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Review

An Overview of Energy Replenishment Strategies for the Electric Vehicle Routing Problem: Models and Solution Algorithms

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Abstract

The electric vehicle routing problem (EVRP) is constrained by the limited driving range and time-consuming energy replenishment. These characteristics shift the focus of the EVRP from simple path optimization to an integrated optimization of routing and energy replenishment. Consequently, the energy replenishment strategy becomes a critical determinant of the feasibility and economic viability of EVRP solutions. This paper presents a systematic literature review structured around a core classification of replenishment strategies. The strategies are categorized into two primary modes: charging and battery swapping. This framework addresses common gaps in existing research, such as imprecise strategy definitions and fragmented analyses. For the charging strategy, we establish a three-dimensional classification framework, which comprises the charging function, charging policy, and charging station type. Within this context, wireless charging is considered as a special method of energy replenishment. The battery swapping strategy relies on battery swapping stations (BSSs): the EVRP with BSSs (EVRP–BSSs) and the BSS location-routing problem with electric vehicle (BSS–EV–LRP). Our review identifies several limitations in the current body of research. These include an imbalance between modeling accuracy and computational efficiency, insufficient coverage of diverse operational scenarios, and a superficial integration of emerging technologies. Furthermore, many studies lack a multi-stakeholder perspective that considers collaborative solutions. Future research should prioritize addressing these gaps. Key directions include developing effective methods for solving nonlinear charging functions and expanding research into more specialized scenarios. Additionally, there is a need to improve collaborative algorithms for battery swapping and to develop shared BSS models that serve multiple enterprises. The strategy-driven framework proposed here offers a clear reference for modeling and scenario adaptation in future EVRP studies.

Keywords: electric vehicle; vehicle routing problem; battery technology; charging stations; battery swapping

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Academic Editor: Kwok Tong Chau

Received: 18 October 2025
Revised: 20 November 2025
Accepted: 21 November 2025
Published: 26 November 2025

Citation: Zhou, Y.; Lei, Q.; Li, L.; Wu, Z. An Overview of Energy Replenishment Strategies for the Electric Vehicle Routing Problem: Models and Solution Algorithms. *Energies* **2025**, *18*, 6196. https://doi.org/10.3390/en18236196

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1. Introduction

The logistics sector's pursuit of low-carbon operations and green transformation has accelerated the adoption of electric vehicles (EVs). Due to their absence of exhaust emissions and lower operating costs, EVs are increasingly replacing internal combustion engine (ICE) vehicles as a primary mode of transport in urban logistics and regional freight [1,2]. This transition has, in turn, expanded the traditional vehicle routing problem (VRP) into the more complex electric vehicle routing problem (EVRP).

In contrast to ICE vehicles, EVs face significant operational constraints, namely, limited driving range and prolonged energy replenishment times. These characteristics fundamentally alter the structure of the problem. The focus shifts from pure routing optimization to the integrated optimization of routing and energy replenishment [3]. Ignoring EV energy constraints can lead to operational failures, such as mid-route power depletion and missed deliveries. Therefore, the energy replenishment strategy is a critical determinant of both feasibility and economic viability in EVRP solutions.

A key distinction of the EVRP is its multi-cost nature, which requires balancing synergistic and competing cost components. Compared with VRP, the EVRP must additionally account for costs and efficiencies associated with energy replenishment [4]. For instance, charging strategies must evaluate the impact of charging costs and durations on overall delivery schedules. Similarly, battery swapping strategies involve a trade-off between the capital investment in swapping station (SS) infrastructure and the operational efficiency gained from rapid replenishment.

To illustrate these trade-offs, consider a delivery route serving multiple suburban customers that exceeds an EV's single-charge range. A full charging strategy may necessitate a long stop at a charging station (CS) but can reduce the frequency of subsequent stops. Conversely, a partial charging strategy enables quicker departure but introduces the risk of later delays due to more frequent stops and queuing. While battery swapping (BS) offers the fastest replenishment, its viability depends on the spatial density of battery swapping stations (BSSs). A sparse network of stations may increase detour costs, potentially negating the time saved. This example demonstrates that the energy replenishment strategy is secondary; it is a core decision variable that must be integrated throughout the entire routing process.

This review classifies energy replenishment strategies into two core modes: charging and battery swapping. This classification reflects the dominant technical approaches currently in use. Our objective is to delineate applicable scenarios, modeling methods, and optimization methods for each strategy, thereby addressing gaps in the current literature. The overall framework of the review is illustrated in Figure 1.

The complexity of the EVRP stems from core operational constraints related to energy management. The time-consuming nature of charging and the inherent limitations of vehicle range are primary factors that distinguish the EVRP from the VRP. Consequently, effective solutions require the integrated optimization of routing, scheduling, and energy replenishment. Within this framework, the choice of an energy replenishment strategy becomes the central decision governing trade-offs between operational cost and service quality. Growing academic interest in this field is evident in publication trends. Figure 2 reports the annual number of publications indexed in Web of Science from 2000 to 2025, retrieved using the search terms "electric vehicle routing" or "EVRP". The data indicate a sustained and significant increase in research output, particularly since 2010.

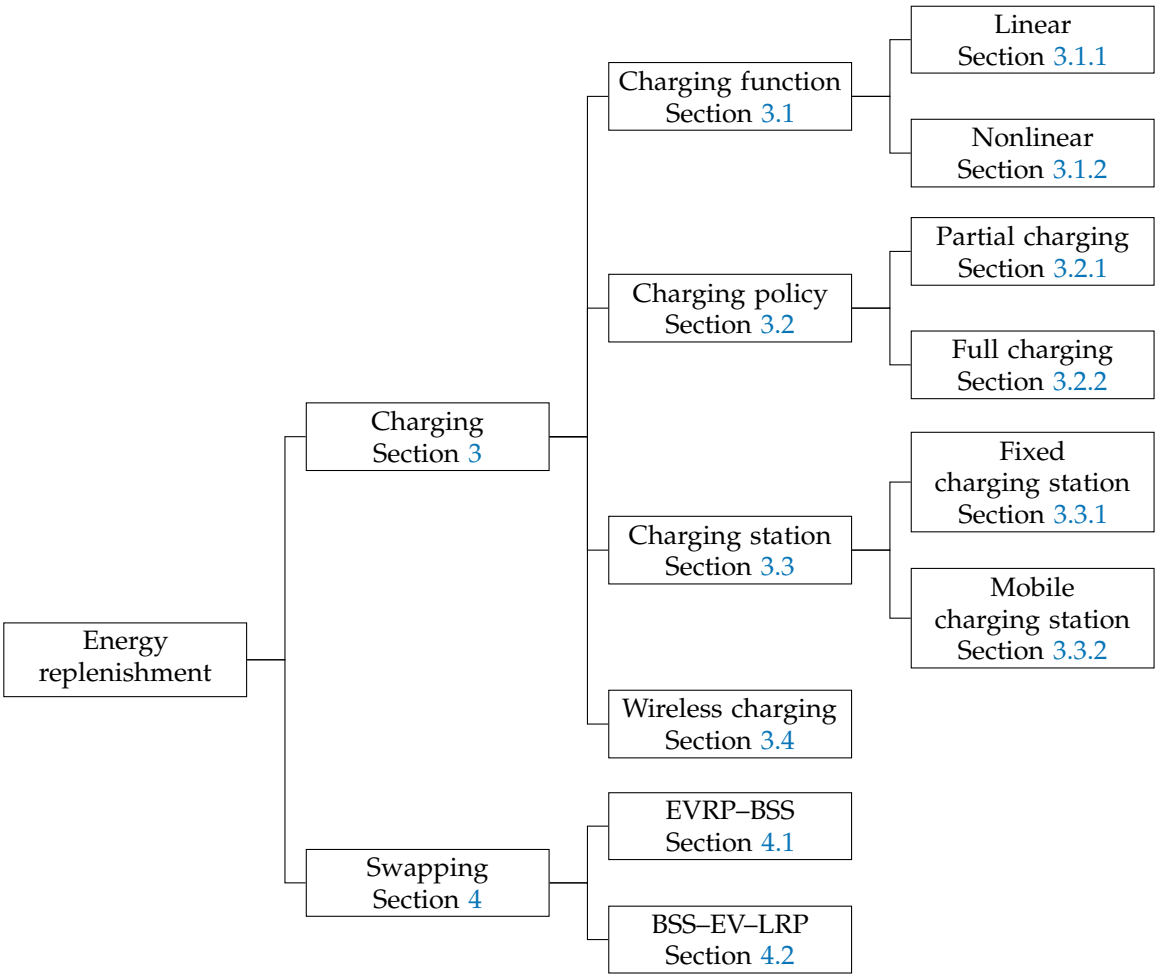

Figure 1. Outline of the different EV energy replenishment methods.

