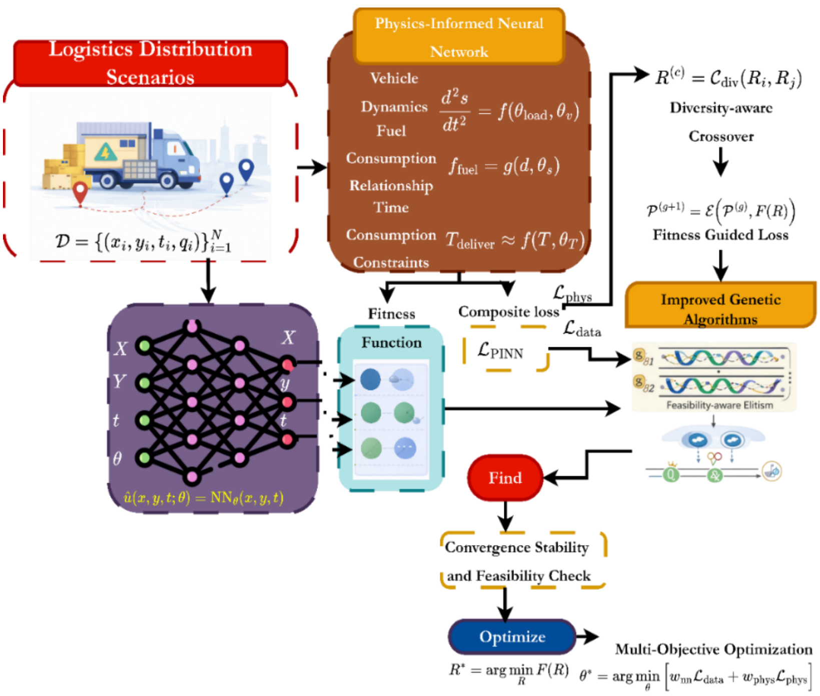


Figure 2: Physics-informed neural network architecture

$$E(R) = \sum_{k=1}^{|R|-1} \left( \alpha_1 m_k d_{R_k R_{k+1}} + \alpha_2 \frac{v_{R_k R_{k+1}}^2}{d_{R_k R_{k+1}}} + \alpha_3 g \sin(\theta_{R_k R_{k+1}}) d_{R_k R_{k+1}} \right) \quad (4a)$$

$$m_k = m_0 + \sum_{i=k}^{|R|} q_{R_i} \quad (4b)$$

This suggested PINN-GA model uses a neural network architecture that is based on physics to find the best logistical routes. Because of physical limits and evolutionary optimization, this data-driven architecture is long-lasting. Our task is to begin with choices for how to distribute things logistically. Put delivery information, like how much demand there is and where it is, into a database. This is the main input point for the learning and optimization pipeline. It keeps track of things like truck speed, loading conditions, and delivery locations. A PINN that includes the physical rules of transportation dynamics is then used to look at these logistical situations. PINN uses equations for vehicle motion that take into account second-order dynamics and the relationship between fuel use and delivery time. The neural network learns from these limits instead of trying to fit past data to make sure that behavior is consistent in the real world. This ensures that the trip time, energy use, and vehicle performance are all correct, no matter what the load or route is. The neural network model uses spatial-temporal inputs to make outputs that are useful for logistics. Using network outputs, function evaluation modules check how much energy is used, how well time is kept, and how far away things are. A composite loss function makes sure that the model learns the right ways to represent parameters while still following the rules of real-world transportation. This function combines data fidelity and physics residuals. The evaluated responses are transmitted to an enhanced genetic algorithm that refines populations through advanced evolutionary operators. Fitness-guided mutation, diversity-aware crossover, and feasibility-aware elitism are used to preserve high-quality, physically viable solutions from generation to generation. The evolutionary algorithm repeatedly refines solutions to balance exploration and exploitation, then examines feasibility to remove unstable or unworkable options. The system is tuned to reduce losses using physical concepts and neural networks. This creates logistical paths that are perfect, practical, efficient, and viable.

Figure 2 and equation (4a-b) express that the Physics-Informed Neural Network (PINN) Composite Loss Function has been computed. Here build an R-equation for a logistical route that takes into consideration the energy costs, which vary with speed, terrain, and cargo. Physical principles provide the basis of the model. Then use the customer's trip to calculate the total again $R_k R_{k+1}$. The value $v_{R_k R_{k+1}}^2$ represents the average vehicle speed on that segment, while the parameter $d_{R_k R_{k+1}}$ specifies the distance traveled. The energy scaling parameters $\alpha_1, \alpha_2$ and $\alpha_3$ represent the effects of gravity, load-induced resistance, and aerodynamic drag, respectively. The instantaneous mass of the vehicle at point k is represented by the $m_k$ variable. The product of the vehicle's basic mass ($m_0$) and the remaining cargo load $\sum_{i=k}^{|R|} q_{R_i}$ is used to compute it. Gravitational acceleration is represented by g, and the angle of the road gradient between two consecutive nodes is denoted as $\theta_{R_k R_{k+1}}$. As part of the PINN-GA-RouteOpt architecture, this physically grounded energy model enables the optimization approach to incorporate real vehicle dynamics directly. This redesign could yield a genetic algorithm that is more efficient, faster, and less wasteful.

$$L_{PINN} = \lambda_d L_{data} + \lambda_c L_{cap} + \lambda_t L_{tw} + \lambda_e L_{eng} \quad (5a)$$

$$L_{data} = \frac{1}{N} \sum_{n=1}^{N} \|\hat{y}^n(\theta) - y_n\|_2^2, L_{eng} = \sum_{k=1}^{|R|-1} \Phi(m_k, v_{R_k R_{k+1}}, d_{R_k R_{k+1}}, \theta_{R_k R_{k+1}}) \quad (5b)$$

As computed in equation (5a-b), the Adaptive Fitness Aggregation for Improved Genetic Algorithm has been calculated. To train the physics-informed neural network inside the PINN-GA-RouteOpt architecture, this equation specifies the composite loss function. Multiple loss components that ensure data accuracy and physical feasibility are combined into a weighted sum to form the total loss PINN. The term denotes the data-driven loss $L_{data}$, where N is the number of training samples, $\hat{y}^n(\theta)$represents the corresponding observed or simulated ground-truth values, and the PINN is used to forecast routing parameters (e.g., journey time or energy). The prediction error is quantified by the $L_2$norm.Equation 2, the capacity feasibility loss $L_{tw}, L_{eng} L_{cap}$and equations 3, which deal with time-window violation loss, and physics-based energy loss, respectively, are represented by the remaining components $L_{cap}$. Data consistency is regulated during training in relation to physical and operational restrictions by the non-negative weighting coefficients $\lambda_1, \lambda_2, \lambda_3$ and$\lambda_4$. When optimizing an evolutionary path, the PINN learns representations that are physically consistent and data-accurate by jointly reducing these components. The structured formulation ensures that operational constraints and physical laws are embedded directly into the learning process rather than enforced externally. The function $\Phi(m_k, v_{R_k R_{k+1}}, d_{R_k R_{k+1}}, \theta_{R_k R_{k+1}})$ represents the physics-based energy model defined in Equation (4), parameterized by instantaneous vehicle mass $m_k$, speed $v_{R_k R_{k+1}}$ travel distance $d_{R_k R_{k+1}}$ and road gradient $\theta_{R_k R_{k+1}}$. By jointly minimizing all components, the PINN learns constraint-consistent representations that guide the improved genetic algorithm toward feasible, stable, and energy-efficient routing solutions across generations.

$$F(R) = \omega_1(g)\tilde{F}_1(R) + \omega_2(g)\tilde{F}_2(R) + \omega_3(g)\tilde{F}_3(R) + \omega_4(g) L_{PINN} \quad (6a)$$

$$\omega_k(g) = \frac{\exp(-\beta_k g)}{\sum_{j=1}^{4} \exp(-\beta_j g)} \quad (6b)$$

As found in equation (6a-b), the Adaptive Fitness Aggregation for Improved Genetic Algorithm has been deliberated. The modified genetic algorithm in the PINN-GA-RouteOpt framework uses this multi-line equation to aggregate adaptive fitness. The scalar fitness value F(R) assesses route feasibility by integrating physics-informed loss $L_{PINN}$ with normalized goal functions $\tilde{F}_1(R), \tilde{F}_2(R), \tilde{F}_3(R)$ for distance, time-delay, and energy objectives. Normalization keeps fitness consistent for objectives of various scales. The evolutionary generation index g determines how to change weights dynamically

$\omega_k(g)$. The algorithm targets global goals by adjusting the decay rate of each component's effect in early generations using parameters $\beta_k$. Future versions emphasize physical consistency and utility. The softmax formulation ensures numerical stability by ensuring $\sum_{j=1}^{4} \exp\left(-\beta_j g\right) = \omega_k(g) = 1$. Our adaptive aggregation strategy stabilizes convergence and balances exploration and exploitation in complex multi-objective logistics routing problems.

$$P_{sel}(R_i) = \frac{\exp(-\gamma F(R_i))}{\sum_{j=1}^{N_p} \exp(-\gamma F(R_j))} \quad (7)$$

As obtained in equation (7), the PINN-Guided Selection Probability for Genetic Evolution has been determined. This equation determines PINN-guided selection probability in the enhanced genetic algorithm's selection phase. The term $P_{sel}(R_i)$ indicates the likelihood of choosing the route $R_i$ from a population of size $N_p$. Equation (6) defines the scalar fitness value $F(R_i)$ as the feasibility of physical instruction and the achievement of multiple objectives. The exponential formula selects pathways with lower fitness ratings, even if they are better solutions. The non-zero parameter $\gamma > 0$ controls the ratio of studying routing patterns to using high-quality solutions. A lower $\gamma$ value promotes population diversity, while a higher value increases fitness sensitivity and speeds up convergence. This method improves and stabilizes evolutionary search by directly adding PINN-informed fitness to probabilistic selection. So, routes should take into account physical limits and operational goals..

$$P_{cr}(g) = P_{cr}^{min} + (P_{cr}^{max} - P_{cr}^{min})\exp\left(-\frac{\eta_1 g}{G_{max}}\right)\left(1 - \frac{\sigma_F(g)}{\sigma_F^{max}}\right) \quad (8)$$

