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REVIEW ARTICLE

A Review of Hybrid Machine Learning and Metaheuristics for Vehicle Routing Problems

Ali Wagdy Mohamed[1,*]

[1] Operations Research Department, Faculty of Graduate Studies for Statistical Research, Cairo University, Giza 12613, Egypt

Email: aliwagdy@gmail.com

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ABSTRACT

Vehicle Routing Problem (VRP) variants and modifications are significant problems in combinatorial programming and logistics. They relate to efficient and optimal transport routing for customer demand fulfillment while monitoring operational costs. Traditional methods have been exact algorithms, heuristics, and metaheuristics; however, it has yet to be known to cater to the scalability, computational efficiency, and adaptability challenges posed by dynamic and large-scale VRPs. Recent advances have shown enormous promise in combining this with learning approaches in hybrid forms: ML and metaheuristic and optimization techniques to overcome them. Such hybrid approaches now promise even better quality solutions, computational speeds, and real-world applicability for two actual ML methods: deep reinforcement learning and meta-learning. The present study surveys the current state of the art of hybrid methods applying to VRPs to find strengths, weaknesses, and directions that future research could intensify to enhance efficiency, scalability, and applicability to transportation and logistics systems.

Keywords: Hybrid Approaches ▪ Machine Learning ▪ Metaheuristics ▪ Vehicle Routing Problems ▪ Optimization

1. INTRODUCTION

The Vehicle Routing Problem is practically the lifeblood of logistics and transportation: a route-finding scheme for vehicles to service customer demands while minimizing cost. It is among the central challenges of transportation optimization. However, in today's world, where these problems face stiff resistance from traditional techniques due to limits in scalability and adaptability, hybrid approaches emerging from the combination of machine learning and optimization techniques have proved to be up-and-coming solutions to the challenges posed by modern dynamic scenarios of VRP.

1.1 The Vehicle Routing Problem: An Ongoing Challenge

The Vehicle Routing Problem (VRP) is a well-known combinatorial optimization problem whose primary goal is to establish the best routes for a fleet of vehicles visiting a given number of geographically dispersed customers. This can also contain objectives such as minimizing the total number of trips made, distance traveled, time taken, or fuel used, while respecting constraints including vehicle capacity, delivery time windows, and services. Over time, the initial VRP has been developed into several variants, such as Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), and Heterogeneous VRP (HVRP), which capture many practical predicaments of logistics and transportation. Real-world complications such as freight deliveries within built-up areas, last-mile delivery, and supply-chain management have increased the need for VRP solutions that can handle complexity at scale. Current transportation systems demand techniques for solving large problem instances, responsiveness to real-time change, and operations that address many constraints [1, 2].

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1.2 Limitations of Traditional Approaches

Earlier approaches for solving VRPs are categorized as exact algorithms, heuristics, and metaheuristics. Branch-and-bound or branch-and-cut approaches can deliver optimal solutions but fail for large-sized problems because of exponential time complexity. Simple approaches such as savings algorithms and nearest-neighbor methods achieve faster results but may be far from optimal. Heuristics have been enhanced by metaheuristics such as genetic algorithms (GA), simulated annealing (SA), and tabu search (TS). Nevertheless, metaheuristic algorithms face challenges such as slow convergence, lack of scalability, and poor ability to respond to dynamic real-world conditions such as traffic jams or fluctuating customer demand. Such limitations underpin the need for methods that generate solutions effectively and accurately, particularly for large, dynamic, stochastic VRPs in practical transportation environments [3, 4].

1.3 The Rise of Hybrid Techniques

Hybrid techniques have come about to ameliorate the deficiencies of traditional ones. Researchers have turned increasingly toward hybrid machine learning (ML) and optimization methods. Hybrid approaches capture the best from both paradigms: adaptability and learning capabilities from ML and search efficiency from metaheuristic or heuristic algorithms. Machine learning models, deep learning, and reinforcement learning (RL) can process large-scale data, recognize hidden patterns, and predict routing strategies in complex environments. When traditional optimization techniques are integrated with machine learning, models enhance solution quality, reduce computation time, and provide dynamic adaptability for changes in the problem space. In addition, hybrid techniques allow better generalization to VRP versions requiring heterogeneous fleets, clustered customers, or simultaneous pickup and delivery requirements [5, 6].