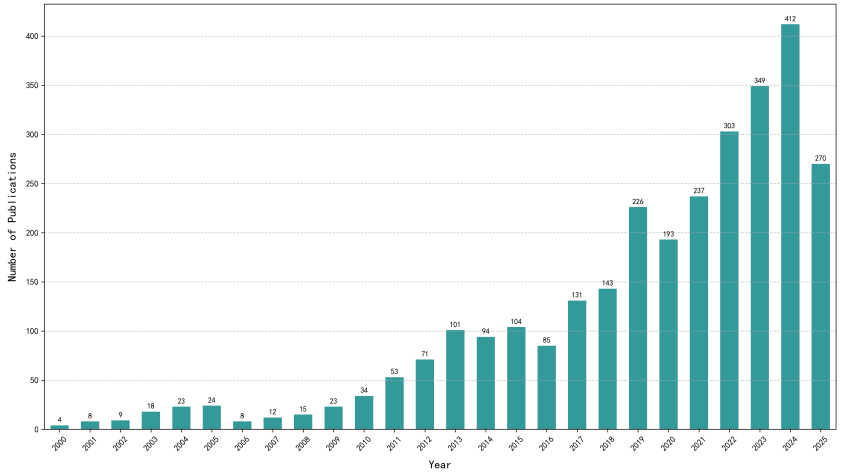

Figure 2. Number of publications on EVRP from 2000 to 2025 (Source: Web of Science, search terms: "electric vehicle routing" OR "EVRP", data as of September 2025).

1.1. Screening

Study selection followed a multi-stage PRISMA-aligned screening protocol (see Figure 3). Each stage imposed progressively stricter inclusion and exclusion criteria to refine the corpus. An initial set of 245 records was retrieved from Web of Science and citation snowballing. After the removal of 11 duplicates, 234 unique records proceeded to title–abstract screening, during which non-routing studies (e.g., EV user behavior analyses) were excluded. Full-text assessment then removed articles whose focus did not match this

review's scope (for example, studies addressing station siting without linking to routing), leaving 111 articles included in the final sample.

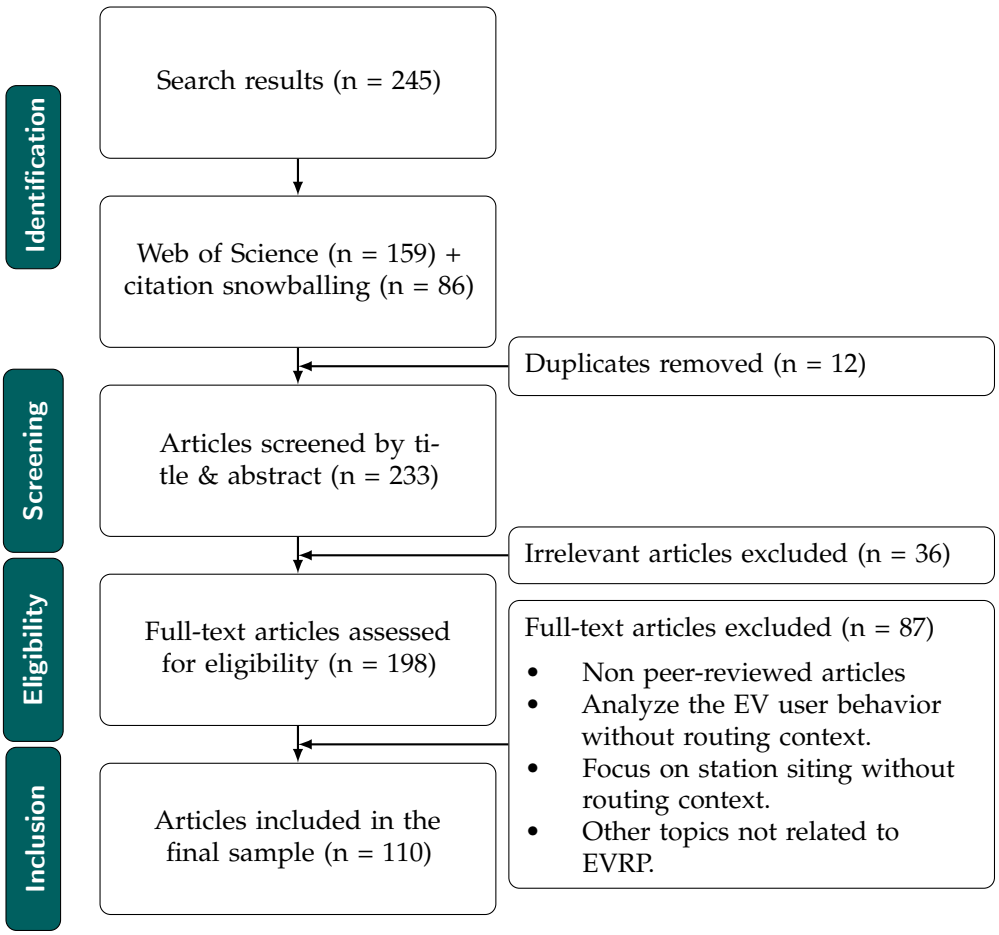

Figure 3. Screening flow of the literature selection process (PRISMA-style).

1.2. Contribution and Structure

A review of the existing EVRP literature shows that prior surveys have concentrated predominantly on two thematic areas. The first concerns the construction of broad theoretical or conceptual frameworks [5–7]. The second focuses on specific technical dimensions (e.g., energy modeling, constraint treatment, or uncertainty) [8–10]. Table 1 summarizes representative review articles in terms of their classification schemes and organizing frameworks. However, a notable gap persists in the extant literature. Specifically, a systematic classification explicitly contrasting the two primary energy replenishment modes—charging and battery swapping—is lacking. Moreover, comprehensive analyses of modeling distinctions and comparative assessments of the scenario applicability for each strategy are absent. This article addresses the gap by providing a structured review centered on the two distinct energy replenishment strategies.

Although valuable, existing reviews often treat energy replenishment strategies as subordinate constraints within broader EVRP formulations. This perspective overlooks the critical fact that the choice of replenishment strategy is a foundational design decision rather than a secondary operational detail. It fundamentally shapes the logistics system model and alters the mathematical structure of the routing problem. Consequently, a systematic review organized explicitly around these two distinct replenishment strategies is absent.

Table 1. Comparison of existing review articles on EVRP.

Literature	Classification	Framework
Yernar and Turan [10]	uncertainty-solution method-constraint condition	Uncertainty modeling → Robust optimization → Real-time adaptive algorithms
Ye et al. [5]	model constraints-charging strategy	Battery constraint modeling → Charging strategy design → Hybrid algorithm solution
Martin et al. [6]	routing problem type-operating condition	Battery management → Route planning → Operating condition adaptation
Mogire et al. [7]	research theme-geographical distribution	Technological innovation → Policy support → Scenario adaptation
Xiao et al. [8]	energy consumption-charging-constraint	Energy consumption decomposition → Linearization processing → MILP model solution
Zhan et al. [9]	full life cycle of BSSs	Siting planning → Capacity configuration → Scheduling algorithms → Cost accounting
This review	energy replenishment strategy	Charging function → Charging policy → Charging station type/BSS scenario

The core contribution of this article is the first comprehensive review that adopts energy replenishment strategy as the primary classification criterion. This classification offers a more operationally grounded and intuitive perspective on EVRP research. The main contributions are summarized as follows:

- Novel classification framework: We organize the literature around a clear, strategy-driven taxonomy distinguishing charging and swapping.
- Comprehensive coverage: The review synthesizes models, charging policies, station forms, and algorithmic approaches across charging and swapping settings.
- Future outlook: We identify research gaps and methodological directions emerging from the strategy-centered perspective.

The structure of the remainder of the article is as follows. Section 2 presents a general EVRP mathematical model that underpins subsequent sections. Sections 3 and 4 examine charging and swapping strategies, respectively. Section 5 discusses algorithmic comparisons, challenges, and future directions, and Section 6 concludes the review.

2. The Electric Vehicle Routing Problem

This section introduces the notations and a general mathematical programming model for the EVRP. Subsequent sections use this model as a reference framework.

2.1. Problem Description

The EVRP is a classic combinatorial optimization problem in operations research (see Conrad and Figliozzi [11], Schneider et al. [12]). First, we consider the limited range EVRP. The problem is defined on a complete directed graph $G = (N, A)$, where N is the set of nodes and A is the set of arcs. The node set N comprises the customer set N_0, and a central depot 0. For notational convenience, an end depot $n + 1$ is added to terminate routes. A fleet of m homogeneous EVs is available. Each vehicle has battery capacity B and

load capacity Q. Each customer $i \in N_0$ has demand q_i. Traversing arc $(i, j) \in A$ incurs cost c_{ij} and consumes energy w_{ij}. Both c_{ij} and w_{ij} are treated as exogenous parameters [12–15]. Table 2 summarizes notation.

Table 2. Symbols and descriptions.