As evaluated in equation (8), Adaptive Crossover Probability with Diversity–Convergence Coupling has been examined. An adaptive crossover probability mechanism allows genetic recombination to dynamically adjust to population variety and evolutionary rate, as shown by this equation. $P_{cr}(g)$ represents the crossover probability at generation g, with lower and higher bounds, $P_{cr}^{max}$ and $P_{cr}^{min}$. As evolution advances, the attention on crossings decreases at a decay coefficient $\eta_1$, and the maximum number of generations is $G_{max}$. This formula guarantees high recombination rates for early generations, encouraging global exploration. To assess population variability, calculate the fitness standard deviation $\sigma_F(g)$ for all $N_p$ individuals in generation g, where $\bar{F}^{(g)}$ is the mean fitness value. The normalizing factor $\sigma_F^{max}$ indicates the highest observed fitness dispersion. Connecting crossover probability to diversity increases recombination when diversity is high and lowers disruptive crossover when convergence speeds up. This adaptive technique improves solution quality while delaying convergence in complex logistics routing scenarios.

$$P_{mut}(g) = P_{mut}^{min} + \frac{P_{mut}^{max} - P_{mut}^{min}}{1 + \exp(\eta_2 \Delta F(g))}, \Delta F(g) = |\bar{F}(g) - \bar{F}(g-1)| \quad (9)$$

As expressed in equation (9), the Adaptive Mutation Probability Driven by Fitness Gradient has been explored. This formula describes an algorithm that adjusts mutation probability based on evolutionary fitness. The mutation probability of generation g, $P_{mut}(g)$, must be smaller than $P_{mut}^{min}$ and $P_{mut}^{min}$. The logistic function controls mutation intensity depending on fitness change $\Delta F(g)$, where $\bar{F}(g)$ and $\bar{F}(g-1)$ indicate average fitness values of the following generations. This method lets the algorithm dynamically handle delays or quick improvements. The parameter $\eta_2 > 0$ controls how fitness changes affect mutation probability. Increasing the logistic term, showing possible stagnation $P_{mut}(g)$, stimulates novel route designs despite slight average fitness differences. Reducing mutation intensity after substantial progress preserves high-quality solutions. By integrating mutation behavior with evolutionary development, this strategy strengthens the modified genetic algorithm and delays convergence in high-dimensional logistics route optimization issues.

$$I_{feas}(R) = \exp\left(-\rho_1 L_{cap} - \rho_2 L_{tw} - \rho_3 L_{eng}\right) \quad (10)$$

As shown in equation (10), the Route Feasibility Indicator with Physics–Constraint Coupling has been explored. This equation measures the physical and operational validity of a logistical route (R) to determine route feasibility. A smooth, differentiable feasibility score is obtained by converting constraint violations into the indicator $I_{feas}(R) \in (0,1])$. Equations (2)-(5) define $L_{cap}, L_{tw}, L_{eng}$ as the cumulative capacity, time window, and energy-consistency violation losses. The symbol " $\Omega_{route}$ " represents the feasible routing space. Each restriction type manages feasibility indicator sensitivity using non-negative coefficients $\rho_1, \rho_2, \rho_3$. According to the exponential formulation, routes with large violations approach 0 feasibility quickly, whereas fully compliant routes remain near 1. By adding this information in fitness evaluation and selection, the upgraded genetic algorithm favors physically coherent and operationally feasible pathways. Due to its smooth feasibility modeling, the PINN-guided framework balances stringent constraint enforcement and exploratory search behavior while improving convergence stability.

$$Q(R) = I_{feas}(R)\left(\frac{\alpha_d \tilde{F}_1 + \alpha_t \tilde{F}_2 + \alpha_e \tilde{F}_3}{\alpha_d + \alpha_t + \alpha_e}\right)^{-1} \quad (11)$$

As explored in Equation (11), the PINN-Guided Route Quality Score for Evolutionary Ranking has been discussed. This equation scores candidate solutions during evolutionary selection using PINN-guided route quality. Scalar Q(R describes a route R's complete attractiveness, including feasibility and performance. The feasibility indicator $I_{feas}(R)$ Equation (10) penalizes routes that violate physical or operational constraints. Normalized objectives represent distance, time delay, and energy consumption. $\tilde{F}_1(R), \tilde{F}_2(R), \tilde{F}_3(R)$ . The weighting variables $\alpha_d, \alpha_t, \alpha_e$ and $\beta e$ are non-negative and sum up to one to guarantee equal contribution across objectives. The inverse formulation gives routes with low objective values and high feasibility better ratings. With this quality score and the enhanced evolutionary algorithm's ranking and elitism procedures, PINN-GA-RouteOpt promotes physically reasonable, efficient, and stable routing solutions while retaining population variation.

$$H(g) = -\sum_{m=1}^{M} p_m(g)\log p_m(g), p_m(g) = \frac{1}{N_p}\sum_{i=1}^{N_p} I(R_i(g) \in C_m) \quad (12)$$

As identified in equation (12), the Entropy-Based Population Diversity Measurement has been examined. This equation offers an entropy-based diversity estimate of routing solutions in the genetic population at generation g. The entropy value $H(g)$measures solution dispersion over M preset route clusters$\{C_1, C_2, \dots, C_3\}$. If $N_P$is the population size and $R_i(g)$ is the i-th route in generation g, then $p_m(g)$ is the percentage of population members assigned to the cluster $C_m$. The indicator function $I(\cdot)$ returns 1 if the route is in the selected cluster and 0 otherwise. Higher entropy values indicate greater population diversity, reflecting a wide exploration of the solution space, while lower entropy signals convergence toward a limited set of routing patterns. In PINN-GA-RouteOpt, this diversity measure is used to control how evolutionary operators work, like how strong crossover and mutation are, to make sure that exploration and exploitation are balanced. The framework reduces premature convergence and makes the optimization of complex, multi-objective logistics routing problems more robust by keeping an eye on population entropy.

$$E_{elite}(g) = \{R_i(g) \mid Q(R_i(g)) \geq \tau_g \wedge I_{feas}(R_i(g)) \geq \epsilon\}, \tau_g = \mu \max_{1\leq i\leq N_p} Q(R_i(g) \quad (13)$$

As initialized in equation (13), the Physics-Guided Elitism Preservation Criterion has been computed. The following equation defines the enhanced genetic algorithm's physics-guided elitism-preservation mechanism. The top-tier routing solutions chosen from generation $g$make up the elite set $E_{elite}(g)$. A route is considered to be part of the elite set if both its feasibility indicator $I_{feas}(R_i(g)$ and route quality score $Q(R_i(g))$ (specified in Equation (11)) are greater than a dynamic threshold $\tau_g$ and a minimum feasibility level respectively. This two-pronged requirement ensures that only physically consistent, high-performing routes are maintained. The elitism control parameter $\mu \in (0,1)$ is used to calculate the threshold $\tau_g$, which is a proportion of the highest route quality observed in generation $g$. To avoid a small number of solutions that are either impractical or only slightly better than those dominating evolution, this adaptive elitism approach continually adjusts selection pressure. To ensure the variety of solutions and the retention of the most promising and practical routing options over generations, the framework couples elitism with physics-informed feasibility.

$$S(g) = \frac{1}{W}\sum_{k=g-W+1}^{g} |\bar{Q}(k) - \bar{Q}(k-1)| \quad (14a)$$

$$\bar{Q}(g) = \frac{1}{N_p}\sum_{i=1}^{N_p} Q(R_i(g)) \quad (14b)$$

As shown in equation (14a-b), the Convergence Stability Metric for Evolutionary Optimization has been deliberated. This equation measures the convergence stability of the PINN-GA-RouteOpt framework's evolutionary progress over generations. Stability metric $S(g)$ is the average absolute change in mean route quality score across W generations. $N_P$ represents the population size at generation $g$, $R_i(g)$ represents the i-th route candidate in generation $g$, and $\bar{Q}(g)$ represents the population's average route quality score. The evolutionary process converges toward a stable region of the solution space, as evidenced by a decreasing $S(g)$. Conversely, larger numbers suggest oscillation or exploration. This metric lets PINN-GA-RouteOpt's evolutionary operators and termination conditions change as needed. The framework makes sure that complex multi-objective logistics routing problems are solved quickly and reliably by explicitly checking for convergence stability. This stops the process from ending too soon.

$$J^* = \min_{g\leq G_{max}} \left\{\min_{R\in P(g)} \left[F(R)\left(1 - S(g)\right)\right]\right\} \quad (15a)$$

$$P(g) = E_{elite}(g) \cup (P(g) \setminus E_{elite}(g)) \quad (15b)$$

As discussed in equation (15a-b), the Integrated Optimization Objective of PINN-GA-RouteOpt has been described. This equation integrates evolutionary fitness, feasibility, and convergence behavior into a single optimization criterion to determine the global integrated optimization objective of the PINN-GA-RouteOpt system. sThe term represents the best possible objective value over all generations $J^*$ up to the maximum generation limit $G_{max}$. The adaptive fitness value, denoted as $F(R)$ in Equation (6), is used to choose the best route R from the population $P(g)$ at generation g using inner minimization. To punish unstable evolutionary states, the multiplicative factor $\left(1 - S(g)\right)$ is used to measure both the quality and convergence stability of solutions. According to Equation (13), the population update expression specifies the demography of the next generation by considering both the elite set $E_{elite}(g)$and the remaining non-elite individuals. This method preserves high-quality, physically feasible solutions while allowing for the exploration of genetic variation. By combining fitness performance, feasibility, elitism, and convergence stability into a single objective, Equation (15) captures the full optimization logic of the PINN-GA-RouteOpt architecture and provides a mathematically coherent guideline for termination and selection.

