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ELECTRIC VEHICLE ROUTING PROBLEM: A REVIEW OF RECENT APPROACHES AND ALGORITHMS

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Abstract. With the rapid advancement of new energy vehicles, electric vehicles (EVs) have become integral to modern transportation systems. Compared with traditional fuel vehicles, EVs are limited by their limited battery capacity and require reasonable charging planning to complete the designated routes efficiently. Therefore, the effective routing of EVs has emerged as a critical research focus in transportation and logistics. This study comprehensively reviews recent advancements in the Electric Vehicle Routing Problem (EVRP) over the past three years. First, the concepts of EVRP are introduced. Then, the problem is classified according to energy consumption models, charging strategies, and constraints. Subsequently, various algorithms employed in these studies are analyzed and summarized. Finally, based on the current state of development in this field, the main challenges faced by EVRP and future research directions are discussed.

1. Introduction

In recent years, greenhouse gas emissions have gained global attention as a critical environmental issue. According to statistics from the European Union, carbon dioxide emissions from road transport contribute approximately one-fifth of the EU's total emissions [1]. In response to climate change, the European Parliament enacted the European Climate Act, which endorses the European Commission's proposal to achieve zero carbon emissions for cars and trucks by 2035 [2]. In this context, logistics distribution, a vital component of urban road transport systems, has increasingly embraced electric vehicles (EVs) as a key strategy to mitigate carbon emissions.

Schneider et al. [38] extended the Vehicle Routing Problem (VRP) by incorporating constraints on time windows and recharging and proposed a Mixed-Integer Programming (MIP) model. This study represents a significant step in optimizing Electric Vehicle Routing Problem (EVRP). Since then, with the rapid advancement of the electric vehicle industry, research on EVRP has significantly increased. To

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systematically explore the evolution and research directions within the EVRP domain, several scholars have conducted comprehensive literature reviews and analyses [34, 51, 22, 40, 48, 19]. Among these, Ye et al. [51] conducted a classified review of 110 studies, categorizing EVRP research. In contrast, Kucukoglu et al. [22] provided a comprehensive review of 136 papers across five key dimensions: objective functions, energy consumption models, constraints, fleet configurations, and solution methodologies. However, existing review studies primarily focus on research published before 2022, and there is a notable lack of systematic reviews covering EVRP developments over the past three years. Therefore, the present study conducts an in-depth review of recent EVRP research from 2022. A total of 42 papers from journals with an impact factor greater than 4 were selected (to ensure high-quality, impactful research and a feasible review scope). This study aims to provide a comprehensive literature review of high-quality research on EVRP conducted over the past three years. First, the fundamental concepts of EVRP are outlined. Then, the objective functions adopted in recent studies are reviewed, and the EVRP are categorized based on three dimensions: energy consumption calculation, charging strategies, and constraints. Subsequently, various solution algorithms proposed in recent studies are analyzed in depth, and their characteristics are summarized. Finally, this field's current state of the art is summarized, and future research directions and potential challenges are presented.

This paper is organized as follows: Section 2 introduces EVRP. Section 3 reviews and categorizes the relevant literature from various perspectives within the scope of this study. Section 4 explores the solution approaches for EVRP. Section 5 discusses a comparison of standard algorithms and provides future research directions. Finally, Section 6 concludes the paper.

2. Electric vehicle routing problem

The EVRP aims to optimize routes for a fleet of EVs, ensuring that all customer nodes are served while minimizing operational costs. Each route starts and ends at a designated depot, and EVs must comply with constraints such as battery capacity limits and time windows[54, 17]. Here, we present the mathematical formulation of the EVRP [38]. Let $V = \{1, 2, \ldots, n\}$ be the set of customer nodes, with nodes 0 and $n + 1$ representing the initial and final depots. Define $V_0 = V \cup \{0\}$ and $V_{N+1} = V \cup \{n+1\}$. Let F be the set of charging stations and F' be the set of dummy nodes required to allow multiple visits to charging stations. The extended sets are defined as $V' = V \cup F', V'_0 = V' \cup \{0\}, V'_{N+1} = V' \cup \{n+1\}, V'_{0,N+1} = V' \cup \{0, n+1\}$. A fleet of homogeneous EVs K is considered. Each EV $k \in K$ travels between nodes $i, j \in V'_{0,N+1}$, with distance d_{ij}, energy consumption rate h, and battery capacity Q. Let x^k_{ij} be a binary variable equal to 1 if the vehicle k travels from the node i to the node j and 0 otherwise; y^k_i be the decision variable used to track the battery level of the vehicle k when it reaches node i. The MIP model for the EVRP is described as follows:

$$\min \sum_{i \in V'_0} \sum_{j \in V'_{n+1}} \sum_{k \in K} d_{ij} x^k_{ij} \tag{1}$$

$$\sum_{j\in V'_{n+1}}\sum_{k\in K} x_{ij}^k = 1, \quad \forall i \in V \tag{2}$$

$$\sum_{j\in V'_{n+1}}\sum_{k\in K} x_{ij} \leq 1, \quad \forall i \in F' \tag{3}$$

$$\sum_{j\in V'} x_{0j}^k \leq 1, \quad \forall k \in K \tag{4}$$

$$\sum_{i\in V'_{n+1}} x_{ji}^k = \sum_{i\in V'_0} x_{ij}^k, \quad \forall j \in V', \forall k \in K \tag{5}$$

$$y_j^k \leq y_i^k - (h\cdot d_{ij})x_{ij}^k + Q(1-x_{ij}^k), \quad \forall i \in V, \forall j \in V'_{N+1}, \forall k \in K \tag{6}$$

$$y_j^k \leq Q - (h\cdot d_{ij})x_{ij}^k, \quad \forall i \in F' \cup \{0\}, \forall j \in V'_{N+1}, \forall k \in K \tag{7}$$

$$y_0^k \leq Q, \quad \forall k \in K \tag{8}$$

The objective function (1) aims to minimize the total distance of electric vehicles. Constraint (2) handle the connectivity of the customer nodes. Constraint (3) ensure that each dummy charging station can be visited at most once. Constraint (4) make sure that each electric vehicle can be used only in one route plan. Constraint (5) ensure that the total number of outgoing arcs is equal to the total number of incoming arcs at customer and charging station nodes, which provides continuity in the routes. Constraints (6)-(8) specify the battery level of an electric vehicle and ensure that it never falls below 0.

3. Classifications of the EVRP

The EVRP is formulated to address real-world logistics distribution needs, thus involving multiple constraints and problem variants in different application scenarios. In order to systematically sort out the research framework of EVRP, this section classifies and summarizes the problem from multiple perspectives, including the objective function, energy consumption model, charging strategies, and constraints.

3.1. **Objective function.**

The objective function is the core component of the EVRP model, directly determining the direction of the optimization problem. This section categorizes EVRP based on commonly used objective functions in the literature. From the collected studies, we classified and summarized 13 common optimization objectives for EVRP:

(1) Total travel distance
(2) Total travel time
(3) Total number of vehicles used
(4) Total energy consumption
(5) Total fixed costs
(6) Total penalty cost
(7) Total recharging cost, recharging time or swapping battery cost
(8) Total waiting time for electric vehicles at charging stations
(9) Total delivery cost

(10) Battery degradation costs
(11) Costs of carbon emissions
(12) Customer service costs
(13) Other costs

In VRP, commonly considered objective functions include environmental costs, travel distance, and travel time [20]. By analyzing Table 1, it can be observed that EVRP shares common objective functions with traditional VRP but also exhibits unique characteristics specific to EVs. Among these, objectives (1), (2), and (3) are more common in both VRP and EVRP studies, which mainly focus on the essential factors of path optimization, such as the minimization of travel distance, travel time, and the number of vehicles used. In contrast, objective (4) highlights the characteristics of EV batteries, which have become one of the core topics in EVRP research. Furthermore, compared to traditional fuel-powered vehicles, the energy replenishment process of EVs is considerably slower. Consequently, optimizing charging time (objective (7)) has emerged as a crucial research focus in EVRP, aiming to meet routing requirements while enhancing delivery efficiency and reducing operational costs.