Symbol	Description
Sets and Indices	
N	Set of all nodes, including customers and depots
N_0	Set of all customer nodes
i, j	Node indices
Parameters	
c_{ij}	Distance from node i to node j
q_i	Demand of customer i
m	Total number of available vehicles
Q	Maximum load capacity of a single vehicle
B	Maximum battery capacity of a vehicle
E_i	Minimum required battery level upon arrival at node i
w_{ij}	Energy consumption for traversing arc (i, j)
a	Vehicle acceleration parameter
G	Gravity constant
θ_{ij}	Road angle on arc (i, j)
C_r	Rolling resistance coefficient
wc	Weight of the empty EV
l_{ij}	Payload on arc (i, j)
v_{ij}	Average speed on arc (i, j)
γ	Coefficient related to EVs, $\gamma = 0.5 C_d A \rho$
C_d	Traction coefficient
A	Windward area of the vehicle
ρ	Air density
Decision Variables	
x_{ij}	Binary variable, 1 if a vehicle travels directly from i to j, 0 otherwise
u_i	Continuous variable, representing the SoC upon arrival at node i
y_i	Continuous variable, denoting the load of the vehicle upon arrival at node i

2.2. Estimating Arc-Level Energy Consumption

In logistics operations, EV energy consumption depends on multiple factors, including speed, acceleration, mass, frontal area, travel distance, and road conditions. Speed variability arises from aerodynamic drag and traffic congestion, thereby affecting power demand and energy use. Vehicle mass comprises curb weight and payload; the payload decreases as customers are served. Following Li et al. [16], Bektaş and Laporte [17], the energy consumption on an arc (i, j) can be estimated as

$$w_{ij} \;=\; a_{ij}\,(wc + l_{ij})\,c_{ij} \;+\; \gamma\, v_{ij}^2\, c_{ij}, \tag{1}$$

where $a_{ij} = a + G \sin\theta_{ij} + G C_r \cos\theta_{ij}$ aggregates grade and rolling-resistance effects on arc (i, j). For the meaning of other parameters, please refer to Table 2.

Remark 1. *There are diverse factors affecting energy consumption. These factors include, but are not limited to, geographical location, settlement density, population density; geographical conditions encompassing plains, mountains, and hills; climatic conditions such as cold, hot, and humid environments; road infrastructure involving the availability of expressways, intercity roads, and urban roads; and traffic modes including urban, intercity, and highway transportation. However,*

considering all these factors in one model would be overly complex and computationally intractable. Therefore, for modeling simplicity, we focus on the primary determinants of energy consumption.

2.3. A Mathematical Programming Model for EVRP with Limited Driving Range

This subsection introduces a concise mixed-integer linear programming (MILP) formulation for the EVRP under limited driving range. The presented model intentionally abstracts several features found in studies [11,12,18] in order to focus on the primary operational constraints—vehicle capacity, flow conservation, and battery state of charge (SoC) limits—that determine route feasibility. The simplified formulation is designed to serve as a baseline model: it captures the structural implications of energy constraints on routing decisions while allowing the omitted mechanisms to be incorporated through straightforward extensions in later sections. The formulation of P1 is given below.

(P1):

$$\min z = \sum_{i \in N} \sum_{j \in N, j \neq i} c_{ij} x_{ij} \tag{2}$$

$$\text{s.t.} \quad \sum_{j \in N, j \neq i} x_{ij} = 1, \qquad \forall i \in N_0 \tag{3}$$

$$\sum_{i \in N, i \neq j} x_{ij} = 1, \qquad \forall j \in N_0 \tag{4}$$

$$\sum_{j \in N_0} x_{0j} \leq m \tag{5}$$

$$\sum_{i \in N_0} x_{i,n+1} \leq m \tag{6}$$

$$y_j \leq y_i - q_j + Q(1 - x_{ij}), \qquad \forall i, j \in N, i \neq j \tag{7}$$

$$u_j \leq u_i - w_{ij} + B(1 - x_{ij}), \qquad \forall i, j \in N, i \neq j \tag{8}$$

$$E_i \leq u_i \leq B, \qquad \forall i \in N \tag{9}$$

$$x_{ij} \in \{0, 1\}, \qquad \forall i, j \in N, i \neq j \tag{10}$$

Model P1 addresses the variant in which all customers are mandatory. Objective (2) minimizes the total travel cost, computed as the sum of c_{ij} over selected arcs (i, j). Feasibility is enforced by the following constraints.

Flow Constraints (3) and (4) enforce one incoming and one outgoing arc per customer. Because every customer is mandatory, each must have exactly one predecessor and one successor. This guarantees single visitation feasibility for all customers. Constraints (5) and (6) bound departures and returns by fleet size m.

Notably, traffic congestion effects are deliberately excluded from the baseline formulation. Variation in traffic intensity induces alternating idling, acceleration, and braking phases that reshape the speed profile and, consequently, tractive energy demand per unit distance. Higher congestion elevates acceleration variance and kinetic energy dissipation, potentially altering route feasibility under a fixed initial SoC. Empirical and modeling studies [19–21] show that the dominant pathway through which congestion influences propulsion energy is via changes in average speed and acceleration patterns. To preserve parsimony, these effects are treated implicitly through the precomputed arc energy parameters w_{ij}, which can embed typical speed regimes when derived from historical telemetry, traffic simulation, or enriched GIS data. Accordingly, no explicit congestion state variable or constraint is introduced here; extensions may endogenize congestion via time-dependent energy coefficients, stochastic speed classes, or piecewise acceleration profiles if finer operational realism is required.

Constraints (7) manages vehicle load levels, ensuring that the load y_j upon arrival at customer j accounts for the demand q_j served there. EV-specific energy dynamics appear in (8). Simultaneously, these constraints act as subtour elimination constraints. It links arrival SoC u_j to prior SoC u_i minus arc energy consumed w_{ij} when (i, j) is traversed. Constraints (9) bounds SoC within $[E_i, B]$, where E_i is the minimum required SoC upon arrival at node i. Constraints (10) enforces binary routing decision.

Model P1 assumes that initial battery SoC suffices for each tour. En-route recharging is excluded. This applies to instances whose route lengths fit within a single charge. Therefore, it is suitable for scenarios where vehicle ranges are long enough to complete all assigned tasks without needing to recharge.

In practice, EVs often require en-route recharging because of limited battery capacity. To accommodate this extension, we adjust the model structure. First, a set of charging station nodes, denoted by F, is introduced. The set of nodes is now the union of customer nodes $N = N_0 \cup F \cup \{0, n+1\}$. A new continuous decision variable v_i is introduced to represent the departure SoC at node i. Additional parameters used in the new constraints and in later sections are listed in Table 3. The baseline model is thus extended to an EVRP with linear charging functions. The formulation of P2 is provided as follows:

Table 3. Additional notation.

Symbol	Description
Parameters	
F	Set of charging stations
S	Set of swapping stations
g	The charging rate at a station (e.g., energy units per unit of time)
s_i	The service time required at customer node i
t_{ij}	The travel time from node i to node j
t_{swap}	The time of swapping battery
c_s	The cost of swapping battery
c_e	The cost of per unit of energy
Decision Variables	
A_i	The arrival time of a vehicle at node i
v_i	The battery SoC of the EV as it departs from node i

(P2):

$$\min z = \sum_{i \in N} \sum_{j \in N, j \neq i} c_{ij} x_{ij} + c_e \sum_{i \in F} (v_i - u_i) \tag{11}$$

$$\text{s.t.} \quad \sum_{j \in N, j \neq i} x_{ij} = \sum_{j \in N, j \neq i} x_{ji}, \qquad \forall i \in F \tag{12}$$

$$u_i \leq v_i \leq B, \qquad \forall i \in N_0 \cup F \tag{13}$$

$$v_i = u_i, \qquad \forall i \in N_0 \tag{14}$$

$$u_j \leq v_i - w_{ij} + B(1 - x_{ij}), \qquad \forall i, j \in N, i \neq j \tag{15}$$

$$A_j \geq A_i + s_i + (v_i - u_i)/g + t_{ij} - M(1 - x_{ij}), \qquad \forall i, j \in N, i \neq j \tag{16}$$

$$(2b) - (2f), (2h) - (2i) \tag{17}$$

In Objective (11), the cost of charged energy is taken into account, compared with model P1. Constraints (12) extends flow conservation constraints to charging stations, balancing inbound and outbound flows at each station. Constraints (13) bounds the departure SoC v_i at both customer nodes and charging stations. Constraints (14) enforces $v_i = u_i$ at customers, implying no charging at the customer node. Constraints (15) updates

arrival SoC u_j at node j, using the departure SoC v_i and arc energy consumption w_{ij}. Finally, Constraints (16) guarantees time consistency by combining service times, charging times, and travel times between nodes. M denotes a sufficiently large constant.

Remark 2. *In model P2, w_{ij} is treated as a parameter input to the MILP. It can be computed offline using (i) physics-based energy models, (ii) telemetry or regression models fitted to vehicle GPS/OBD data, or (iii) microscopic or macro traffic simulators combined with GIS elevation and weather data. The parameter g denotes average charging power at a charging station. If charging power is SoC-dependent, replace $(v_i - u_i)/g$ with a piecewise or a precomputed charging-time lookup table.*

3. Charging

The chosen charging strategy model directly determines model realism and the feasibility and optimality of its solutions. Overly simple charging assumptions can yield impractical routes, whereas overly complex ones can render the model computationally intractable. Accordingly, this section systematically reviews, categorizes, and analyzes charging strategies and scenarios reported in the existing literature. The analysis covers conventional charging models characterized by linear and nonlinear charging functions. It also includes innovative approaches, such as wireless charging. The objective is to provide a comprehensive overview of the current state of research in this domain.