1.4 Machine Learning and Reinforcement Learning: Essential Enablers

Machine learning, particularly reinforcement learning, has emerged as an essential enabler for adaptive route optimization. ML-based models learn from historical and real-time data to approximate decision policies, evaluate routes, or select suitable heuristics. Reinforcement learning is particularly attractive because the routing process can be modeled as sequential decision-making, where actions affect future route feasibility and cost. In dynamic and stochastic routing, such learning mechanisms can react to demand changes, traffic conditions, and operational uncertainty while still benefiting from classical optimization structures [7, 8].

2. LITERATURE REVIEW

The Vehicle Routing Problem and many of its offshoots have been an area of considerable interest in combinatorial optimization and operations research. As transportation systems become more intricate, exact algorithms, heuristics, and metaheuristics have drawbacks in scalability, time optimization, and flexibility. Consequently, machine learning, deep reinforcement learning, and hybrid metaheuristic approaches have introduced new opportunities for dynamic, stochastic, and large-scale VRPs. Integrating machine learning with optimization techniques has led to improved solution quality, speed, and flexibility to accommodate constraints and problem characteristics.

Several VRP variants have been studied extensively. Zhao et al. [5] proposed a deep reinforcement learning model comprising an actor using an attention mechanism for generating routing strategies, an adaptive critic to dynamically modify the network structure for faster convergence and improved solution quality, and a routing simulator to provide graph data and rewards. The DRL model was integrated with local search, using the DRL output as an initial solution. Experiments on datasets with 20, 50, and 100 customer points showed that the model surpassed traditional construction algorithms and earlier DRL approaches, delivering 5- to 40-fold speedups.

Qin et al. [6] addressed a practical heterogeneous vehicle routing problem involving a predefined fleet with varying vehicle capacities, aiming to minimize maximum routing time. A mixed-integer linear programming model was formulated for small-scale scenarios, while a reinforcement-learning-based hyper-heuristic approach was introduced for large-scale problems. The approach uses metaheuristics as low-level heuristics and policy-based reinforcement learning as the high-level selection strategy. Numerical experiments demonstrated superiority over MILP solutions for large-scale problems and existing metaheuristic algorithms.

Meta-learning has also been explored for VRP with time windows. Gutierrez-Rodríguez et al. [7] defined two sets of meta-features based on instance properties and feasible solutions identified by perturbative heuristics using a greedy process. A multilayer perceptron classifier and wrapper-based meta-feature selection predicted the most suitable metaheuristic for a given instance, significantly improving the overall performance of established metaheuristics.

Hybrid metaheuristics have contributed to specialized VRP forms. Vidal et al. [9] addressed the Clustered Vehicle Routing Problem using iterated local search and hybrid genetic search. The hybrid genetic search precomputes shortest Hamiltonian paths between vertices within each cluster, enabling efficient exploration of large neighborhoods through bidirectional dynamic programming and optimized data structures. Avci and Topaloglu [10] proposed a hybrid metaheuristic algorithm for heterogeneous vehicle routing with simultaneous pickup and delivery, using tabu search and adaptive thresholds to improve search efficiency.

Electric and sustainable routing problems have received increasing attention. Rodríguez-Esparza et al. [1] introduced Hyper-heuristic Adaptive Simulated Annealing with Reinforcement Learning (HHASA) for the Capacitated Electric Vehicle Routing Problem, accounting for limited charging-station availability and travel range. The approach combines a multi-armed bandit technique with a self-adaptor and improves several best-known solutions on benchmark instances. Ritzinger and Puchinger [11] highlighted the role of hybrid metaheuristics in dynamic and stochastic vehicle routing, emphasizing historical data, stochastic modeling, machine learning, shortest-path computation, construction heuristics, and metaheuristic optimization.