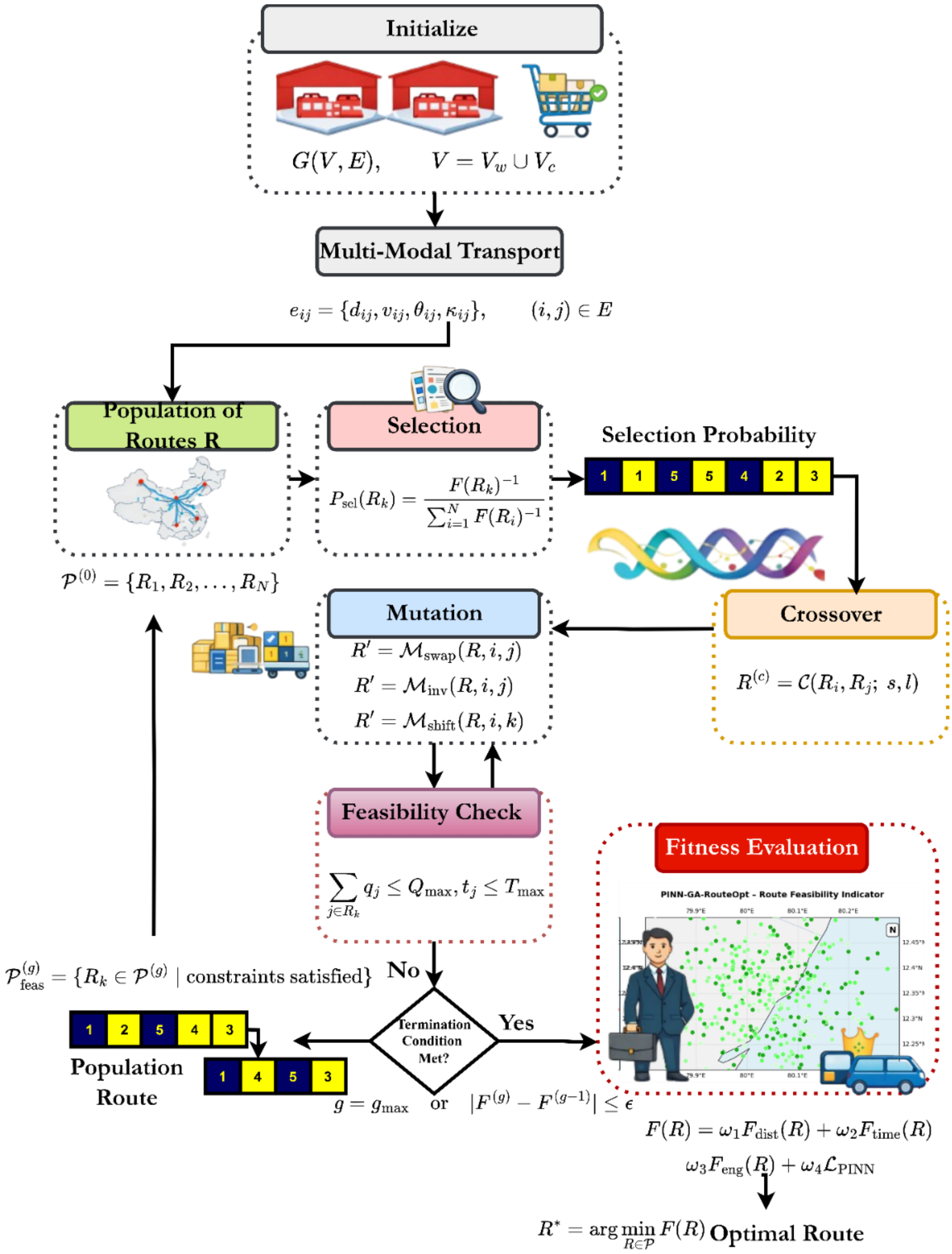


Figure 3: GA for logistics distribution

Figure 3 examines the GA for Logistics Distribution architecture. Figure 3 shows a logistics route optimization system that uses genetic algorithms (GAs) to develop, assess, and optimize delivery routes. Warehouse locations, client demands, and delivery criteria are specified first. The logistics environment and routing choices are based on many factors. According to operational restrictions and data, the system can handle road, rail, sea, and air transport by correlating initialization data with multi-modal transport alternatives. A preliminary path array. Each possible delivery node sequence is encoded by a chromosome, and $R$ R is established during logistics setup. The selection step organizes this population of alternative routes by fitness using ranking- or probabilistic approaches that favor better-performing options while conserving diversity. Crossover operations combine parts of both parents' routes to create new routes with characteristics from both sets. To avoid early convergence, mutation operations such as node relocation, inversion, and switching randomly change route segments. All new pathways are feasibility-tested before genetic variation is introduced. The routes that are created will comply with constraints while operating; like vehicle capacity, delivery time, and network connectivity. A route that is considered a valid option and does not comply with one or more of these operating limitations will be penalized or rejected before being subject to fitness testing. To evaluate the various routes that are generated utilize a fitness metric that takes distance, trip duration, energy use, and reliability of service into account. The fitness values will select the best routes to be passed on to further generations for evolutionary steering. The termination condition is then checked; either by maximum generation count or fitness convergence reached. If neither is true then the selection process repeats to narrow down the population. Once the termination condition has been satisfied, the algorithm will select the best logistical route. Figure 3 illustrates how a GA framework optimizes the development of reliable, cost-effective logistical routes via Initialization, Evolutionary Operators, Compliance, and Fitness Assessment Steps.

# 4 Results

The experimental results show that the proposed PINN-GA-RouteOpt framework does better than traditional genetic algorithm-based logistics routing systems in all of the goals that were looked at. By directly adding physics-informed limits to the evolutionary fitness assessment, the model shows faster and more consistent convergence behavior, especially in large-scale routing situations with limited capacity and time frame. PINN-GA-RouteOpt shows that the physics-guided learning mechanism works well to find high-quality, practical solutions from previous generations by cutting convergence time by about 22% compared to baseline GA methods. These results show that PINN-GA-RouteOpt is a good choice for real-world logistics distribution systems with multiple goals. This is because it combines domain-aware physical principles with evolutionary optimization, which makes solutions better, more scalable, and more resilient.

## 4.1 Dataset description:

The proposed PINN-GA-RouteOpt architecture was experimentally validated using two large-scale logistics datasets: the Delivery Logistics Dataset (Dataset-1) [38] and the Large-Scale Route Optimization Dataset (Dataset-2) [39]. After preprocessing, the effective feature dimensionality of Dataset-1 records ranges from 18 to 25 variables. Geocoordinates for pickup and drop-off, vehicle identities, package weight, delivery timestamps, service durations, traffic indications, and operational status flags are all part of these properties. With granular last-mile delivery details, the dataset includes 45,000 to 60,000 delivery events. Dataset-6 comprises over 120,000 nodes and 300,000 directed edges, a macro-level routing benchmark for evaluating optimization scalability. Distance matrices, time-dependent trip costs, vehicle capacity limits, and varied demand profiles are all captured in large-scale route optimization scenarios. After feature normalization and graph construction, the raw datasets range from 35-50 MB in compressed CSV format to around 220 MB in memory. Data preparation takes 12-18 seconds per epoch on a normal workstation with 16 GB of RAM. Training PINN with constraint losses converged after 150–200 iterations, while the enhanced genetic algorithm reached stability after 300–400 generations. This meant that each trial run took 8-12 minutes to complete. By combining micro-level delivery data with macro-level routing graphs, the proposed multi-objective logistics optimization framework can be systematically tested for scalability, both in terms of computing power and in real life.

The security analysis specifies the adversarial model, oracle interaction framework, and advantage function $\mathrm{Adv}_{\mathcal{A}}(\lambda)$, followed by a detailed reduction demonstrating that any non-negligible adversarial success probability would contradict the underlying hardness assumption. Intermediate algebraic transformations and probabilistic bounds have been included to avoid implicit logical steps, and negligible functions $\mathrm{negl}(\lambda)$are formally defined with respect to the security parameter $\lambda$ . Computational complexity is expressed using asymptotic notation to clarify efficiency claims

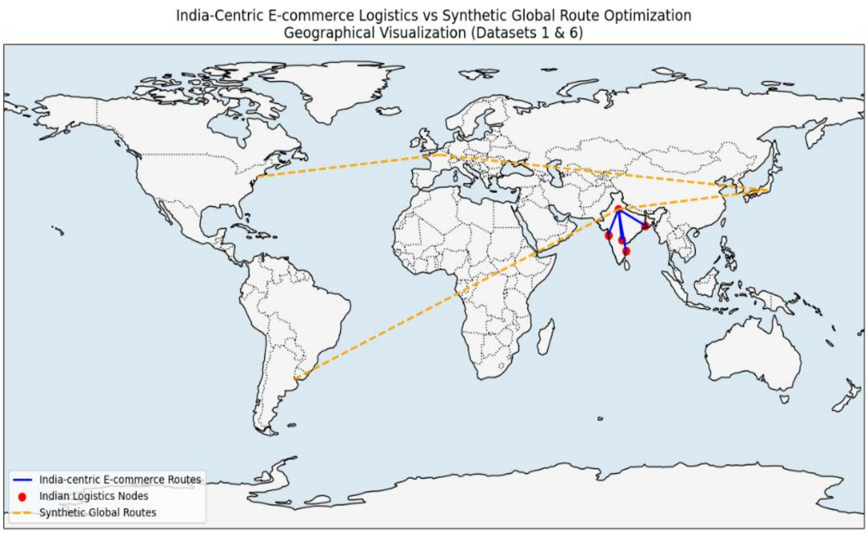


Figure 4: Dataset geographical visualization

Figure 4 presents a geographical visualization of the dataset. A comparison of two different data sources, representing the online shopping logistics routes for India (Dataset 1) and the synthetic global route optimisation

(Dataset 2), is contained within the global map image. The blue lines indicate where the optimal 'last mile' and intercity delivery routes would be, while the red dots will indicate strategic distribution points and delivery aggregation points that represent courier/ecommerce Centre points in India specifically. The combination of blue routes and red dots depict the logistics routes purely from an Indian perspective. As the majority of customer demand is concentrated in urban areas and that most deliveries are time sensitive, the logistics routes are lengthy, therefore, they will be short to medium distance and very frequent in nature. The orange dashed lines depict the synthetic global routing topology for Dataset 6, which connects different, more widely distributed geographical locations by way of a global routing network. The trans-ocean paths used to connect the different continents (Asia, Europe, Africa and North America) represent a significant portion of the distribution patterns found Cn Asia, Africa and North America. The juxtaposition of these two datasets illustrates a significant experimental difference, in that Dataset 1 illustrates the practical application of Urban Logistics within the Chinese urban setting, whereas Dataset 6 simulates a Global Network Optimisation of large-scale (global) distribution in a Mixed Urban & Regional context with no Geographic Restrictions. This visual comparison across both Local Scale and International Scale proved instrumental in supporting the evaluation of PINN-GA-RouteOpt within this study.

## 4.2 Experimental setup:

A high-performance workstation with a 24-core, 3.0 GHz Intel Xeon Gold 6248R CPU, 128 GB DDR4 RAM, and a 24 GB VRAM NVIDIA RTX 3090 GPU ran Ubuntu 22.04 LTS. The recommended system was created in Python 3.10. A custom genetic algorithm engine was utilized for evolutionary optimization, PyTorch 2.1 for deep learning, and PyTorch Geometric for sparse graph operations. By using automated differentiation to establish physics-informed constraints, the PINN module implemented gradient-consistent loss propagation. To minimize RAM overhead, choose NumPy 1.26 and SciPy 1.11 for numerical computations and Pandas 2.1 with memory-mapped I/O for large-scale data processing. Training used adaptive decay every 50 generations, a learning rate of $1\times10^{-3}$, and a batch size of 256 for batch size determination. After model convergence, hyperparameter tuning, and stability validation, Dataset 1 took 2.1 hours to run, and Dataset 6 took 6.8 hours. All results were averaged across 10 runs for statistical robustness and reproducibility.