3.2. **Energy consumption calculation.** Energy consumption models can generally be categorized into two types: simple linear models that directly correlate energy consumption with travel distance or travel time and nonlinear models based on vehicle driving power and terrain load, as discussed in Lera-Romero et al. [24], Fan et al. [15], Xiong et al. [49], Kim and Chung [21], Ren et al. [35], Wang et al. [43], Amiri et al. [5], Ma et al. [28]. Unlike linear models, nonlinear models provide a more comprehensive representation of the complex factors influencing vehicle operations.

Goeke and Schneider [16] introduced key factors such as air resistance, rolling resistance, and gravitational force into energy consumption modelling, converting these resistances into mechanical power and proposing a nonlinear approach to quantify energy consumption. Lera-Romero et al. [24], Fan et al. [15], Xiong et al. [49], Fan [14] conducted EVRP studies based on this model. Among them, Xiong et al. [49] believes that the drivetrain of an EV will lead to a certain amount of energy loss in the process of converting battery energy into wheel torque. So the original model was improved by considering the loss of the driveline.

Ren et al. [35] explicitly incorporated time integration to account for dynamic variations in speed and acceleration while also integrating factors such as departure time, travel speed, travel distance, and load. This comprehensive approach enhances the model's applicability to real-world scenarios. Furthermore, Ma et al. [28] extended energy consumption models by incorporating terrain factors, motor power losses, driving resistance, and energy consumption associated with acceleration and deceleration, thereby improving the model's accuracy and reliability. In the solid waste management context, Peña et al. [32] refined energy models by extending traditional mechanical power calculations. Their approach accounts for energy use during waste loading, compaction, unloading, and regeneration during crushing, addressing gaps in prior research and improving model comprehensiveness for waste management applications.

TABLE 1. Objective functions of EVRP (Numbers 1-13 correspond to the common objective functions, ✓indicates the presence of a corresponding objective function in the study).

Paper	1	2	3	4	5	6	7	8	9	10	11	12	13
Jia et al. [18]	✓												
Peña et al. [32]	✓												
Zhou et al. [54]	✓			✓	✓								
Kim and Chung [21]				✓									
Fan et al. [15]		✓			✓		✓				✓	✓	
Woo et al. [44]		✓		✓									
Ouyang and Wang [31]				✓	✓	✓							
Ren et al. [35]				✓									✓
Yao et al. [50]		✓	✓				✓						✓
Zhou et al. [55]	✓							✓					
Duman et al. [12]	✓												
Bezzi et al. [6]				✓									
Zhang et al. [52]					✓	✓	✓		✓				
Wang et al. [43]			✓		✓	✓	✓					✓	
Wang et al. [42]	✓												
Rodríguez-Esparza et al. [36]	✓												
Moradi and Boroujeni [30]	✓		✓			✓							
Liu et al. [25]		✓											
İslim and Çatay [17]				✓						✓			
Comert and Yazgan [10]	✓		✓	✓				✓					✓
Cai et al. [7]	✓												
Xiao et al. [46]	✓												
Xia et al. [45]	✓												
Qian et al. [33]	✓					✓	✓						
Dong et al. [11]	✓		✓				✓						
Sadati et al. [37]	✓		✓										
Ma et al. [29]			✓	✓		✓					✓		✓
Longhitano et al. [27]				✓		✓				✓			
Erdem et al. [13]	✓					✓	✓						
Amiri et al. [5]						✓	✓						✓
Agrali and Lee [3]	✓												
Wang and Zhao [41]	✓				✓								
Lera-Romero et al. [24]		✓											
Fan [14]		✓			✓		✓					✓	
Zhou and Zhao [53]	✓		✓			✓	✓						✓
Xiao et al. [47]				✓	✓		✓						
Ma et al. [28]	✓	✓		✓		✓							
Xiong et al. [49]				✓									
Souza et al. [39]	✓												✓
Liu et al. [26]	✓		✓				✓						
Lam et al. [23]	✓						✓						
Çatay and Sadati [8]				✓									✓