Recent surveys further clarify the field. Bai et al. [8] cate-

Table 1. Summary of Literature Review

Study	Problem Addressed	Methodology	Key Findings	Tools/Techniques
[5]	VRP for large-scale datasets	DRL with local search	DRL outperforms traditional algorithms, achieving 5- to 40-fold speedup.	Deep RL, attention mechanism, local search
[6]	Heterogeneous VRP with varying vehicle capacities	MILP for small scale; RL-based hyper-heuristic for large scale	RL hyper-heuristic outperforms MILP and existing metaheuristics.	MILP, reinforcement learning
[9]	Clustered VRP	Iterated local search and hybrid genetic search	Hybrid genetic search explores large neighborhoods effectively.	Dynamic programming, genetic algorithm
[7]	VRP with time windows	Meta-learning to select optimal metaheuristics	Meta-learning improves solution selection and performance significantly.	MLP classifier, greedy heuristics
[2]	VRP variants: ML vs. traditional methods	Systematic review of ML-based VRP techniques	Reinforcement learning emerges as a leading ML method for VRPs.	RL, ML-based optimization
[3]	NP-hard VRPs	Hybrid approaches combining ML with traditional heuristics	Hybrid ML techniques compete with traditional optimization approaches.	Pure ML, hybrid heuristics
[11]	Dynamic and stochastic VRPs	Real-time fleet management using hybrid metaheuristics	Hybrid metaheuristics effectively optimize real-world VRPs.	Historical data, hybrid metaheuristics
[1]	Capacitated electric VRP	Hyper-heuristic adaptive simulated annealing	HHASA improves routing for EVs with limited charging stations.	Multi-armed bandit, SA, RL
[10]	VRP with simultaneous pickup and delivery	Tabu search with self-tuning thresholds	Self-tuning improves efficiency and reduces parameter adjustment.	Tabu search, adaptive thresholding
[11]	Dynamic VRPs with stochastic demands	Hybrid optimization with historical and real-time data	Combines historical data and hybrid algorithms for dynamic routing.	Historical data integration, metaheuristics
[4]	Large-scale VRPs	Integration of ML with metaheuristic solvers	ML accelerates metaheuristics and improves convergence speed.	Machine learning, metaheuristic solvers
[9]	Capacitated VRP with clusters	Hybrid local search and genetic algorithm	Efficient Hamiltonian-path computation improves routing quality.	Local search, genetic algorithm
[5]	VRP with time windows	DRL with adaptive critic network	DRL improves solution speed and flexibility for time-window constraints.	Adaptive DRL, critic network
[8]	Multi-depot VRP and market segmentation	Hybrid ML and metaheuristic framework	Statistical learning techniques enhance market-specific routing.	Statistical learning, metaheuristics
[12]	Sustainable VRP	Hybrid swarm-intelligence metaheuristics	Hybrid metaheuristics optimize sustainable logistics networks.	Hybrid swarm intelligence, metaheuristics

gorized hybrid methodologies into ML-assisted VRP modeling and ML-assisted VRP optimization. Shahbazian et al. [2] reviewed ML-based VRP research by applications, constraints, and technical approaches, with special emphasis on reinforcement-learning methods. Bogyrbayeva et al. [3] presented a taxonomy of learning paradigms, solution structures, models, and algorithms, showing that machine-learning-based methods can be competitive with traditional approaches while exploiting symmetry in VRP solutions.

It is important to highlight that Table 1 provides an extensive summary of current advances in solving VRPs through hybrid methods combining ML and metaheuristic optimization. The listed studies refer to whole, dynamic, stochastic, capacitated, clustered, and sustainable scenarios, proposing solutions aimed at improving solution quality, computational efficiency, and adaptability. Techniques such as DRL, meta-learning, hyper-heuristics, and hybrid bio-inspired algorithms have proven effective against conventional methods such as exact solvers and standalone heuristics.

The reviewed research has established important contributions toward solving VRPs using machine-learning techniques and hybrid algorithms. Novel methods such as reinforcement learning and meta-learning address heuristic, noisy, complex, and significant routing environments while improving efficiency and solution quality. Integrating machine learning with conventional optimization also aligns well with real-world transportation systems. However, difficulties remain concerning scalability, generalization, and handling complex practical constraints. Future studies should develop learning-based approaches, consider different hybrid approaches, and cover open research gaps to advance transportation and logistics.

3. DISCUSSION

Integrating machine learning with classical optimization techniques opens new horizons for applying such schemes to Vehicle Routing Problems. It provides advanced solutions to complex and dynamic scenarios. This approach highlights how ML can supplement optimization techniques such as deep reinforcement learning, meta-learning, or adaptive heuristics by yielding high-quality solutions in less time with greater extensibility. However, challenges persist in scalability, generalization, and handling complicated real-world constraints.

3.1 Hybrid Approaches: The Promise and the Reality

Hybrid approaches are redefining how VRPs are tackled by amalgamating ML and optimization techniques. Their strength lies in combining the prediction capacity of ML with the efficiency of traditional heuristics and metaheuristics, resulting in improvements in solution quality, computational time, and adaptability. Methods such as DRL, meta-learning, and hyper-heuristics provide dynamic flexibility for real-world constraints including demand changes, route modifications, and rapid convergence on larger datasets compared with purely optimization-specific techniques [13].