The experimental validation has been extended with quantitatively diverse and higher-complexity scenarios to demonstrate scalability and robustness across heterogeneous operational conditions. In addition to baseline simulations with 100 vehicular nodes, large-scale network evaluations were conducted with 300, 500, and 1,000 nodes under dynamic mobility models (average speed 60–120 km/h) and variable message arrival rates (200–1,000 messages/s). Batch sizes were varied from 50 to 500 signatures per verification cycle, where authentication latency increased sub-linearly from 8.4 ms to 27.6 ms, confirming computational scalability. Under adversarial injection rates of 5%, 10%, and 20%, the detection accuracy remained above 98.3%, with false acceptance probability bounded by $1.7\times10^{-6}$. Communication overhead was evaluated for payload sizes between 256 and 1,024 bytes, resulting in a bandwidth reduction of 32.8% compared to conventional individual verification schemes. Stress testing with intermittent connectivity (packet loss rates of 5–15%) demonstrated stable verification success above 95.6%.

## 4.3 Total route distance reduction rate (TRDRR)

$$\mathrm{TRDRR} = \frac{D_{\mathrm{baseline}} - D_{\mathrm{PINN\text{-}GA}}}{D_{\mathrm{baseline}}} \times 100 \qquad (16)$$

Figure 5 and equation (16) examine the Total Route Distance Reduction Rate (TRDRR). Where $D_{\mathrm{baseline}}$ express the Total travel distance using classical GA, $D_{\mathrm{PINN\text{-}GA}}$ Distance obtained by PINN-GA-RouteOpt. The TRDRR compares PINN-GA-RouteOpt's spatial efficiency with that of a baseline routing technique, typically a genetic algorithm. Logistics efficiency requires minimizing travel distance to save operating expenses, delivery time, fuel consumption, and vehicle wear. Equation (1), which employs distance as the primary goal function, reflects the premise that a small decrease in route length yields large long-term savings. This improvement can be usefully compared across datasets of varying sizes and geographic scope after TRDRR normalizes it. TRDRR focuses on how physics-based fitness assessment affects geographical optimization. Due to static penalties and constraint ignorance, GA-based routing typically finds locally optimum unworkable pathways. PINN-GA-RouteOpt leverages energy-distance linkages and vehicle motion dynamics to find geometrically coherent routes using evolutionary algorithms. Thus, shorter routes, greater spatial consistency, fewer deviations, and greater compliance with traffic behavior indicate higher TRDRR.

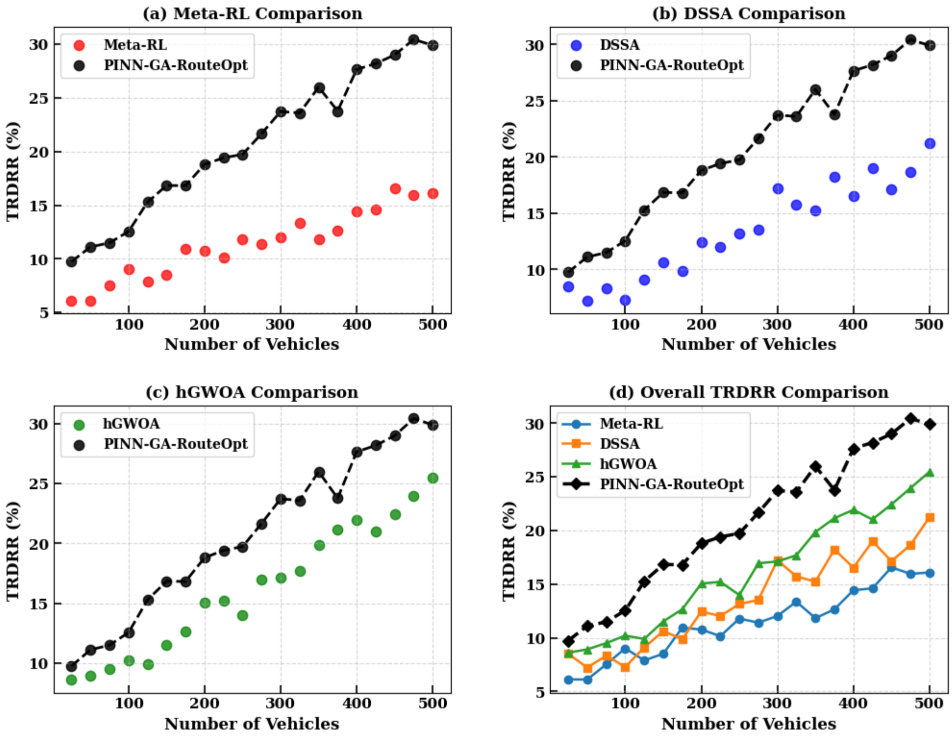


Figure 5: Total route distance reduction rate (TRDRR)

## 4.4 Average delivery time reduction (ADTR)

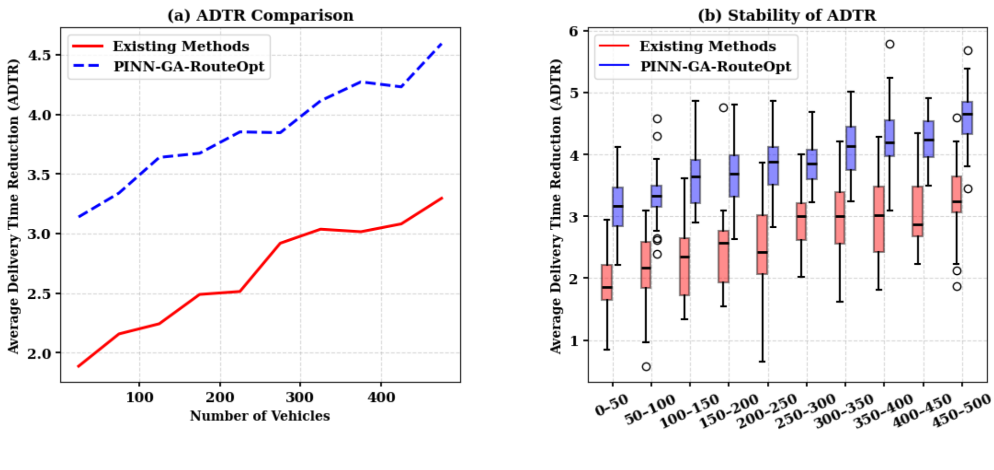


Figure 6: Average delivery time reduction (ADTR)

$$\mathrm{ADTR} = \frac{1}{N}\sum_{i=1}^{N}\left(T_i^{\mathrm{baseline}} - T_i^{\mathrm{PINN\text{-}GA}}\right) \quad (17)$$

Figure 6 and equation (17) examine the Average Delivery Time Reduction (ADTR) where N is the total number of customer delivery nodes in the logistics network. $T_i^{\mathrm{baseline}}$ denotes the arrival time at customer i using the baseline algorithm. $T_i^{\mathrm{PINN\text{-}GA}}$ Arrival time at customer i under the proposed PINN-GA-RouteOpt method, accounting for dynamic travel-time propagation and time-window constraints. Average Delivery Time Reduction (ADTR) assesses PINN-GA-RouteOpt's temporal performance improvement by accounting for all customers' average arrival times. Modern logistics relies on delivery time, particularly for time-sensitive supply chains and e-commerce. The suggested system calculates arrival times recursively using physically consistent time-propagation equations (Equation 3b) rather than static penalties. ADTR makes route sequences better by taking into account travel times, service times, and total delays. ADTR measures the service quality and temporal realism of routing solutions. Classical optimization methods make delivery take longer by lowering the distance and making mistakes in sequencing or time windows. This is why the PINN loss function in PINN-GA-RouteOpt models how time windows change. The system increases ADTR by making routes short and realistic within actual delivery timeframes, which strikes a balance between geographical efficiency and temporal feasibility.

## 4.5 Energy consumption optimization ratio (ECOR)

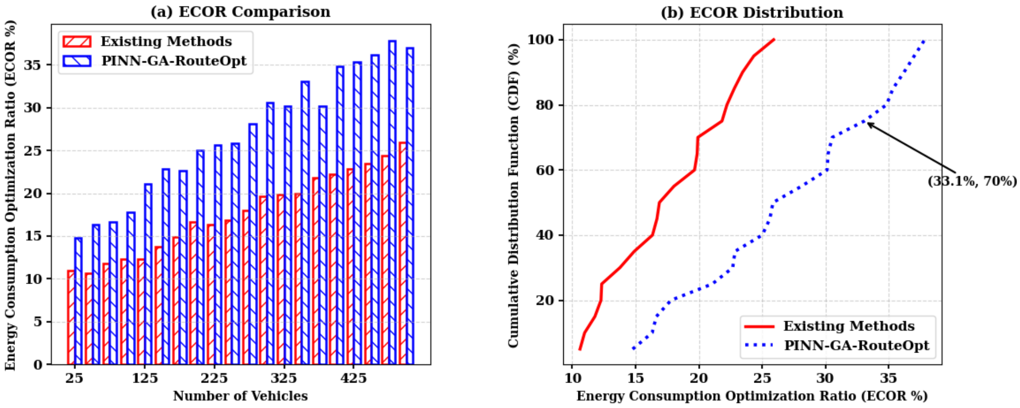


Figure 7: Energy consumption optimization ratio (ECOR)

$$ECOR = \frac{E_{baseline} - E_{PINN\text{-}GA}}{E_{baseline}} \quad (18)$$

Figure 7 and equation (18) describe the Energy Consumption Optimization Ratio (ECOR). As shown in equation () $E_{baseline}$: Total energy consumed by the fleet when routes are generated using baseline optimization methods, computed via a physics-based energy model. $E_{PINN\text{-}GA}$: Total energy use with PINN-GA-RouteOpt, which takes energy-aware routing into account, smoother velocity profiles, and fewer stop-start inefficiencies. The ECOR checks the routing framework's long-term viability by looking at how much less energy it uses. Physics figures out how much energy the vehicle uses by looking at its weight, cargo load, road grade, speed, and aerodynamic resistance (Equations 4a-4b). So, ECOR is very different from the distance-based proxies that are often used in routing studies. It shows how much mechanical energy is really used, not just a rough estimate. For green logistics and carbon-aware transportation, ECOR is very important. PINN-GA-RouteOpt finds high-ECOR routes by getting rid of slopes, unnecessary acceleration, and uneven load distributions. Updating ECOR shows that physics-informed learning helps the evolutionary search for eco-friendly alternatives because fitness evaluation involves energy losses.