3.1. Charging Function: Linear vs. Nonlinear

In EVRP, the charging function form (linear or nonlinear) directly affects the accuracy with which the EV charging process is modeled. The linear charging function assumes a constant rate, simplifying assumptions and reducing computational complexity. By contrast, nonlinear charging functions more faithfully capture state-of-charge-dependent battery charging behavior. The choice between linear and nonlinear functions has significant methodological and computational implications. It governs the estimation of key parameters, notably charging time and energy costs. Moreover, this choice influences routing algorithm design and computational tractability. Consequently, the charging function distinction constitutes a primary classification dimension in EVRP charging research. A charging function specifies the mapping between elapsed charging time and battery SoC. This choice remains central to charging-aware EVRP formulations. To date, no consensus has emerged on balancing modeling fidelity against computational efficiency for large-scale instances.

Table 4 compares the linear and nonlinear charging functions across four key dimensions: modeling accuracy, computational efficiency, applicable scenarios, and limitations. This comparison highlights the trade-offs inherent in each approach, providing insights into their respective strengths and weaknesses.

3.1.1. Linear Charging Function

The linear charging function assumes a constant charging rate, which simplifies computation but deviates from the actual charging characteristics of EVs. Table 5 lists the papers that employ linear charging function, organized by charging policy, charging station type, algorithm, and constraints.

Conrad and Figliozzi [11] first introduced the recharging VRP (RVRP) by allowing EVs to charge their batteries at customer locations. However, the charging time was modeled as a fixed penalty term. Schneider et al. [12] introduced the EVRPTW with a full-charge strategy. The authors defined the recharge duration as a linear function of charged energy, dependent on the battery SoC. Desaulniers et al. [22] investigated four linear recharging strategies for the EVRPTW. The authors designed customized branch-price-and-cut (BP&C) algorithms for each variant, combining monodirectional and bidirectional

labeling algorithms. Desaulniers et al. [23] improved those results by modifying the route-generation labeling algorithm.

Table 4. Comparison of linear and nonlinear charging functions.

Comparison Dimension	Linear	Nonlinear	Examples
Modeling Accuracy	Low	High	Linear: Schneider et al. [12]; Nonlinear: Montoya et al. [24]
Computational Efficiency	High	Low	Linear: Desaulniers et al. [22]; Nonlinear: Wang et al. [25]
Applicable Scenarios	Low charging time proportion; low accuracy requirements	Sensitive to charging time; requiring precise planning	Linear: Keskin et al. [26]; Nonlinear: Zhou et al. [27]
Limitations	Deviations in charging time estimation	Complex algorithm design	

Table 5. EVRP with linear charging function.

Reference	Charging Policy	Charging Station	Algorithm [1]	Constraints [2]
Keskin and Çatay [28]	Partial	FCS	ALNS	C/TW
Schneider et al. [12]	Full	FCS	VNS-TS	C/TW
Macrina et al. [29]	Partial	FCS	HLNS	C/TW/MF/BSoC
Keskin et al. [26]	Partial	FCS	ALNS	C/TW/CSW
Schiffer and Walther [30]	Partial	FCS	MIP	C/TW
Cortés-Murcia et al. [31]	Partial	FCS	ILS	C/TW/CSC
Wang and Zhao [32]	Partial	FCS	LNS	C/TW/MF
Desaulniers et al. [22]	Partial	FCS	BP&C	C/TW
Bezzi et al. [33]	Partial	FCS	B&P	C/TW

[1] Algorithm: ALNS: Adaptive large neighborhood search; LNS: Large neighborhood search; BP&C: Branch-price-and-cut; ILS: Iterative local search; B&P: Branch-and-price; MIP: Mixed- integer programming; HLNS: Hybrid large neighborhood search; VNS: Variable neighborhood search; TS: Tabu search. [2] Constraints: C: Load capacity; TW: Time window; MF: Mixed fleet; BSoC: Battery SoC; CSW: Charging station waiting; CSC: Charging station capacity.

The EVRPTW was extended by Keskin and Çatay [28], considering a partial linear recharging function. Schiffer and Walther [30] proposed an adaptive large neighborhood search (ALNS) for the location routing problem with intra-route facilities and a linear linear function. Cortés-Murcia et al. [31] studied the EVRP with time windows, partial linear recharging function, and satellite customers. Keskin et al. [26] considered the EVRPTW with stochastic waiting times, using a linear charging function. Macrina et al. [29] investigated a mixed-fleet VRP with different linear recharging speeds. Wang and Zhao [32] incorporated a partial linear recharging function into the electric fleet size and mix VRP (E-FSMFTW-PR). These linear models provide a straightforward way to represent charging, facilitating integration into optimization algorithms. Bezzi et al. [33] considered partial-charging

policy and multiple recharging technologies at stations with differentiated charge rates and costs. They developed a branch-and-price (B&P) algorithm that solves instances with up to 30 customers, 5 FCSs, 7 EVs, and 3 technologies. However, the linear assumption departs from real charging behavior and may introduce bias in time estimates.

3.1.2. Nonlinear Charging Function

Nonlinear functions, such as exponential functions, improve modeling fidelity but increase the computational complexity of routing optimization. In reality, battery charging typically follows three stages: (i) an initial transient/conditioning stage; (ii) a constant-current (CC) stage, where the battery is charged at approximately constant current; and (iii) a constant-voltage (CV) stage, during which current declines as the battery approaches full SoC. Because instantaneous charging power depends on battery SoC and station hardware, the time required to raise SoC is generally nonlinear.

Nonlinear charging functions capture the fact that SoC is not a linear function of the charging time [34]. Such functions improve modeling fidelity but increase the computational complexity of routing optimization. Consequently, charging time cannot be computed as $(v_i - u_i)/g$. Figure 4 illustrates a K-segment piecewise-linear approximation of a CC–CV charging curve. Increasing the number of breakpoints K improves approximation accuracy but also increases model size. In many cases, charging time grows nonlinearly with delivered energy, which increases modeling difficulty.

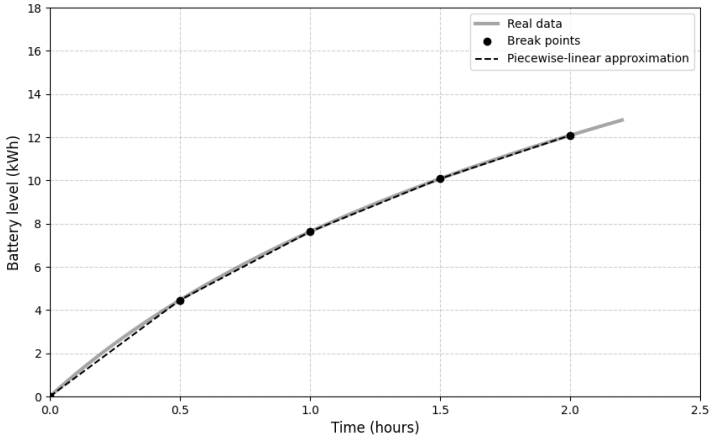

Figure 4. Piecewise linear approximation of battery charging.

This modeling choice aligns with physical reality and can improve routing feasibility and operational cost [35]. The EVRP with nonlinear charging function (EVRP-NL) was first formalized by Montoya et al. [24] to model a more accurate charging process. The authors proposed a piecewise-linear approximation of the charging process and considered multiple charging technologies. Pelletier et al. [36] used the same piecewise-linear approximation and considered the electric freight vehicles charge scheduling problem. In 2019, Keskin et al. [37] incorporated time-dependent queuing at CSs and a piecewise charging function, extending the EVRPTW. Froger et al. [38] proposed a path-based model for EVRP-NL as an effective alternative model that avoids replicating charging stations. Kancharla and Ramadurai [39] incorporated load-dependent discharging and applied a piecewise-linear approximation to charging time. Lee [40] studied the EVRP with concave, non-decreasing charging functions. Zhou et al. [27] addressed the electric bus charging scheduling problem with a nonlinear charging function and battery degradation effects. Kullman et al. [41] introduced an EVRP with public–private recharging strategy (EVRP-PP) in a single-vehicle setting, considering nonlinear charging functions with realistic queuing at the CS.

Accounting for charging station capacity restrictions, Froger et al. [42] extended EVRP-NL. Lera-Romero et al. [43] integrated time-dependent travel and waiting at CSs into EVRP-NL. Wang et al. [25] introduced a heterogeneous-fleet EVRP with nonlinear charging functions (HEVRP-NL). The authors presented a path-based model that solves small-scale instances to optimality and developed an efficient iterative local search (ILS) framework for large-scale instances. Overall, incorporating nonlinear charging functions improves the realism and accuracy of the charging representation. This yields more feasible and cost-effective routing decisions by better capturing the complexities of real-world charging dynamics. Lam et al. [44] incorporated time windows into EVRP-NL (EVRPTW-NL). They developed a BP&C algorithm that solved 34% of 100-customer instances. Nafstad et al. [45] extended EVRPTW-NL with heterogeneous charging technologies. Their BP&C solved instances with up to 100 customers and 21 FCSs within one hour. Although nonlinear functions better represent the actual charging process, they incur higher computational complexity and longer runtimes.