3.3. **Charging strategy.** Energy replenishment of EVs can be implemented in three methods: wired charging, wireless charging, and battery swapping. In early research, wired charging was considered the primary method for replenishing the energy of EVs [38]. Although research has expanded into various charging strategies, wired charging remains the most widely adopted method. Excluding battery swapping, charging methods can generally be divided into two categories: full charging and partial charging. Under the full-charge strategy, the EV will fully charge the battery at a charging station [21, 55, 12, 43, 30, 25, 17, 46, 45, 11, 28, 49, 23]. In contrast, the partial charging strategy allows vehicles to terminate charging and leave the charging station once sufficient energy has been acquired to complete the next segment of the journey [15, 31, 6, 42, 10, 37, 27, 13, 5, 3, 41, 47, 14].

Since EVs require some time to charge at charging stations, some researchers have proposed battery swapping as an alternative strategy [35, 52, 7, 33, 29, 53, 39, 26, 8]. In this approach, EVs can swiftly replace their depleted batteries with fully charged ones upon arrival at swapping stations, thereby enhancing operational efficiency in logistics and reducing costs. Meanwhile, some researchers believe that wireless charging technology also effectively reduces the waiting time during the charging process by incorporating it into the EVRP model [35, 31, 4]. Based on the principle of inductive power transfer, wireless charging technology enables EVs to recharge without requiring physical connectors [9]. A key advantage of this technology is its capability to facilitate dynamic charging while the vehicle is in motion.

Furthermore, to improve the accessibility of EV charging and reduce infrastructure costs, researchers have redirected their efforts toward mobile energy replenishment solutions [47, 35, 8, 52]. In this paradigm, dedicated mobile energy vehicles can travel to the location of EVs to provide on-site charging services [47] or battery swapping services [35, 8, 52], thereby alleviating the limitations of the inflexible layout of traditional charging stations.

3.4. **Constraints of the EVRP.** The EVRP involves a range of complex constraints arising from the unique characteristics of EVs and the practical demands of their real-world deployment. In addition to vehicle load and battery capacity limitations, commonly addressed constraints include time windows, pickup and delivery operations, multi-depot configurations, and open and closed routing constraints. This section categorises and summarises the literature concerning these common constraints.

3.4.1. *Time windows.* In the context of EVRP, time constraints can be categorized into hard and soft time windows depending on the degree of flexibility allowed. Hard time windows, which are time constraints currently used in recent studies [54, 35, 55, 12, 52, 30, 17, 7, 46, 33, 37, 13, 3, 41, 47, 26, 23, 8], impose strict time constraints that require the service to be completed within a predetermined window. On the other hand, soft windows provide some flexibility, allowing for slight deviations from the designated schedule; however, exceeding the allowed time window incurs penalty costs. This type of constraint has been gaining increasing attention in recent research [31, 42, 5, 28]. To further enhance customer satisfaction, Zhang et al. [52] proposed the multiple prioritized time windows model, which enables customers to specify one or more prioritized time slots in advance. In addition, Zhou and Zhao [53] introduced the concept of mixed time windows, classifying each delivery point's time constraints into the expected time window and the acceptable time window. Deliveries made within the expected time window incur no penalties, whereas those within the acceptable time window are subject to penalty costs.

3.4.2. *Pickup and Delivery.* In most EVRP models, the primary role of EVs is to deliver goods. For instance, Duman et al. [12] proposed the Flexible Delivery EVRP, an extension of the traditional delivery-based EVRP. In this model, each customer can be associated with multiple delivery locations, each with a corresponding time window. EVs are dispatched from a centralized depot, and deliveries are completed at the customer's pre-specified locations within the predetermined time window. However, in real-world logistics operations, customer demands can generally be categorized into three types: pickup, delivery, or both pickup and delivery. When EVs must simultaneously accommodate pickup and delivery requests, the problem is the EVRP with Pickup and Delivery. Relevant studies in this domain include [31, 55, 46, 3, 26]. Notably, Agrali and Lee [3] explored an innovative pickup and delivery model by introducing transhipment nodes, enabling the efficient transfer and reallocation of goods across different delivery routes.