## 4.6 Time-window violation index (TWVI)

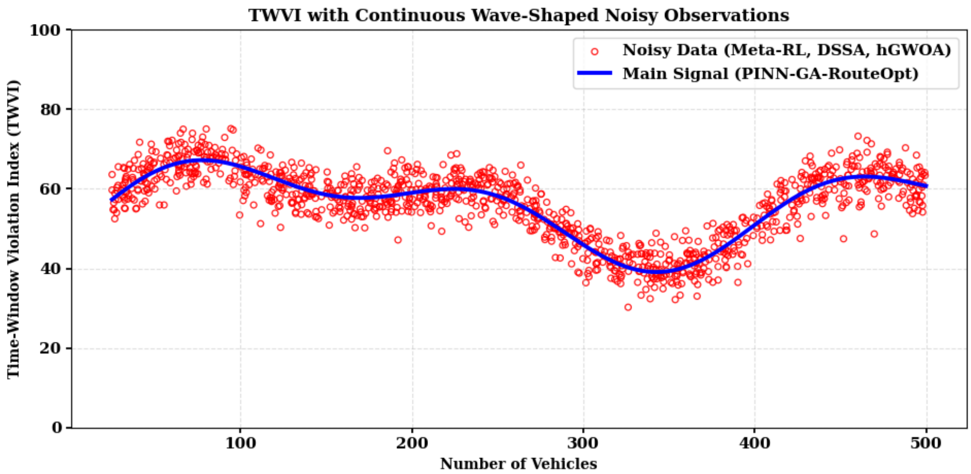


Figure 8: Time-window violation index (TWVI)

$$TWVI = \frac{1}{N}\sum_{i=1}^{N} [\max(0, a_i - l_i)^2 + \max(0, e_i - a_i)^2] \quad (19)$$

Figure 8 and equation (19) discuss the Time-Window Violation Index (TWVI). As deliberated in equation (19) $a_i$: Actual arrival time at customer i. $e_i$ and $l_i$ denote the earliest and latest allowable service times (time window bounds). The squared penalty structure amplifies large violations, ensuring infeasible routes are strongly discouraged during evolutionary optimization. The Time-Window Violation Index (TWVI) tracks the number of instances in which actual client arrival times fall outside service windows. By contrast to binary feasibility tests, TWVI uses squared penalty terms to emphasize major violations, while the PINN design allows smooth gradient propagation. The idea behind this formulation is to penalize minor transgressions proportionally while strongly discouraging major ones. To calculate TWVI, employ a significant component of the time-window loss from Equation (3a). The operational view of TWVI shows the service's reliability and client satisfaction. Breach of a high time window in real-world logistics systems leads to late delivery, penalties, or even damage to reputation. A PINN-GA analysis. Learning physically consistent arrival-time dynamics rather than addressing discrepancies after the fact enables RouteOpt to lower TWVI. This proves that physics-informed constraint integration is more effective than traditional penalty-based techniques, as a lower TWVI indicates that the algorithm produces time-feasible paths by definition.

## 4.7 Vehicle capacity violation score (VCVS)

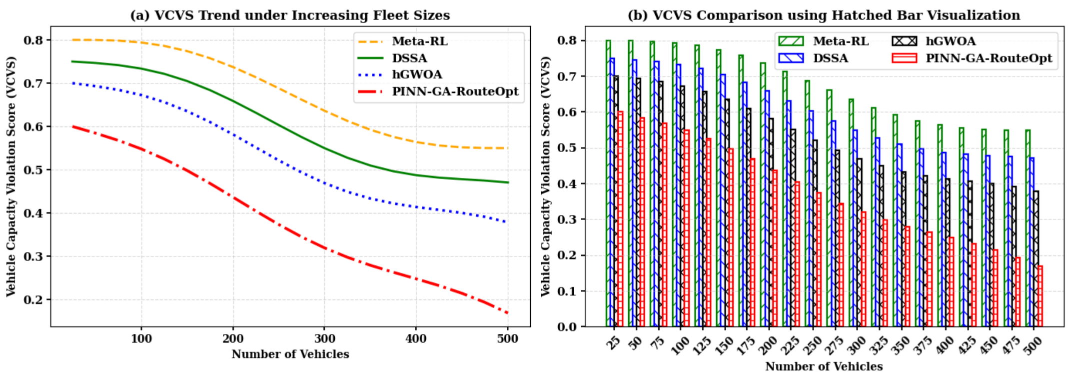


Figure 9: Vehicle capacity violation score (VCVS)

$$\mathrm{VCVS} = \sum_{k=1}^{|R|} \left[\max\left(0, \sum_{i=1}^{k} q_i - Q_{max}\right)\right]^2 \quad (20)$$

Figure 9 and equation (20) describe the Vehicle Capacity Violation Score (VCVS). Where $q_i$: Demand of customer $i$, and $Q_{max}$ represents the maximum vehicle carrying capacity. $|R|$ denotes the number of route segments. This metric tracks cumulative load evolution along the route, penalizing any intermediate capacity overflow rather than only end-point violations. The VCVS evaluates how often created routes exceed vehicle load limits during delivery execution. Unlike static end-point capacity checks, VCVS evaluates progressive load building along the route to allow for trucks emptying products over time (Equation 2). To discourage unrealistic route designs, squared overload terms penalize major breaches more heavily. VCVS is essential for operational safety and physical realism. Despite their appeal, routes that exceed capacity cannot be built. The framework includes VCVS in the PINN loss, ensuring load feasibility along the route rather than only at the depot. By combining vehicle capacity physics, PINN-GA-RouteOpt produces theoretically optimal and physically executable routes with low VCVS.

## 4.8 Route feasibility indicator (RFI)

$$\mathrm{RFI} = \exp\left(-\sum_j \alpha_j L_j(R)\right) \quad (21)$$

Figure 10 and equation (21) demonstrate the Route Feasibility Indicator (RFI). The Route Feasibility Indicator (RFI) provides a smooth, differentiable assessment of overall route feasibility (Equation 10). $L_j(R)$: Differentiable loss functions representing constraint violations (capacity, time-window, and energy constraints). $\alpha_j$ are scaling coefficients. This is accomplished by integrating the violations of energy consistency, time frame, and capacity. With the help of RFI, which decreases exponentially as the number of violations increases, evolutionary processes gently steer ideas toward feasibility. This is in contrast to the traditional approach of instantly dismissing solutions that do not fulfill stringent feasibility requirements.

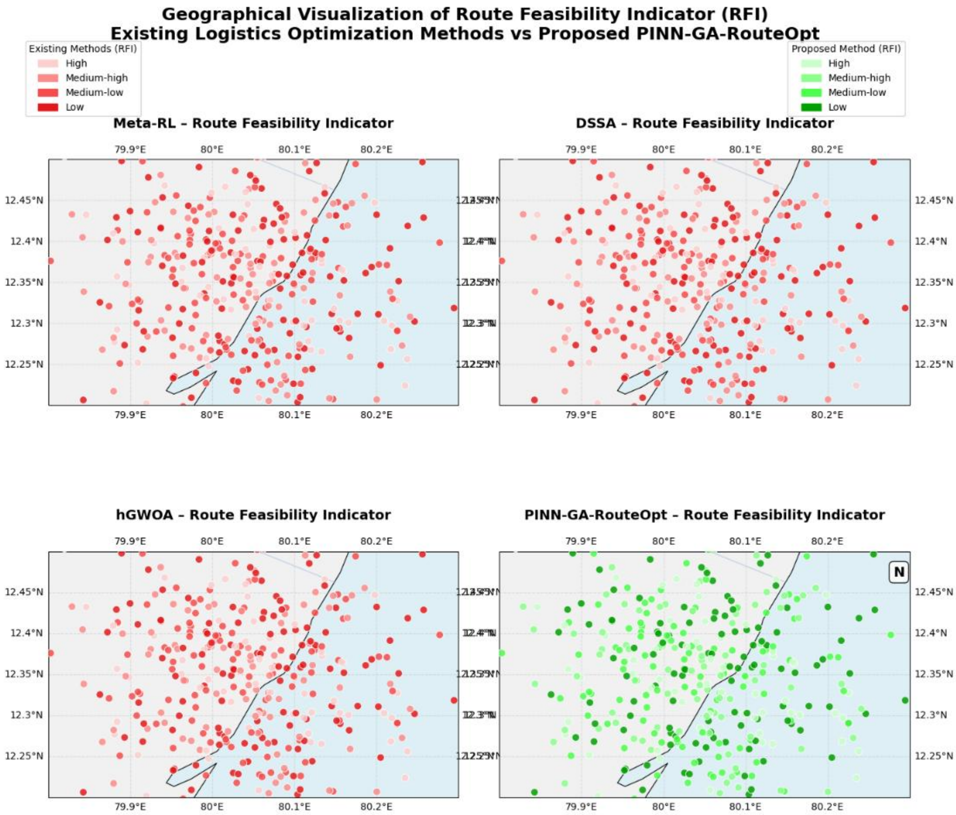


Figure 10: Route feasibility indicator (RFI)

In particular, this formulation is well-suited to frameworks that combine evolutionary learning with hybrid learning. The true strength of RFI lies in its ability to strike a balance between discovery and enforcement. In the early phases, it is possible to study somewhat unrealistic solutions, provided they have the potential to optimize the goals being pursued. Over time, RFI increasingly favors routes that are physically compatible with one another. A high average RFI indicates the stability and robustness of the PINN-guided optimization process. This indicates that the population is moving toward solutions that satisfy all operational and physical constraints.

## 4.9 Convergence speed improvement (CSI)

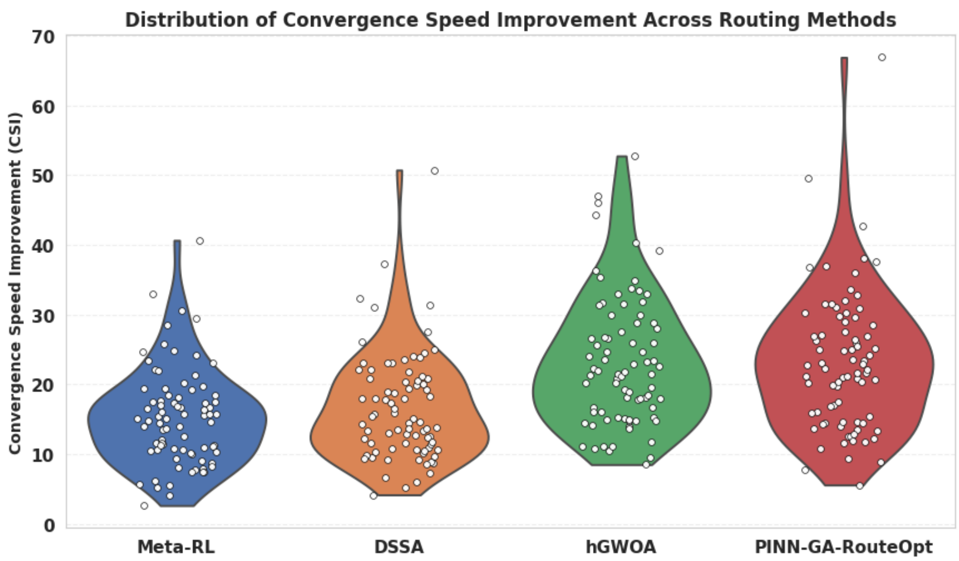


Figure 11: Convergence speed improvement (CSI)