3.2. Charging Policy: Full vs. Partial

The charging policy specifies the amount of energy replenished at a CS and thus links the charging function to operational requirements in distribution. In the literature, two policies are commonly used to determine the charging amount at a station: full charging and partial charging. A full-charging policy fully charges the battery, reduces the decision space for charging amount, and suits scenarios with stringent computational efficiency requirements. Under a full-charging policy, the battery SoC of the EV upon leaving CS is full; naturally, $v_i = B, \ \forall i \in F$. A partial-charging policy flexibly determines the charging amount based on the energy requirements of the subsequent route segments, thereby avoiding unnecessary charging time. The choice between these two policies directly affects routing feasibility and economic efficiency. Policy selection should account for customer time windows and the availability and density of CSs.

Figure 5 presents a decision tree for selecting charging policies based on station density and route constraints. The process begins by evaluating the density of charging stations along the route. If stations are sparse, and subsequent route requirements are clear, a full-charging policy is recommended to ensure sufficient range. Conversely, if stations are dense and customer time windows are strict, a partial-charging policy is preferable to improve time efficiency. When sparse station coverage coexists with strict time windows, a segmented policy that combines full and partial charging is advisable. This decision tree provides guidance for selecting an appropriate charging policy given specific route and station conditions.

3.2.1. Full-Charging Policy

Full charging refers to recharging the battery to fully charged capacity and is suitable for routes with sparse coverage of CSs and clear subsequent range requirements. An overview of EVRP studies employing a full-charging policy is provided in Table 6.

Although Conrad and Figliozzi [11] employed a full-charging policy, the model abstracted from the technical details of the charging process. Schneider et al. [12] adopted a full-charging strategy in EVRPTW, but did not incorporate realistic charging-curve effects. Goeke and Schneider [14] addressed limitations arising from fixed charging time and unspecified power–SoC relationships. The authors proposed a method that dynamically relates charging time to arrival SoC at the CS. Combined with the physical-based energy consumption model, the resulting routes better reflect operational conditions.

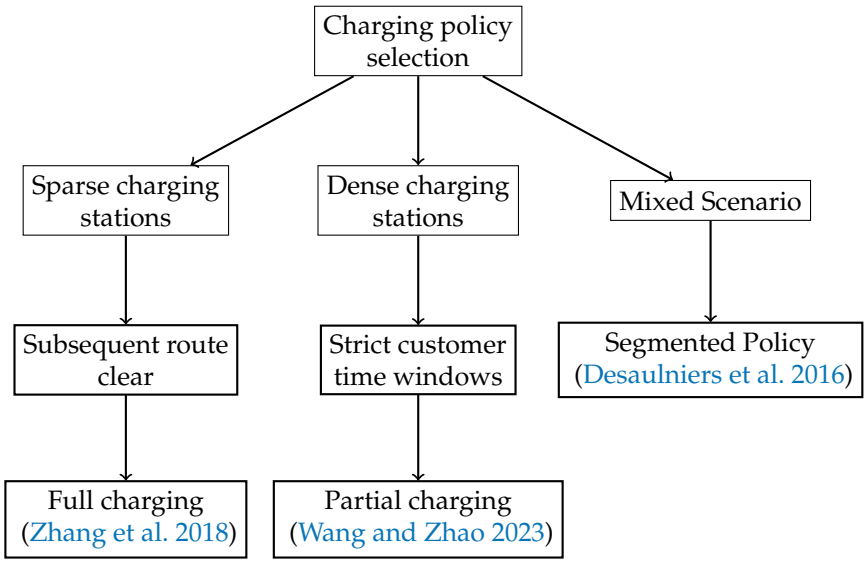

Figure 5. Charging policy selection decision tree (based on station density and route constraints) [22,32,46].

Table 6. EVRP with swapping stations.

Reference	Charging Function	Charging Station	Objective [1]	Algorithm [2]
Conrad and Figliozzi [11]		FCSs	FC	
Schneider et al. [12]	Linear	FCSs	TC	VNS
Goeke and Schneider [14]	Linear	FCSs	TC/FC/EC	ALNS
Zhang et al. [46]		FCSs	EC	ALNS
Hiermann et al. [47]	Linear	FCSs	FC/TC	B&P/ALNS
Liu et al. [48]	Linear	FCSs	FC/EC/PC	ACO
Shahbazian et al. [49]		FCSs	TC/PC	VNS
Erdelić and Carić [50]	Linear	FCSs	FC/TC, EC	ALNS
Wu and Zhang [51]	Linear	FCSs	FC/EC	B&P

[1] Objective: EC: Energy cost; FC: Fixed cost; PC: Penalty cost; TC: Travel cost. [2] Algorithm: ALNS: Adaptive large neighborhood search; ACO: Ant colony optimization; VNS: Variable neighborhood search; B&P: Branch-and-price.

Hiermann et al. [47] introduced a more comprehensive model in which recharging time is a function of various factors. Recharging time depends on the remaining energy when arriving at the CS, the maximum energy capacity of the vehicle, and the recharging rate. They provided a new benchmark set with bounds computed via a B&P solver and proposed a hybrid ALNS for large instances. Zhang et al. [46] explicitly adopted a full-charging strategy in scenarios without time window constraints. The authors simplified the variable dimensions for selecting charging amount in charging decisions. Charging time was linked implicitly to a comprehensive energy-consumption model, aligning the charging strategy with the objective of minimizing energy use. Coupled with ant colony optimization (ACO), the approach demonstrated that the decision simplification under full charging can be achieved without sacrificing optimization efficiency.

A comparison between two policies was conducted in Erdelić and Carić [50]. The results showed that partial recharge reduced the number of vehicles by 4.05% and the total travel distance by 1.82% compared to the full-recharging policy. Liu et al. [48] studied the delivery of perishable goods, introducing an EVRP with variable vehicle speed and soft time windows (EVRP-VS). The authors proposed an adaptive hybrid ACO (AHACO), integrating a two-stage speed optimization strategy. The numerical experiments showed that the two-stage speed optimization strategy can significantly reduce delivery costs. Wu and Zhang [51] considered ICE vehicles in the first echelon and a full-charging policy for

EVs in the second echelon. They developed a column generation (CG)algorithm to solve it. In the first echelon, the columns were generated by solving the elementary shortest path problem (ESPP). A bidirectional labeling algorithm was then used to obtain feasible routes of EVs.

Intra-firm collaboration was considered in Vahedi-Nouri et al. [52]. The authors introduced bi-objective collaborative capacitated EVRP (CoCEVRP). Their approach integrated the multi-objective Keshtel algorithm (MOKA) with a mathematical model, outperforming NSGA-II in convergence and solution diversity. Gil-Gala et al. [53] proposed a genetic programming (GP) hyper heuristic algorithm, integrating proxy evaluation to automatically generate routing strategies. Chen et al. [54] addressed the issues of dynamic scenario adaptation in EVRP. By dividing the requirements into three categories, a multi-objective model was constructed. The authors proposed a solution framework combining Q-learning initialization with a two-stage genetic algorithm (GA). Shahbazian et al. [49] extended Chen et al. [54] to multi-depot EVRPTW, proposing a hybrid optimization framework that incorporates knowledge-guided multi-agent deep reinforcement learning (MARL) and variable neighborhood search (VNS). Across these studies under a full-charging policy, models are concise, easy to linearize, and efficient in sparse station scenarios. However, they often ignore the SoC dependent charging curve, queuing and time-varying effects, battery attenuation, and operational heterogeneity, which limit applicability and accuracy in complex real-world settings.

3.2.2. Partial-Charging Policy

Partial charging refers to charging only to the energy required for the forthcoming route segment, which is suitable for scenarios where CSs are dense and flexible path adjustments are needed. This approach mitigates unnecessary dwell time arising from full charging [28]. Desaulniers et al. [22] examined two full-charging variants of VRPTW: (i) at most a single recharge per route is allowed and (ii) multiple recharges are allowed. The quantitative comparison showed that the multi-charging full-charging variant reduced routing costs by an average of 2.29% and reduce the number of vehicles by 3.45% versus the single-charging full-charging variant. Schiffer and Walther [15] presented an ALNS enhanced with local search and dynamic programming (DP) components. The authors assessed the competitiveness of the developed algorithm on the EVRPTW for partial recharging and derived new best-known solutions. Full charging obliges the vehicle to reach full SoC, often increasing total charging time.

In order to avoid potential path timing conflicts under customer time window constraints, Yu et al. [55] adopted a partial charging strategy in the green mixed-fleet VRP with realistic energy consumption and partial recharges (GMFVRP-REC-PR). The authors designed an ALNS integrating DP and the time-efficient evaluation of neighborhoods. Results showed that the algorithm obtained high-quality solutions for all medium- and large-scale instances within a reasonable computational time.