3.4.3. *Multiple Depots.* The configuration of multiple depots makes path planning more reductive to actual logistics scenarios, where vehicles can depart from multiple depots and return after completing the assigned tasks. This model has significant advantages in solving complex distribution needs and optimizing resource allocation. The EVRP models of Fan [14], Wang et al. [43], Agrali and Lee [3] all adopt the configuration of multiple depots.

3.4.4. *Open/Close.* In EVRP models, 'open' and 'closed' are commonly used to define whether vehicles must return to their depot upon task completion. In the closed model, vehicles must return to their initial depot after completing assigned tasks, making it the most widely applied approach in EVRP studies. A different configuration, the half-open model, permits vehicles to return to the nearest depot rather than return to their original departure depot [14].

4. Recent solution approaches to EVRP

The solution approaches for the EVRP are generally classified into exact and heuristic algorithms. Exact algorithms rely on mathematical programming and commonly utilize approaches such as Branch-and-Price and Dynamic Programming to achieve optimal solutions. In contrast, heuristic and metaheuristic algorithms employ flexible and efficient search strategies to approximate optimal solutions within a computationally feasible time. The distribution of EVRP solutions in this study is shown in Figure.1. Representative methods include Large Neighborhood Search (LNS), Variable Neighborhood Search (VNS), Branch-and-Price (BP), Ant Colony Optimization (ACO), Simulated Annealing (SA), Genetic Algorithm (GA), and Tabu Search (TS).

This section presents an in-depth discussion of the exact and heuristic algorithms applied in EVRP.

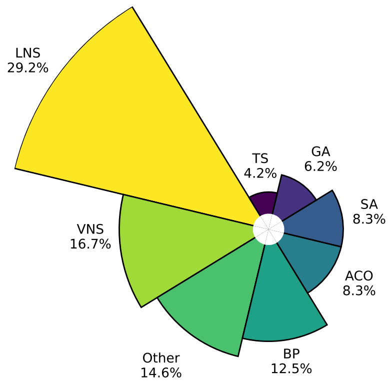

FIGURE 1. Distribution of EVRP solution approaches (% is obtained by reporting the number of uses for each algorithm to the total number of algorithms used in all research methods).

4.1. **Large Neighborhood Search.** LNS, as a practical heuristic approach, has been widely applied to solving the EVRP[44, 31, 35, 52, 42, 29, 13, 5, 3, 41, 47, 28, 49, 55]. This method iteratively removes and reinserts subsets of routes to explore better solutions efficiently. Researchers have improved its computational efficiency and solution optimality for large-scale problems through integration with various optimization techniques. For example, Ren et al. [35] introduced an LNS-QL algorithm based on Q-learning (QL) for joint drone and EV delivery, dynamically selecting destruction and repair operators through reinforcement learning, significantly enhancing solution flexibility and adaptability. In the continued development of LNS, researchers have proposed various improved Adaptive Large Neighborhood Search (ALNS) algorithms to handle the complex constraints and uncertainties of EVRP effectively. For instance, Zhang et al. [52] proposed an extended ALNS incorporating the Variable Neighborhood Descent strategy to achieve the simultaneous optimization of EVs and battery swapping vehicles.

4.2. **Variable Neighborhood Search.** VNS enhances search efficiency by dynamically switching between multiple neighborhood structures, enabling the algorithm to escape local optima. Due to its flexibility and effectiveness in exploring diverse search neighborhoods, VNS and its variants have gained increasing attention in EVRP research [54, 17, 25, 33, 39, 8]. İslim and Çatay [17] introduced a hybrid approach that integrates VNS with a mathematical solver to address battery degradation issues in EVs. This method employs a piecewise linear degradation cost model based on the depth of discharge and state of charge (SoC) to assess the impact of varying charging depths. Liu et al. [25] presented a double adaptive generalized VNS framework, which dynamically adjusts the neighbourhood selection mechanism, substantially improving computational efficiency for unmanned EV routing problems. Moreover, Souza et al. [39] developed an optimization algorithm based on Flexible VNS, incorporating adaptive perturbation and local search strategies.