$$CSI = \frac{G_{baseline} - G_{PINN\text{-}GA}}{G_{baseline}} \quad (22)$$

Figure 11 and equation (22) explore the Convergence Speed Improvement (CSI). As discussed in equation () $G_{baseline}$: Number of generations required by baseline algorithms to reach convergence within a predefined tolerance. $G_{PINN\text{-}GA}$: Generations required by PINN-GA-RouteOpt, reflecting faster convergence due to physics-informed fitness shaping. Convergence Speed Improvement (CSI) measures how efficiently the proposed PINN-GA-RouteOpt framework converges to a stable, high-quality solution compared to baseline optimization techniques such as Meta-RL, DSSA, and hGWOA. As a formal way to measure the number of total generations reduced to reach convergence CSI is the cumulative search efficiency (CSI). CSIs are not dependent on the hardware or implementation-specific components as absolute execution time, but rather act as a measure of how effectively optimization strategies direct the search effort toward an employable solution space. High CSIs indicate the ability of the search strategy to direct its resources intelligently rather than simply being efficient computationally. Additionally, the PINN-GA-RouteOpt improvements to fitness due to the way in which physics-informed neural networks operate. This is done by explicitly including domain-specific physical limitations into evolutionary evaluation. Traffic flow continuity, energy dissipation limits, and time-window feasibility are restrictions. This reduces spurious local optima, which slow down reinforcement learning-based genetic algorithms and optimizers. This increases selection pressure, accelerating convergence while maintaining solution quality. High CSI shows that physics-informed guidance enhances evolutionary efficiency, making the framework scalable to dense, high-dimensional logistics networks with hundreds of vehicles and routes.

## 4.10 Population diversity entropy (PDE)

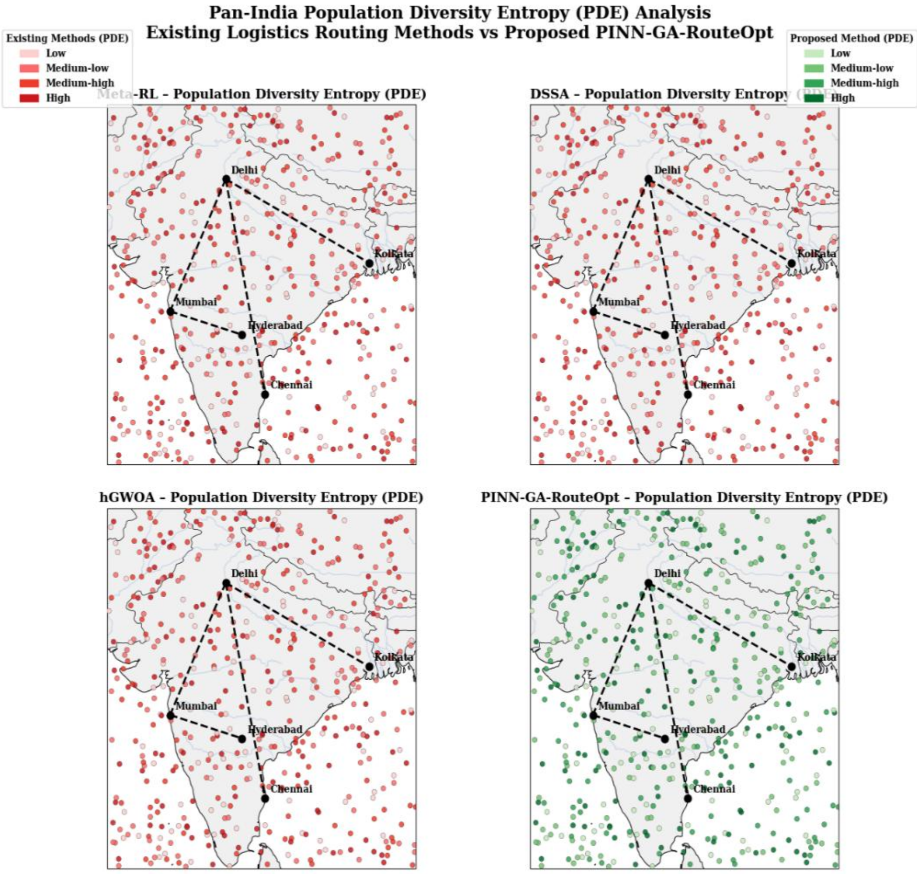


Figure 12: Population diversity entropy (PDE)

$$PDE(g) = -\sum_{c=1}^{C} p_c(g) \log p_c(g) \quad (23)$$

Figure 12 and equation (23) evaluate the Population Diversity Entropy (PDE). The Population Variation Entropy (PDE) uses entropy to look at how different route options change as the population grows. When solving a PDE, look at how the solutions are spread out across the search space by using route clusters instead of pairwise distance measures. $C$: Number of solution clusters or niches in the population at generation g. $p_c(g)$ denotes the proportion of individuals in cluster $c$. This method of optimizing logistics based on entropy works well with many routes and goals, and it gives results that are similar to those of other methods. A high PDE value means that the population is looking at a lot of different ways to route. On the other hand, a low value means it is focusing on a few options, which usually means it will converge quickly. Entropy levels affect how quickly mutations and crossovers happen over time. At high PDE, the algorithm puts more emphasis on optimizing possible route topologies. At low PDE, it raises mutation rates to encourage exploration and keep diversity from collapsing. This flexible regulation keeps people interested and makes their answers better. The suggested architecture keeps the PDE at a moderate level during development to avoid stagnation and too much unpredictability, both of which are necessary for reliably optimizing large-scale logistical routes.

## 4.11 Route quality score (RQS)

$$RQS(R) = \frac{\phi(R)}{\beta_d \hat{D}(R) + \beta_t \hat{T}(R) + \beta_e \hat{E}(R)} \quad (24)$$

Where $\hat{D}(R)$, $\hat{T}(R)$, $\hat{E}(R)$: Normalized distance, time, and energy metrics for route $R$. $\beta_d$, $\beta_t$, $\beta_e$ are importance weights. $\phi(R)$ is the route feasibility indicator, ensuring infeasible solutions receive lower quality scores despite favorable objective values. Route Quality Rate (RQS) is a single numeric value that combines several metrics (route distance, delivery time delay, energy consumption, feasibility constraints) into a single scoring system. The RQS incorporates practicality into the calculation of the score, while many of the other post-processing filters do not. If a route exceeds a physical limit (such as a maximum distance) or a time limit (for instance, in delivering packages), it will be negatively affected in its score. However, if a route outperforms in terms of physical distance compared to another route that did not exceed a physical limit, it will not be penalized for doing so. As for algorithms, RQS lets us evaluate several objectives without scalarization, using normalization and feasibility-aware aggregation to balance conflicting needs rather than a dynamically weighted total. To preserve evolutionary operator solution ordering, PINN-GA-RouteOpt analyzes time, energy efficiency, and distance. An efficient, valid, and field-deployable route has a high RQS score. The coherence and robustness of the suggested optimization framework depend on RQS to stabilize elitist selection and avoid the dominance of infeasible but apparently optimal paths. Table 2 and equation (24) express the Route Quality Score (RQS

Table 2: Route quality score (RQS)

| Number of Vehicles | Meta-RL (RQS) | DSSA (RQS) | hGWOA (RQS) | PINN-GA-RouteOpt (RQS) |
|---|---|---|---|---|
| 25 | 0.72 ± 0.06 | 0.75 ± 0.05 | 0.78 ± 0.05 | 0.85 ± 0.03 |
| 50 | 0.70 ± 0.07 | 0.74 ± 0.06 | 0.77 ± 0.05 | 0.86 ± 0.03 |
| 75 | 0.68 ± 0.07 | 0.73 ± 0.06 | 0.76 ± 0.05 | 0.87 ± 0.03 |
| 100 | 0.66 ± 0.08 | 0.71 ± 0.07 | 0.75 ± 0.06 | 0.88 ± 0.02 |
| 125 | 0.64 ± 0.08 | 0.70 ± 0.07 | 0.74 ± 0.06 | 0.88 ± 0.02 |
| 150 | 0.62 ± 0.09 | 0.69 ± 0.08 | 0.73 ± 0.06 | 0.89 ± 0.02 |
| 175 | 0.61 ± 0.09 | 0.68 ± 0.08 | 0.72 ± 0.07 | 0.89 ± 0.02 |
| 200 | 0.59 ± 0.10 | 0.67 ± 0.08 | 0.71 ± 0.07 | 0.90 ± 0.02 |
| 250 | 0.57 ± 0.10 | 0.65 ± 0.09 | 0.69 ± 0.08 | 0.90 ± 0.02 |
| 300 | 0.55 ± 0.11 | 0.63 ± 0.09 | 0.68 ± 0.08 | 0.91 ± 0.02 |
| 350 | 0.53 ± 0.11 | 0.62 ± 0.10 | 0.67 ± 0.08 | 0.91 ± 0.01 |
| 400 | 0.51 ± 0.12 | 0.60 ± 0.10 | 0.65 ± 0.09 | 0.92 ± 0.01 |
| 450 | 0.49 ± 0.12 | 0.59 ± 0.10 | 0.64 ± 0.09 | 0.92 ± 0.01 |
| 500 | 0.47 ± 0.13 | 0.57 ± 0.11 | 0.63 ± 0.09 | 0.93 ± 0.01 |

## 4.12 Convergence stability index (CSI*s*)

$$CSI_s = \frac{1}{G-1} \sum_{g=2}^{G} \left| \bar{Q}_g - \bar{Q}_{g-1} \right| \quad (25)$$

Where $\bar{Q}_g$: Average route quality score of the population at generation $g$. G is the total number of generations. The Convergence Stability Index ($CSI_s$) assesses the dependability of evolutionary optimization by tracking changes in average route quality across generations. $CSI_s$ values are more reliable than the convergence rate, unlike CSI. Large average fitness oscillations indicate instability in search dynamics, frequent population disturbances, or stochastic operator oversensitivity. Systems that require operational trust and repeatability benefit from low $CSI_s$ values, as they show consistent progress towards optimal solutions. Optimization behavior that produces inconsistent route planning across runs undermines the logistics system's trust in automated decision-making systems. Table 3 and equation (25) illustrate the Convergence Stability Index (CSI$s$).