Wang and Zhao [32] developed a hybrid heuristic, combining a large neighborhood search (LNS) algorithm with a set partitioning component. The authors used the heuristic algorithm to solve a newly designed instance set from a real-world dataset. The results indicate the following: (i) across 168 large E-FSMFTW instances, compared to the full-charging policy, the partial-charging policy reduced average cost; (ii) on a JD real dataset (including 1000 customers and 100 CSs), partial-charging policy have reduced costs by an average of 0.79% (100 customer instances) to 0.82% (1000 customer instances) compared to JD's original fixed time full charging strategy. Vani et al. [56] proposed a bat optimization algorithm, presenting higher effectiveness. In Moradi et al. [57], the authors introduced the concept of robot-aided, presenting robot-aided EVRP with lockers and prime customer

prioritization (REVRP-LPCP). The developed LNS-based metaheuristic combined with simulation annealing (SA) (LNS-SA) improved the average solution quality by 2.79% compared to Gurobi. These studies show that partial-charging policy can enhance the flexibility and efficiency. However, they increase modeling and computational complexity and often omit battery-degradation and operator-behavior considerations.

Though full- and partial-charging policies are widely used in modeling EVRP, in practice, the charging policy depends on various factors. Drivers can choose an option for themselves based on requirements, for instance, frequent partial charging with short charging intervals, or full charging with relatively long stops. Notably, powerful DC charging stations can significantly reduce charging time, speeding up this process. Additionally, the operating mode of the EV also influences the charging policy. For example, service providers in large cities are likely to choose frequent partial charging to ensure continuous operation. Electric transport in the form of electric buses can be partially charged at stops using wireless charging.

3.3. Charging Station: Stationary vs. Mobile

Because EVs depend on CS infrastructure, the layout of CSs is a key constraint for EVRP. According to the spatial characteristic, the CSs can be divided into fixed charging stations (FCSs) and mobile charging stations (MCSs). FCSs and MCSs constitute two principal forms of energy replenishment infrastructure. Research on these facilities focuses on adapting to EV operational requirements and addressing practical distribution challenges, offering both conceptual and practical value.

3.3.1. Stationary Charging Stations

In practice, FCSs have become the mainstream choice for urban intensive distribution due to their characteristics of stable location, high power, and controllable cost.

Charging infrastructure types can be broadly classified by nominal power. For example, there are lower-power (Level-1/Level-2 AC) chargers that enable slow, overnight, or depot charging, and higher-power (DC fast/ultra-fast) chargers that enable short, high-power replenishment sessions. These classes primarily affect the achievable charging power and the time–energy trade-off at a stop, and thus alter the effective charging-time function used in routing models. However, because this review emphasizes the operational role of charging locations within routing and replenishment frameworks rather than technology-level station design, charger types are not differentiated in the core formulations.

In Conrad and Figliozzi [11], the recharging was available at only a few customer locations. Erdoğan and Miller-Hooks [58] treated FCSs as special nodes under the frame work of EVRP. Thereafter, the investigation of FCS visits emerged as a core research theme in the EVRP. However, this aspect introduces modeling complexities, primarily due to four attributes of FCS nodes. First, unlike customer nodes, FCS nodes are optional. Second, in contrast to customer nodes, which permit only a single visit by one vehicle, each FCS node can be accessed repeatedly by multiple vehicles without any upper limit on visit frequency. Third, every FCS operates under capacity constraints. Extended charging durations directly correspond to elevated occupancy levels at the FCS, and, in such cases, advance reservation mechanisms may be necessitated to ensure operational order. Fourth, the quantity of FCS nodes may be substantially large, often exceeding the number of customer nodes by a significant margin. This numerical disparity exerts a negative impact on the computational efficiency of the model's solution process.

Many studies have focused on modeling the FCS visit. Using the dummy-node technique [59], Erdoğan and Miller-Hooks [58] replicated FCS visits with multiple dummy nodes. This enables EVs to visit a station once or multiple times. Çağrı Koç and

Karaoglan [60] argued that the maximum number of station visits cannot be estimated a priori. Consequently, stations must be replicated generously, which significantly increases computational complexity. The authors introduced a three-dimensional binary decision variable x_{ijk} to indicate if an EV detoured to visit FCS k during the delivery from customer i to customer j. Leggieri and Haouari [61] improved the formulation by incorporating duration limit.

The mathematical formulations were streamlined to an arc detour approach [62]. This simplification leverages the conventional two-dimensional variable. This variable was paired with an additional two-dimensional variable, which denotes whether an EV will make a visit to an FCS. Xiao et al. [8] presented a new fixed arc detour technique. In this methodological framework, each arc connecting two customer nodes is assumed to possess a fixed, optimal detour route associated with an FCS visit. Such detours can be precomputed in preprocessing. As a result, there is no longer a requirement for complex mathematical models to ascertain whether an FCS visit takes place. Instead, only a single binary variable is sufficient to denote whether the nearest FCS relative to the arc is accessed during the traversal of that arc. Xia et al. [63] introduced pseudo nodes in the EVRP model to reduce complexity.

In Jia et al. [64], the EVRP was treated as a bilevel optimization problem, and a novel bilevel ACO algorithm was accordingly proposed. This algorithm decomposes EVRP into two hierarchical subproblems, namely, (i) the capacitated VRP (CVRP) and (ii) the fixed-route vehicle charging problem. In the upper-level subproblem, the electricity constraint is disregarded. For the lower-level subproblem, a newly designed effective heuristic method is employed to determine the charging schedule within the generated routes. Fan et al. [65] split FCS into traditional and new energy type with and without carbon emission. Their objective comprised operational cost and environment cost. Izdebski et al. [66] proposed an innovative method to reduce the energy consumption of EVs used in municipal services. Their approach specifically accounts for the operational uncertainties within the charging infrastructure. The core challenge is to determine EV driving routes that schedule arrivals at FCSs during intervals with the lowest probability of equipment failure.

Zhou et al. [67] introduced a pickup and delivery problem with EVs and time windows considering queues (PDPTWEV-Q). The authors took the scheduling of multiple EVs operating at the same site into account. They formulated an ALNS algorithm for moderately large-scale problem instances. Moreover, the competitive performance of this proposed algorithm was further validated by the identification of nine new optimal solutions. However, the algorithm's applicability to dynamic factors such as sudden tasks still needs further expansion.

Li et al. [68] first presented a novel approach to EVRP with charging/discharging based on time-of-use (TOU) electricity pricing and diverse FCSs. For the first time, the vehicle-to-grid (V2G) charging and discharging were integrated into the EVRP model. The EVs are allowed to charge when electricity prices are low and discharge to the grid when prices are high. An adaptive NSGA-II algorithm was developed that dynamically adjusted the crossover and mutation probabilities to balance global and local search capabilities. To address the issues of fixed charging timing and fixed charged energy existing in traditional EVRP models as well as partial charging strategies, Yang et al. [69] presented an EVRP with flexible charging strategy. The authors collected charging data from a category of mainstream EVs and then simulated the instantaneous charging power under real-world scenarios. But their reinforcement learning (RL) operators did not fully consider the time window and charging cost that can easily lead to guidance bias and did not explore the impact of learning rate on algorithm search performance.

3.3.2. Mobile Charging Stations

According to Afshar et al. [70], MCSs refer to the charging stations in the forms of trucks and vans equipped with charging platforms. They can be classified into four types: (i) battery-less MCSs, (ii) battery-integrated MCSs, (iii) robot-like MCSs, and (iv) mobile battery swapping (MBS) stations. The battery-less MCS does not rely on an energy storage unit for power supply; instead, it is equipped with power electronics and multiple charging connectors. The battery-integrated MCS is equipped with a power storage system, and it travels to EVs to provide recharging services at the locations and times requested by users. It is important to note that this type of MCS also requires recharging to support its own travel operations. The robot-like MCS is an autonomous mobile charging system, which performs EV recharging in shared areas and can be easily repositioned to supply energy to EVs. This category of MCS is considered suitable in scenarios where multiple vehicles require energy supply at the same location, such as parking lots. The MBS station integrates the functional characteristics of both battery swapping and mobile charging. Since our focus is on the impact of mobile charging stations on routing, we do not differentiate the specific details of mobile charging station settings and refer to it simply as MCS in the remainder of the review. The defining difference between MCS and FCS is mobility.

MCSs, on the other hand, aim to achieve breakthroughs in energy replenishment for scenarios where fixed facilities are difficult to cover. The construction cost of FCSs can be high and the utilization rate may be low. MCSs can be dynamically dispatched to the vicinity of distribution nodes as needed, reducing the detour distance and time for EVs to replenish energy. In emergencies, such as sudden power shortage in an EV or the temporary failure of FCSs, MCSs can respond more quickly to avoid distribution interruptions. In addition, during peak periods such as e-commerce promotions, MCSs can also serve as a supplement to FCSs to alleviate congestion in fixed facility queues. The synchronous optimization model will not be elaborated on herein. However, relevant details of this model can be retrieved from the research work by Çatay and İhsan Sadati [71].