4.3. **Branch-and-Price.** BP algorithms that combine branch-and-bound and column generation are widely used in EVRP [31, 6, 12, 24, 23]. Ouyang and Wang [31] proposed an improved BP algorithm combined with LNS to overcome formulation challenges faced by conventional methods. Bezzi et al. [6] introduced a path-based BP algorithm incorporating multiple charging technologies and partial charging, using Bi-Directional Dynamic Programming to improve pricing efficiency for large-scale problems. Duman et al. [12] developed a Pulse-enhanced bi-directional BP algorithm with a novel column generation technique that alleviates computational bottlenecks compared to traditional labeling methods. Lera-Romero et al. [24] proposed a BCP algorithm for Time-Dependent EVRP with Time Windows, integrating a customer-based routing heuristic and an efficient labeling algorithm to optimize delivery routes.

4.4. **Ant Colony Optimization.** ACO simulates the pheromone-based foraging behavior of ants and improves path selection through probabilistic decision-making and pheromone updating iterations to efficiently solve EVRP [15, 10, 18]. Fan et al. [15] introduced an improved ACO, which incorporates an adaptive heuristic factor that dynamically adjusts pheromone weights based on the specific characteristics of the problem, achieving a balance between global exploration and local exploitation. Comert and Yazgan [10] investigated three distinct types of multi-objective EVRP and proposed a hierarchical hybrid heuristic approach. The first stage employs a hybrid ACO algorithm, integrating local search operations and the SA criterion to expedite the convergence process of the initial solution. In the second stage, the artificial bee colony algorithm is utilized to refine the solution further, ensuring high-quality results.

4.5. **Simulated Annealing.** SA has been extensively applied to the EVRP due to its capability of accepting suboptimal solutions during the optimization process, thereby facilitating escape from local optima [44, 10, 3, 30, 36]. By effectively balancing exploration and utilization, SA demonstrates strong problem-solving capabilities when combined with other heuristics. SA is frequently combined with LNS. Woo et al. [44] proposed an optimization framework that integrates Adaptive Large Neighborhood Search (ALNS) with SA to provide an effective solution for intelligent fleet management. Agrali and Lee [3] proposed the SA-LNS algorithm, which leverages a greedy heuristic for initial solution generation, SA to escape local optima via the Metropolis criterion, and LNS for iterative refinement through destruction and repair, enhancing routing and charging station optimization. Rodríguez-Esparza et al. [36] proposes a hyper-heuristic algorithm to optimize the paths using adaptive SA and reinforcement learning to minimize the total distance traveled and verifies its superiority on a dataset for large-scale problems.

4.6. **Genetic Algorithm.** GA utilizes its selection, crossover, and mutation mechanisms to navigate the solution space under complex constraints efficiently, providing a practical approach for solving EVRP [27, 43, 32]. In this context, Longhitano et al. [27] proposed a GA-based EVRP approach, which comprehensively considers key state parameters of EVs, including the SoC and the state of health. Furthermore, Wang et al. [43] proposed a bi-objective nonlinear model, utilizing Gaussian Mixture Clustering to classify customers and reduce computational complexity. They further introduced an improved multi-objective GA with TS to balance local and global search, enhancing solution quality.

4.7. **Tabu Search.** TS is a local search-based heuristic that uses a tabu list to avoid revisiting recent solutions, helping to escape local optima. Sadati et al. [37] proposed a hybrid heuristic combining VNS and granular TS. The approach starts with a greedy insertion heuristic for initial solution construction, followed by perturbation techniques such as position exchange and route consolidation. It concludes with a local search to optimize customer sequencing and charging decisions. Wang et al. [42] tackled perishable goods distribution by designing multi-compartment vehicles to meet diverse storage needs. They developed a hybrid ALNS-TS algorithm, where ALNS applies various removal and insertion strategies to optimize routes, and adaptive heuristics adjust temperature and humidity in real-time.