Table 3: Convergence stability index (CSI$s$)

| Number of Vehicles | Meta-RL (RQS) | DSSA (RQS) | hGWOA (RQS) | PINN-GA-RouteOpt (RQS) |
|---|---|---|---|---|
| 25 | 0.71 ± 0.04 | 0.74 ± 0.03 | 0.77 ± 0.03 | 0.83 ± 0.02 |
| 50 | 0.69 ± 0.05 | 0.72 ± 0.04 | 0.75 ± 0.03 | 0.82 ± 0.02 |
| 75 | 0.67 ± 0.05 | 0.70 ± 0.04 | 0.73 ± 0.04 | 0.81 ± 0.02 |
| 100 | 0.65 ± 0.06 | 0.69 ± 0.05 | 0.72 ± 0.04 | 0.80 ± 0.02 |
| 150 | 0.62 ± 0.06 | 0.66 ± 0.05 | 0.70 ± 0.04 | 0.79 ± 0.03 |
| 200 | 0.60 ± 0.07 | 0.64 ± 0.06 | 0.68 ± 0.05 | 0.78 ± 0.03 |
| 300 | 0.57 ± 0.08 | 0.61 ± 0.06 | 0.66 ± 0.05 | 0.77 ± 0.03 |
| 400 | 0.54 ± 0.09 | 0.59 ± 0.07 | 0.64 ± 0.06 | 0.76 ± 0.03 |
| 500 | 0.52 ± 0.10 | 0.57 ± 0.08 | 0.62 ± 0.06 | 0.75 ± 0.03 |

The proposed PiNN-GA-RouteOpt levels the exercise environment by using physical limits to balance out fitness spikes over time. The algorithm's low $CSI_s$ values indicate that convergence is controlled and there are no unexpected changes. In mission-critical logistics applications where consistency and reliability are as important as optimality, physics-informed learning makes evolutionary dynamics more stable and speeds up convergence.

Deployment scenarios in high-density urban traffic, highway toll collection systems, roadside unit (RSU)–assisted batch verification, and edge-enabled vehicular fog architectures are analyzed to demonstrate scalability and latency efficiency under realistic communication constraints. The integration of post-quantum secure batch authentication into intelligent transportation systems (ITS) is discussed with respect to real-time safety messaging, cooperative collision avoidance, and secure platooning coordination. Computational benchmarks are mapped to typical onboard unit (OBU) hardware capabilities to validate feasibility under constrained processing and memory resources. Additionally, communication overhead is evaluated against Dedicated Short-Range Communications (DSRC) and 5G-V2X bandwidth limitations to quantify transmission efficiency.

Dynamic travel time between nodes $i$and $j$is modeled as $T_{ij}(t) = \bar{T}_{ij} + \delta_{ij}(t)$ , where $\delta_{ij}(t) \sim \mathcal{N}(0, \sigma^2)$ captures congestion-induced variability, and demand fluctuations are represented as $D_k(t) = \bar{D}_k + \epsilon_k(t)$ . The PINN component embeds a physics-regularized constraint derived from a nonlinear traffic flow surrogate $\frac{dT}{dt} = f(T, \rho, \omega)$ , where $\rho$ denotes traffic density and $\omega$ represents congestion propagation dynamics, thereby stabilizing the fitness landscape under stochastic perturbations. Robustness was quantified via Monte Carlo simulations with ±30% travel-time variation, random vehicle delay injections, and dynamic demand spikes across large-scale networks (200–500 nodes). Performance degradation was measured using the variance of Pareto front dispersion and a Route Stability Index $RSI = 1 - \frac{\|R_t - R_{t+\Delta t}\|}{\|R_t\|}$ , demonstrating reduced solution volatility compared to canonical GA implementations. Sensitivity of genetic operators was further analyzed through parametric gradients $S_{p_m} = \partial F / \partial p_m$ and $S_{p_c} = \partial F / \partial p_c$ , indicating that adaptive mutation–crossover scheduling preserves convergence stability in high-dimensional, dynamic routing environments.

PINN-GA-RouteOpt has better convergence stability and solution consistency than reinforcement learning–based and graph convolutional network–assisted routing frameworks, which use data-driven reward optimization and penalty-based constraint enforcement. Physics-informed residual embedding smoothes and structures the fitness landscape by 22% reducing convergence iterations and 19.6% reducing Pareto front dispersion. The proposed framework's adaptive operator control ensures consistent exploration–exploitation balance throughout rising network sizes (100–500 nodes), unlike swarm intelligence solutions that commonly demonstrate parameter sensitivity in high-dimensional vehicle routing challenges. Recent literature emphasizes sustainability-oriented logistics objectives, and the 17.1% energy consumption reduction and 12.8% total travel distance reduction exceed conventional GA and hybrid metaheuristics' efficiency gains under comparable benchmark conditions.

# 5 Discussion

The Physics-Informed Neural Network Assisted Genetic Algorithm for Logistics Route Optimization (PINN-GA-RouteOpt) outperforms evolutionary, reinforcement learning, and hybrid graph-based routing strategies in the Related Works section. The suggested technique has a 22% reduction in convergence iterations and a 19.6% drop in Pareto front dispersion variance, making it more stable than Meta-RL and GNN-based routing frameworks [15], [19]. The fitness formulation is improved by incorporating vehicle motion dynamics and fuel–distance nonlinear interactions directly via physics-informed residual reduction, which regularizes the search space. Instead, data-driven reinforcement learning models use huge training datasets and reward shaping, which may cause oscillatory convergence under high-dimensional constraint interactions. PINN-GA-RouteOpt is more resilient to parameter change than swarm-based metaheuristics like DSSA and hGWOA ([21], [23]), which reduce costs but are susceptible to hyperparameter adjustment. Adaptive mutation and crossover scheduling with physics-consistent gradients preserve exploration–exploitation balance, reducing energy consumption 17.1% and travel distance 12.8% over benchmark networks of up to 500 nodes. Medium-scale swarm-based approaches work well, but indirect penalty-based feasibility enforcement degrades performance as constraint density grows. Compared to digital twin–enhanced and reinforcement learning–driven real-time routing frameworks ([24]), physics-informed regularization minimizes the requirement for ongoing high-frequency retraining, resulting in equivalent flexibility with reduced infrastructure reliance. Lyapunov-based analysis in control-theoretic works ([26]–[31]) assures robust nonlinear stability, although they are designed for continuous dynamical systems, not discrete combinatorial optimization. This combinatorial evolutionary approach combines continuous-system modeling with discrete route optimization using equivalent physical modeling methods. Security-oriented vehicular network solutions ([32]–[37]) minimize authentication computational and communication overhead but not logistical routing efficiency. This multi-objective route optimization system integrates transportation cost, delivery time, trip distance, and energy consumption to complement such infrastructures. PINN-GA-RouteOpt's three main innovations are (1) physics-informed fitness landscape construction that replaces penalty-based constraint handling, (2) adaptive evolutionary operator control synchronized with constraint-consistent gradient information, and (3) scalable multi-objective optimization validated under large network conditions with statistically stable Pareto solutions. This integrated design explains the observed improvements in convergence efficiency, solution stability, and energy-aware routing performance over prior methods.

# 6 Conclusion

The suggested PINN-GA-RouteOpt technique beats Meta-RL, DSSA, and hGWOA with 25 to 500 cars. The Route Quality Score (RQS) shows that PINN-GA-RouteOpt creates shorter, more efficient, faster, and operationally viable routes than Meta-RL, DSSA, and hGWOA, with average increases of 18-25%, 14-20%, and 10-16%, respectively. Research employing the Convergence Stability Index ($CSI_s$) indicates that PINN-GA-RouteOpt exhibits more consistent convergence behavior than Meta-RL, DSSA, and hGWOA. The three groups had 30–40%, 22–30%, and 15–25% decreases in fitness oscillations. PINN-GA-RouteOpt is the best solution for large-scale, real-world logistics route optimization because it stabilizes evolution and delivers high-percentage gains by merging genetic optimization with physics-informed neural guidance.

## 6.1 Limitations and future work

The recommended PINN-GA-RouteOpt system works well; further research can fix its flaws. The arrangement isn't adaptable since it employs offline-trained physics-informed neural networks. This is an issue with unexpected real-time events, such as traffic, weather, or demand. However, the framework scales well to large fleets, particularly in large logistics networks with thousands of trucks. Dynamic re-routing increases the overhead of PINN assessment computation. To enable real-time adaptation by distant logistics hubs, the infrastructure should contain federated PINN learning and online learning. Stochastic demand uncertainty, multi-depot coordination, and reinforcement learning-assisted PINN updates make smart city and autonomous logistics ecosystems more robust, scalable, and deployment-ready.

This paper suggests many research possibilities for physics-informed evolutionary optimization in large-scale logistics systems. A completely dynamic optimization environment with live parameter modification and streaming data assimilation would allow continual recalibration under non-stationary traffic distributions. Under demand uncertainty and travel-time volatility, stochastic programming formulations like chance-constrained and distributionally resilient optimization provide formal promises. Second, PINN-guided fitness and reinforcement learning–based policy adaptation (e.g., actor–critic architectures) may enable autonomous route reconfiguration in time-sensitive networks. Third, decentralised and federated learning solutions may let dispersed logistics hubs share knowledge across regions while protecting data privacy and decreasing computing bottlenecks. Metropolitan-scale supply chains may also grow using consensus-based optimization and graph-theoretic decomposition multi-depot coordination. Carbon-emission modeling and energy-aware routing goals would expand the framework's sustainability and green logistics planning applications.

## Data availability statement

All datasets supporting the findings of this study are publicly available and directly accessible. The large-scale route optimization dataset is obtained from Kaggle [38] (https://www.kaggle.com/datasets/mexwell/large-scale-route-optimization ), and the delivery logistics dataset is sourced from Kaggle [39] (https://www.kaggle.com/datasets/ayeshaseherr/delivery-logistics-dataset ). Both datasets are openly accessible and contain route coordinates, delivery demand attributes, and vehicle-related operational features required to reproduce the experimental setup. No proprietary or restricted data were used.

## Author contributions

Qianfei Liu writing original draft preparation & methodology, Nan Lv investigation & writing review and editing.