Figure 6 shows an example of EVRP with MCSs. In this figure, there are three EVs and one MCS operating in a distribution network. The customer nodes are depicted as circles with numbers. The solid lines with arrows indicate the paths taken by EVs as they travel to the customer locations. The dashed lines represent the routes of MCS, which are dispatched from the depot to specific locations to recharge the EVs during their delivery tours. Locations visited by MCSs are highlighted in green, indicating spatiotemporal synchronization with EVs.

The modeling core of MCSs in EVRP lies in dual-path coordination and dynamic constraint quantification, which are considerably more complex than for FCSs. Existing models fall into two categories: hierarchical and integrated. Hierarchical modeling breaks down the problem into upper-layer MCS scheduling and lower-layer EV routing. The process is to identify the power gap in the EV path and then schedule MCSs to replenish energy. Although it reduces computational difficulty, it is prone to suboptimal solutions due to the separation of the two layers of decision-making. Integrated modeling incorporates MCSs as a mobile node into the EV path diagram, synchronously optimizing both types of paths. Table 7 lists studies employing MCSs, organized by objective, algorithm, charging function, charging position selection, and instance.

Centered on MCSs' operation, there are some pioneering studies. At the planning phase, Zhang et al. [72] put forward the concept of MCSs. They constructed an economic-competitiveness model to conduct a comparative analysis of user convenience and cost between FCSs and MCSs. The findings derived from their research indicated that the adoption of MCSs enables time savings in comparison to the utilization of FCSs. Cui et al. [73] and Ren et al. [74] studied the operation process of MCSs. Li et al. [75] pro-

posed a mixed-integer linear programming (MILP) model and MCS service framework. Chakraborty et al. [76] proposed a scalable framework called peer-to-peer car charging (P2C2), enabling EVs to share power while driving. They also introduced the concept of MCSs, where vehicles equipped with large-capacity batteries recharge the entire vehicle network. Cheng et al. [77] proposed a solution for the problem of sudden depletion of EVs batteries on highways, with mobile charging drones (MCDs) as the core. A centralized fleet ownership model and a decentralized crowdsourcing model are constructed. However, serviced EVs were more like passive users waiting for services.

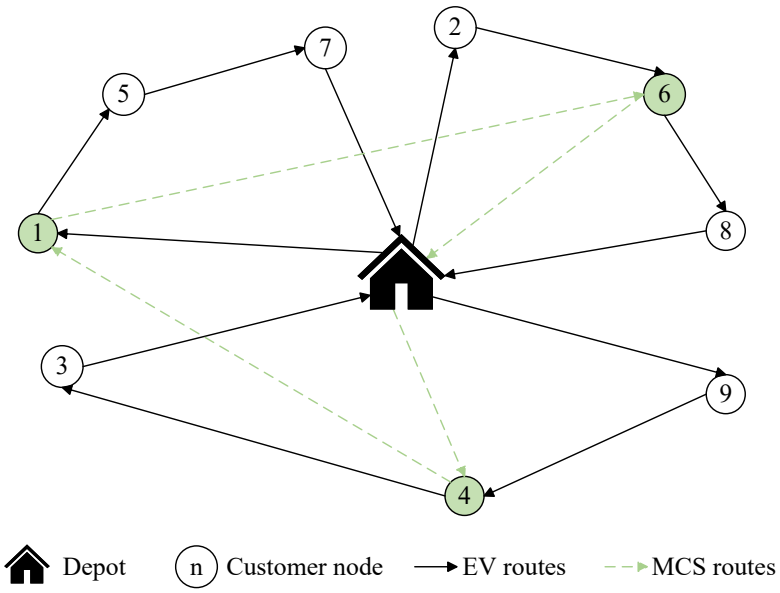

Figure 6. Example of EVRP with MCSs.

Table 7. EVRP with MCSs.

Reference	Objective [1]	Algorithm [2]	Charging Function	Charging Position [3]	Instance
Zhu et al. [78]	TT	B&P/VNS	Linear	CS	Real data
Raeesi and Zografos [79]	FC/TC	LNS	Linear	CV	Extended
Raeesi and Zografos [80]	FC/TC	NDPI/LNS	Linear	CV	Extended
Cai et al. [81]	TC	DAEMTA	Linear	CS	Real data
Ren et al. [82]	FC/EC	LNS-QL	Nonlinear	CV	Real data
Zhang et al. [83]	FC/TC	ALNS	Linear	CV	Extended

[1] Objective: EC: Energy cost; FC: Fixed cost; TT: Travel time; ATD: Average time delay, TC: Travel cost. [2] Algorithm: ALNS: Adaptive large neighborhood search; DAEMTA: Double-assistant evolutionary multitasking algorithm; LNS-QL: Large neighborhood search with Q-learning; B&P: Branch-and-price; NDPI: Non-dominated path identification; VNS: Variable neighborhood search. [3] Charging position: CV: Customer vertex; CS: Charging station.

In the current body of the academic literature, EVRP research focusing on MCSs remains relatively scarce when contrasted with studies dedicated to FCSs. The EVRP considering MCSs is a complex problem. MCS routing must address multiple coupled constraints. A primary challenge is the spatiotemporal synchronization between the delivery time windows of EVs and the charging service times of the MCSs. Furthermore, the routing is constrained by the internal resources of the MCSs, such as their battery capacity and charging rate.

Çatay and İhsan Sadati [71] proposed EVRP with MCSs (EVRPTW–MCS). The authors introduced a mathuristic approach that combines the VNS and an exact method to solve it (MathVNS). The process of the MathVNS algorithm revolves around the core logic of first optimizing EV routes and then precisely planning MCS routes. First, a cheapest-insertion heuristic algorithm is adapted to construct the initial path of the EV. If the EV's battery level is low, the preceding customer nodes are automatically set as potential MCS charging points to ensure that the EV meets the energy requirements for completing the delivery task. Shaking perturbs the current solution randomly by using five problem-specific neighborhood structures. Subsequently, in the first stage of local search, optimize the EV path and clarify the charging nodes that MCS needs to serve and the corresponding charging amounts. Next, an MCS routing problem (MCSRP) was generated, with the goal of minimizing energy cost, solved by integer programming (IP). The results show that the algorithm has shown excellent performance in solution quality, efficiency, and robustness. And, based on the Argos depot case in London, the authors proposed to prioritize the deployment of MCS in weak areas of fixed charging. But the cost of battery degradation over long-term operation was not considered.

Yang et al. [84] extended the EVRPTW-MCS by considering nonlinear battery degradation in urban logistics. The authors proposed an EVRP that includes time windows, mobile charging (relying on MCSs), and nonlinear battery decay (EVRPTW-MCND). To solve this problem, the authors proposed a three-layer algorithm framework that integrates ALNS, DP, and MILP. They customized two destroy operators: (i) time interval removal and (ii) distance interval removal. And a special repair operator called regret-2 heuristic with noise insertion is employed. The MILP model selects the optimal charging label combination and synchronously plans the MCSs path, ensuring the feasibility of the MCSs path. The results showed: (i) MCSs have significant advantages in scenarios with low coverage of FCSs, such as urban edges and remote customer nodes, and (ii) MCSs can serve as an effective alternative to FCSs. Specifically, MCSs can reduce the detour distance of EVs and lower battery attenuation costs. In terms of operational strategy, enterprises should prioritize the configuration of high-power MCSs and constrain the SoC of EVs over a low range to reduce attenuation costs.

In summary, FCSs are suitable for dense distribution in urban core areas. Their core advantages lie in their high power and low cost, which can efficiently meet the frequent charging demands in this area. However, they exhibit coverage gaps and cannot serve suburban or remote locations. MCSs are mainly used to make up for the coverage defects of FCSs, especially in areas where FCS coverage is weak. For instance, Yang et al. [84] found in their study on urban fringe scenarios that MCSs can reduce the detour distance of EVs by 15–20%. In addition, MCSs can also play an important role in emergency scenarios, such as dealing with sudden power outages and peak charging demand during promotion periods. Nevertheless, the application of MCSs needs to solve the dual-path coordination problem, ensuring that the driving routes of EVs are synchronized with the scheduling plans of MCSs.

3.4. Wireless Charging

Wireless-charging EVs (WCEVs) have provided a breakthrough solution for the EVRP owing to synchronous driving and charging. The integration of dynamic charging within production, manufacturing, logistics, and seaport operations is advancing rapidly. The implementation of dynamic charging can be achieved through the application of inductive power transfer (IPT) technology. IPT enables dynamic wireless charging (DWC). For instance, the company Wiferion provides automated wireless-charging systems specifically designed for forklifts, mobile robots, and industrial trucks. As reported in Wiferion [85],

eliminating interruptions caused by stationary charging can increase fleet availability by up to 30%.