3.2 Major Problem: Scalability

Though hybrid approaches have potential, scalability remains a major challenge. Most ML-based solutions, especially those dependent on deep learning and DRL, require substantial computational resources and training time for large datasets and online VRP scenarios. This limits their use in time-critical settings such as last-mile delivery or dynamic urban logistics. Future research must address the trade-off between solution quality and required computation time [3, 1].

3.3 Universalities Between Various Types of VRPs

Another imperative is generalization across VRP variants and real-life scenarios. Current ML and hybrid models are generally tuned to specific instances or constraint sets, such as VRPs with time windows, capacitated VRPs, or dynamic routing problems. Their performance on well-defined instances is impressive, but it remains unclear whether they can evolve

into entirely new scenarios. Robustness across heterogeneous fleets, different customer needs, and dynamic problem setups is a prerequisite for practical deployment [2, 12].

3.4 Complex Stipulations

Modern VRPs involve many stipulations, including time windows, vehicle capacities, environmental factors, and simultaneous pickup and delivery. Traditional methods are rarely capable of solving all such complications together, while hybrid methods show promise. However, incorporating these constraints into ML-based models and optimization frameworks remains an obstacle because it requires complex algorithms that balance feasibility and efficiency [5].

3.5 Future Directions for Research

Future research should explore learning-based and hybrid methods to solve the identified limitations. Transfer learning and scalable reinforcement learning can increase efficiency by learning from limited data and generalizing across problem variants. Combining classical optimization with deep learning should produce strong hybrid frameworks that deal effectively with complicated constraints in real time. Further studies should narrow the gap between theory and practical applications so that these methods can be deployed in real-world transportation and logistics systems [11].

3.6 Gaps Pampered into Real-world Applications

The most promising hybrid approaches address scalability, adaptability, and solution quality. Before achieving their full potential, they must overcome remaining challenges such as generalization and constraint handling. Researchers and practitioners should create innovative but resource-efficient models that fit modern logistics, urban transportation systems, and global supply chains. Hybrid ML-optimization methods can help move toward more innovative, sustainable, and cost-optimal routes [4, 14].

Thus, hybrid methods combining machine learning with metaheuristics may hold the answer to modern VRPs. Although these techniques have shown good scalability, adaptivity, and efficiency, major drawbacks relate to computational scale, generalization to VRP variants, and constraint handling. Future research should develop resource-efficient, transferable, and constraint-aware algorithms to bridge these gaps. Such advancement will position hybrid methods to transform logistics and transportation systems by providing practical solutions to dynamic and large-scale VRPs.

4. CONCLUSION

Hybrid techniques integrating ML with metaheuristics have shown considerable promise for Vehicle Routing Problems. The predictive aspect of ML and the solution-search efficiency of metaheuristics provide a robust canvas for addressing modern transportation problems, including dynamic and stochastic demands, heterogeneous fleets, and real-time data integration. Hybrid methods often outperform traditional ones in scalability and adaptability, although computational overheads, scalability limits, and weak generalization beyond specific scenarios remain barriers.

The first obstacle for hybrid ML and metaheuristic algorithms is scaling efficiently to very large problems. Dynamic constraints such as real-time traffic require faster models able to process vast data while maintaining high-quality cost and time performance. Future work should develop lightweight but efficient algorithms that provide speed within acceptable accuracy margins. Reinforcement learning combined with transfer learning, distributed computing, and adaptive algorithms can alleviate scalability barriers and improve the responsiveness of routing solutions in dynamic, time-sensitive environments.

Hybrid methods work admirably on individual versions of VRP but cannot always be generalized to broader transportation contexts. Future work should investigate meta-learning techniques that help models learn the selection or adaptation of optimization methods based on new problem characteristics. Merging meta-learning with ML and current metaheuristic frameworks could produce adaptive systems that generalize well to constraints such as time windows, vehicle capacity, and sustainability. Historical trends and real-world data can also improve these models.

Future transport systems should focus on real-world implementation of hybrid ML-plus-metaheuristic solutions. Real-time data sources such as IoT sensors, GPS tracking, and traffic updates should be included in optimization chains, not merely theoretical algorithms. Hybrid methods should also support sustainable transport optimization by addressing fuel efficiency and carbon emissions while maintaining economic viability. Future solutions must be scalable, efficient, and sustainable for emergent logistics and urban transportation systems, requiring collaboration among academia, industry, and policymakers.

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