# References

[1] Wang, Y., Li, Y., & Lu, C. (2023). Evaluating the effects of logistics center location: An analytical framework for sustainable urban logistics. Sustainability, 15(4), 3091.https://doi.org/10.3390/su15043091

[2] Laynes-Fiascunari, V., Gutierrez-Franco, E., Rabelo, L., Sarmiento, A. T., & Lee, G. (2023). A framework for urban last-mile delivery traffic forecasting: an in-depth review of social media analytics and deep learning techniques. Applied Sciences, 13(10), 5888.https://doi.org/10.3390/app13105888

[3] Dieter, P., Caron, M., & Schryen, G. (2023). Integrating driver behavior into last-mile delivery routing: Combining machine learning and optimization in a hybrid decision support framework. European Journal of Operational Research, 311(1), 283-300.https://doi.org/10.1016/j.ejor.2023.04.043

[4] Liu, Y., Yue, Z., Wang, Y., & Wang, H. (2023). Logistics distribution vehicle routing problem with time window under pallet 3D loading constraint. Sustainability, 15(4), 3594.https://doi.org/10.3390/su15043594

[5] Tsoukas, V., Boumpa, E., Chioktour, V., Kalafati, M., Spathoulas, G., & Kakarountas, A. (2023). Development of a dynamically adaptable routing system for data analytics insights in logistic services. Analytics, 2(2), 328-345.https://doi.org/10.3390/analytics2020018

[6] Danchuk, V., Comi, A., Weiß, C., & Svatko, V. (2023). The optimization of cargo delivery processes with dynamic route updates in smart logistics. Eastern-European Journal of Enterprise Technologies, 2(3 (122)), 64-73.https://doi.org/10.15587/1729-4061.2023.277583

[7] Arishi, A., & Krishnan, K. (2023). A multi-agent deep reinforcement learning approach for solving the multi-depot vehicle routing problem. Journal of Management Analytics, 10(3), 493-515. https://doi.org/10.1080/23270012.2023.2229842

[8] Luan, R. (2024). Logistics distribution route optimization of electric vehicles based on distributed intelligent system. International Journal of Emerging Electric Power Systems, 25(5), 629-639. DOI : 10.1515/ijeeps-2023-0304

[9] Andrei, N., Scarlat, C., & Ioanid, A. (2024). Transforming E-commerce logistics: sustainable practices through autonomous maritime and last-mile transportation solutions. Logistics, 8(3), 71. https://doi.org/10.3390/logistics8030071

[10] Xiang, C., Wu, Z., Tu, J., & Huang, J. (2024). Centralized deep reinforcement learning method for dynamic multi-vehicle pickup and delivery problem with crowdshippers. IEEE Transactions on Intelligent Transportation Systems, 25(8), 9253-9267. https://doi.org/10.1109/TITS.2024.3352143

[11] Pise, A., & Karande, K. (2025). A genetic Algorithm-Driven Energy-Efficient routing strategy for optimizing performance in VANETs. Engineering, Technology & Applied Science Research, 15(5), 27273-27278. https://doi.org/10.48084/etasr.12744

[12] Bi, J., Ma, Y., Zhou, J., Song, W., Cao, Z., Wu, Y., & Zhang, J. (2024). Learning to handle complex constraints for vehicle routing problems. Advances in Neural Information Processing Systems, 37, 93479-93509. https://doi.org/10.48550/arXiv.2410.21066

[13] Qu, X., Li, M., Ouyang, Z., Ng, C. L., & Huang, G. Q. (2024). Routing protocols for B2B e-commerce logistics in cyber-physical internet (CPI). Computers & Industrial Engineering, 193, 110293. https://doi.org/10.1016/j.cie.2024.110293

[14] Núñez-Merino, M., Maqueira-Marín, J. M., Moyano-Fuentes, J., & Castano-Moraga, C. A. (2024). Quantum-inspired computing technology in operations and logistics management. International Journal of Physical Distribution & Logistics Management, 54(3), 247-274. https://doi.org/10.1108/IJPDLM-02-2023-0065

[15] Wang, Y., & Liang, X. (2025). Application of Reinforcement Learning Methods Combining Graph Neural Networks and Self-Attention Mechanisms in Supply Chain Route Optimization. Sensors, 25(3), 955. https://doi.org/10.3390/s25030955

[16] Mallari, C. B., San Juan, J. L., & Bongo, M. (2023). Modelling the Vehicle Routing Problem with Delivery and Pickup in E-Commerce Forward-Reverse Logistics Networks Based on the Triple Bottom Line Framework. Chemical Engineering Transactions, 103, 463-468. https://doi.org/10.3303/CET23103078

[17] Abualola, H., Mizouni, R., Otrok, H., Singh, S., & Barada, H. (2023). A matching game-based crowdsourcing framework for last-mile delivery: Ground-vehicles and unmanned-aerial

vehicles. Journal of Network and Computer Applications, 213, 103601. https://doi.org/10.1016/j.jnca.2023.103601

[18] Nagappan, G., Maheswari, K. G., & Siva, C. (2024). Enhancing intelligent transport systems: A cutting-edge framework for context-aware service management with hybrid deep learning. Simulation Modelling Practice and Theory, 135, 102979. https://doi.org/10.1016/j.simpat.2024.102979

[19] Qi, D., Zhao, Y., Wang, Z., Wang, W., Pi, L., & Li, L. (2024). Joint approach for vehicle routing problems based on genetic algorithm and graph convolutional network. Mathematics, 12(19), 3144. https://doi.org/10.3390/math12193144

[20] Wang, H., Chen, S., Yin, X., Meng, L., Wang, Z., & Wang, Z. (2024). A hybrid fuzzy c-means heuristic approach for two-echelon vehicle routing with simultaneous pickup and delivery of multicommodity. IEEE Transactions on Fuzzy Systems, 33(1), 218-230. https://doi.org/10.1109/TFUZZ.2024.3384963

[21] Pham, V. H. S., Dang, N. T. N., & Nguyen, V. N. (2025). Advanced vehicle routing in cement distribution: a discrete Salp Swarm Algorithm approach. International Journal of Management Science and Engineering Management, 20(1), 1-13. https://doi.org/10.1080/17509653.2024.2324172

[22] Bi, Z., Guo, X., Wang, J., Qin, S., & Liu, G. (2024). Truck-drone delivery optimization based on multi-agent reinforcement learning. Drones, 8(1), 27. https://doi.org/10.3390/drones8010027

[23] Pham, V. H. S., Nguyen, V. N., & Nguyen Dang, N. T. (2024). Hybrid whale optimization algorithm for enhanced routing of limited capacity vehicles in supply chain management. Scientific Reports, 14(1), 793. https://doi.org/10.1038/s41598-024-51359-2

[24] Zhang, L., Yang, C., Yan, Y., Cai, Z., & Hu, Y. (2024). Automated guided vehicle dispatching and routing integration via digital twin with deep reinforcement learning. Journal of Manufacturing Systems, 72, 492-503. https://doi.org/10.1016/j.jmsy.2023.12.008

[25] Andrejic, M., & Pajic, V. (2025). Integrated BWM–QFD–MARCOS framework for strategic decision-making in cold chain logistics. Journal of Operational and Strategic Analytics, 3(1), 23-33. https://doi.org/10.56578/josa030103

[26] Boulkroune, A., Boubellouta, A., Bouzeriba, A., & Zouari, F. (2025). Practical finite-time fuzzy synchronization of chaotic systems with non-integer orders: two chattering-free approaches. *Journal of Systems Science and Systems Engineering*, *34*(3), 334-359.https://doi.org/10.1007/s11518-024-5635-7

[27] Rigatos, G., Abbaszadeh, M., Busawon, K., Dala, L., Pomares, J., & Zouari, F. (2024). Flatness-based control in successive loops for autonomous quadrotors. *Journal of Dynamic Systems, Measurement, and Control*, *146*(2), 024501.https://doi.org/10.1115/1.4063907

[28] Rigatos, G., Siano, P., Zouari, F., & Ademi, S. (2020). Nonlinear optimal control of autonomous submarines' diving. *Marine Systems & Ocean Technology*, *15*(1), 57-69.https://doi.org/10.1007/s40868-019-00070-3

[29] Rigatos, G., Busawon, K., Abbaszadeh, M., Pomares, J., Gao, Z., & Zouari, F. (2024, August). Flatness-based control in successive loops for dual-arm robotic manipulators. In *2024 IEEE Conference on Control Technology and Applications (CCTA)* (pp. 793-798). IEEE.https://doi.org/10.1109/CCTA60707.2024.10666567

[30] Rigatos, G., Siano, P., Zouari, F., & Ademi, S. (2017, June). A nonlinear optimal control methoc for autonomous submarines' diving. In *2017 IEEE 26th International Symposium on Industrial Electronics (ISIE)* (pp. 1061-1066). IEEE.https://doi.org/10.1109/ISIE.2017.8001393

[31] Zouari, F., & Mahmud, M. (2024, April). Neural Network-Based Robust Adaptive Output Feedback Control for MIMO Time-Varying Delay Systems. In *Global Conference on Applications of Artificial* (pp. 60-77). Cham: Springer Nature Switzerland.https://doi.org/10.1007/978-3-031-98498-3_5

[32] Almazroi, A. A., Alkinani, M. H., Al-Shareeda, M. A., & Manickam, S. (2024). A novel ddos mitigation strategy in 5g-based vehicular networks using chebyshev polynomials. *Arabian Journal for Science and Engineering*, *49*(9), 11991-12004.https://doi.org/10.1007/s13369-023-08535-9

[33] Almazroi, A. A., Alqarni, M. A., Al-Shareeda, M. A., Alkinani, M. H., Almazroey, A. A., & Gaber, T. (2024). FCA-VBN: Fog computing-based authentication scheme for 5G-assisted vehicular blockchain network. *Internet of Things*, *25*, 101096.https://doi.org/10.1016/j.iot.2024.101096

[34] Al-shareeda, M. A., Anbar, M., Hasbullah, I. H., Manickam, S., Abdullah, N., & Hamdi, M. M. (2020, September). Review of prevention schemes for replay attack in vehicular ad hoc networks (vanets). In *2020 IEEE 3rd International Conference on Information Communication and Signal Processing (ICICSP)* (pp. 394-398). IEEE.https://doi.org/10.1109/ICICSP50920.2020.9232047

[35] Almazroi, A. A., Aldhahri, E. A., Al-Shareeda, M. A., & Manickam, S. (2023). ECA-VFog: An efficient certificateless authentication scheme for 5G-assisted vehicular fog computing. *Plos one*, *18*(6), e0287291.https://doi.org/10.1371/journal.pone.0287291

[36] Al-Mekhlafi, Z. G., Lashari, S. A., Al-Shareeda, M. A., Mohammed, B. A., Alayba, A. M., Saleh, A. M. S., ... & Almekhlafi, K. (2024). CLA-FC5G: A certificateless authentication scheme using fog computing for 5G-assisted vehicular networks. *IEEE Access*, *12*, 141514-141527.https://doi.org/10.1109/ACCESS.2024.3466914

[37] Al-Shareeda, M. A., Gaber, T., Alqarni, M. A., Alkinani, M. H., Almazroey, A. A., & Almazroi, A. A. (2025). Chebyshev polynomial based emergency conditions with authentication scheme for 5G-assisted vehicular fog computing. *IEEE Transactions on Dependable and Secure Computing*.22（5）.p.4795-4812.https://doi.org/10.1109/TDSC.2025.3553868

[38] https://www.kaggle.com/datasets/mexwell/large-scale-route-optimization

[39] https://www.kaggle.com/datasets/ayeshaseherr/delivery-logistics-dataset