4.8. **Other Methods.** Beyond commonly used optimization algorithms, alternative approaches have been explored for EVRP. For instance, the Double Assistant Evolutionary Multitasking Algorithm [7], Iterated Local Search [21], and the Whale Optimization Algorithm [53]. Moreover, the Memetic Algorithm (MA) has also been utilized [46, 11], among which Dong et al. [11] introduced an Improved MA combining global and local search, reducing operational costs by 10–25% in Dynamic EVRP.

5. Discussion

This section first discusses and compares the strengths and weaknesses of different algorithms used in the last three years of EVRP research. Then, future research directions are identified based on the current advancements in EVRP research.

5.1. **Comparative analysis of recent algorithms for EVRP.** The combination of the BP algorithm with the column generation method provides a guaranteed lower bound, thereby improving solution efficiency. However, since column generation relies on the efficient solution of the shortest path problem, computational complexity grows rapidly with the increase in problem size. In practical applications, BP needs to be combined with heuristic acceleration strategies to balance efficiency and accuracy [12, 31].

Although GA possesses excellent global search capabilities, it typically requires more iterations to converge to an acceptable solution compared to heuristic methods, leading to higher computational costs. In particular, in Longhitano et al. [27], the integration of vehicle dynamics and SoC modeling significantly increases the computational burden of the optimization process.

ACO can explore multiple solutions simultaneously, making it suitable for global optimization. However, in large-scale EVRP problems, the need to simulate numerous ants leads to increased computation time. Thus current research often employs a two-level or two-stage optimization approach, where the first stage decomposes the problem to reduce the number of variables handled per iteration, and the second stage refines routes and optimizes charging strategies to improve solution quality.

The flexibility and global search capability of VNS make it suitable for various complex constraints in EVRP, such as time windows [54], battery swapping [33], and flexible deliveries [37]. Improved VNS methods, such as Flexi-VNS, dynamically adjust charging strategies to enhance solution adaptability. Additionally, VNS, combined with the alternating direction multiplier method, effectively handles energy constraints, achieving better performance in large-scale instances.

ALNS and its variants dominate EVRP solutions. ALNS is more efficient for large-scale problems and is easily integrated with other algorithms. For instance, ALNS combined with SA and QL can further enhance global search capabilities. Specifically, the combination of QL and LNS proves effective in dynamic EVRP, where QL learns operational strategies and improves the search process based on historical experience.

5.2. **Open issues.** Although significant progress has been made in addressing the EVRP, there are still challenges that require further research. Firstly, EVRP involves multiple optimization objectives, such as minimizing operational costs, carbon emissions, and customer service levels. However, existing studies often lack systematic research on multi-objective trade-offs. Developing more efficient multi-objective algorithms to balance conflicting objectives remains a valuable research direction. Secondly, a single algorithm is often insufficient to handle complex EVRP problems. Future research can explore the combination of multiple algorithms, such as integrating heuristic algorithms with reinforcement learning. Reinforcement learning is effective in handling dynamic environments and learning complex decision-making strategies. Lastly, future studies should also incorporate machine learning models to predict factors such as EV energy consumption, charging demands, and traffic flow. These predictions can be integrated into the routing process to achieve more accurate scheduling.

6. Conclusions and future work

This study presents a comprehensive review of recent advancements in EVRP research over the past three years, analyzing 42 papers from various aspects. It presents various classifications of EVRP and examines commonly used algorithms. In terms of objective functions, recent studies mainly focus on single or limited objectives, lacking systematic research on multi-objectives. Regarding algorithms, LNS is widely adopted as one of the most commonly used optimization methods and is often combined with SA, BP, and QL to improve the depth of exploration of the solution and the ability of local optimization. In the future, enhancing these algorithms or developing novel hybrid optimization approaches will continue to be a promising avenue for research. Moreover, integrating machine learning into demand or traffic predictions can further improve EVRP solutions' adaptability.

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