A comparative analysis of stationary and dynamic recharging scenarios was presented in Duarte et al. [86]. Their case study drew on real-world mobility patterns from Lisbon, Portugal. They further carried out a feasibility assessment for EVs, within which they evaluated various scenarios by taking dynamic and stationary recharging as the basis. The key conclusions are as follows: (i) Wireless recharging supports a wider adoption of EVs; (ii) Required battery capacity can be notably reduced, as stationary recharging required roughly 3.2× the battery capacity relative to wireless recharging. However, so far, DWC has mostly been applied in small areas, such as for vehicles with fixed driving routes or within factories. The application of DWC on a large scale is challenging as this requires significant infrastructure investment.

Hwang et al. [87] focused on the system optimization of DWC-EVs operating in a multiple-route environment. The authors extended single-route optimization to a multi-route setting with shared road segments. A mathematical model was constructed to simultaneously optimize two key decision variables: the allocation of power tracks and the battery size of EVs for each route. To solve the resulting continuous nonlinear program, they proposed a particle swarm optimization (PSO) algorithm. The position vector of particles incorporated battery capacities of each route and start/end points of power tracks. However, they assumed that the vehicle speed was determined and did not take into account the conflict of multiple vehicles charging simultaneously.

Fernández et al. [88] addressed the arc routing problem for EVs, where the EVs can charge while driving along dedicated arcs through IPT technology. To model these complex elements uniformly, they proposed the concept of an energy-indexed graph, which encodes SoC into the nodes and arcs of the graph. A branch-and-cut (B&C) solution framework for the integer linear programming (ILP) formulation and a local search for large-scale instances were derived. The computational experiments on realistic instances showed that DWC significantly mitigates travel time increases caused by small battery size.

4. Swapping

Compared with charging strategies, battery swapping replaces slow charging with rapid battery replacement. Its core advantage lies in shortening the single replenishment time from tens of minutes to a few minutes, thereby improving the operational efficiency. However, dependence on BSSs raises a distinct coordination problem between station operations and routing. Based on the decision scope, the research on battery swapping strategies can be divided into two major scenarios.

The first scenario treats BSS locations and quantities as exogenous (potentially including MBSs). The research focus is on how to reasonably arrange the timing and selection of EV access to BSSs in path planning. The other scenario is a location-routing problem (LRP) that jointly determines BSS siting and EV routing. Instead of treating BSSs as fixed facilities, BSS siting and EV routing are optimized jointly. This formulation aligns with planning practice and requires balancing capital expenditure, spatial coverage, travel distance, and service efficiency. It belongs to the collaborative optimization problem of strategic layer site selection and operational layer path. The two scenarios exhibit a natural progression. The former concerns path optimization under existing facilities. The latter addresses the long-term adaptation of facility layout and routes. Table 8 provides an overview of EVRP with BSSs.

Table 8. EVRP with swapping station.

Reference	Objective [1]	Algorithm [2]	Constraints [3]	Stochastic [4]	Data
Li et al. [16]	EC/FC	AGE-HN	C/S	N	Generated
De Weerdt et al. [89]	TT	MDP	S	Y	Generated
Adler and Mirchandani [90]	ATD	MCDP	C/S	Y	Real data
Jie et al. [91]	TC/EC/LC	ALNS	C/S/MF	N	Extended
Zhou and Zhao [92]	FC/TC/EC/ABU	MWOA	C/TW/S	N	Generated
Mao et al. [93]	FC/TC/EC/WC	ACO	C/TW/S	N	Extended
Ma et al. [94]	TD/TT/EC	ALNS	C/TW/V	N	Extended
Zhang et al. [95]	TC/CCSS	VNS	C/S/D	Y	Extended
Yang and Sun [96]	TC/CCSS	ALNS	C/S	N	Extended
Li et al. [97]	TC/CCSS	ACO	C/CC	N	Extended
Hof et al. [98]	TC/CCSS	ALNS	C/S	N	Extended
Zhang et al. [99]	TC/P	GA	C/TW/S/CC	N	Real data
Souza et al. [100]	TC/CCSS	VNS	C/S	N	Extended
Portela et al. [101]	TC	GRASP-RVND	C/TW/MD/S	N	Extended
Chen et al. [102]	TC/EC	HBP	C/TW/MF/S	N	Extended
Chen et al. [103]	TC/FC	IBP-HL	C/TW/MD	N	Extended

[1] Objective: EC: Energy cost; FC: Fixed cost; TT: Travel time; ATD: Average time delay; LC: Loading cost; ABU: Average battery utilization; WC: Waiting cost; CCSS: Construction cost of swapping station. [2] Algorithm: AGE-HN: Adaptive genetic algorithm combing hill climbing and neighborhood search; MDP: Markov decision process; MCDP: Markov chance-decision processes; ALNS: Adaptive large neighborhood search; MWOA: Multi-objective whale optimization algorithm; ACO: Ant colony optimization; VNS: Variable neighborhood search; SA-K-Means-ACO: Simulated annealing–K-Means–ant colony optimization; GA: Genetic algorithm; GRASP: Greedy randomized adaptive search procedure; RVND: Random variable neighborhood descent; HBP: Heuristic branch-and-price algorithm; IBP-HL: improved branch-and-price algorithm with heuristic–exact labeling. [3] Constraints: C: Load capacity; TW: Time window; MF: Mixed fleet; MD: Multi-depot; S: Station; V: Velocity; D: Demand; CC: Collaborative of construction. [4] Stochastic: Y: Yes; N: No.

4.1. EVRP with Battery Swapping Stations

With the popularization of EVs in the logistics field, limited range and low energy replenishment efficiency remain the primary bottlenecks restricting their large-scale application. BSSs with the advantage of rapid energy replenishment have gradually become the key infrastructure for EVRP. Academic research on the integration of BSSs in the EVRP has evolved significantly. The evolution is marked by a progression from basic to more complex scenarios and a shift from single to diverse optimization objectives. Consequently, a substantial body of work now spans model formulation, algorithm design, and scenario innovation. The formulation of EVRP with fixed BSSs (EVRP–BSSs) (P3) is given as follows.

(P3):

$$\min z = \sum_{i\in N}\sum_{j\in N, j\neq i} c_{ij}x_{ij} + c_s\sum_{i\in S} x_{ij} \tag{18}$$

$$\text{s.t.} \quad \sum_{j\in N, j\neq i} x_{ij} = \sum_{j\in N, j\neq i} x_{ji}, \qquad \forall i \in S \tag{19}$$

$$A_j \geq A_i + s_i + t_{swap} + t_{ij} - M(1 - x_{ij}), \qquad \forall i, j \in N, i \neq j \tag{20}$$

$$(2b) - (2f), (3c) - (3e) \tag{21}$$

In Objective (18), the cost of battery swapping is considered. Constraints (19) modify the flow balance constraint to include BSSs. Finally, Constraint (20) introduces a new time parameter t_{swap} to denote the fixed time of swapping batteries.

4.1.1. Fixed Battery Swapping Station

In 1981, Ichimori et al. [18] first discussed the problem of routing a single vehicle with a limited range to a BSS. De Weerdt et al. [89] extended this setting to multiple EVs. Adler and Mirchandani [90] modeled the online route planning for EVs with replaceable batteries and BSS reservation system as a Markov decision process with chance (MCDP).

By approximating the optimal strategy using approximate DP (ADP) with linear temporal difference, the approach aims to minimize the average delay for all vehicles. Real-time route planning and BSS reservations are achieved through the coordination of a central server and onboard software.

Jie et al. [91] introduced a two-echelon EVRP with BSSs (2E-EVRP–BSS). The authors proposed an IP formulation along with a hybrid algorithm, which integrates CG and ALNS (CG–ALNS). In this paper, the BSSs employ a shared setting rule for two types of EVs, allowing the same EV to access the same battery swapping station multiple times within one tour. The locations of BSSs are randomly generated and their number is 1/5 of the total number of nodes in the road network. There is no maximum service capacity limit set, and only the service of replacing depleted batteries with fully charged batteries is provided. The cost of battery swapping is charged at a fixed rate per transaction, with the first-tier large EV being twice as expensive as the second-tier small EV. The battery replacement time is uniformly set to a fixed value, which only includes the battery replacement operation time. However, they did not consider customer service time windows.

Li et al. [16] developed an integrated energy consumption and carbon emissions model, incorporating multiple physical factors. The authors designed an adaptive GA that combines hill climbing and neighborhood search (AGE-HN) to solve the problem. The results showed that the proposed algorithm outperformed heuristic algorithms in terms of speeds of convergence and probability of obtaining the optimal solution. Two modes of partial charging and battery replacement were integrated as optional strategies in Mao et al. [93]. An improved ACO combining insertion heuristics and enhanced local search was developed.

Range constraints for autonomous EVs and differentiated customer time-window priorities are receiving increased attention. Ma et al. [94] considered BSSs in the delivery scenario of shared autonomous driving EVs (SAEVs) to mitigate their mileage restrictions. They constructed an MILP model, called SAEVs' VRP with speed optimization (SAEVs-VRP-SO), to jointly optimize the segment driving speeds and SAEV route. An ALNS algorithm with embedded speed optimization sub-algorithm (SOA) was proposed. The sensitivity analysis showed that the minimum remaining power ratio of battery capacities can reduce the driving distance of EVs. The smaller battery capacities and lower driving speed can reduce energy consumption.

Furthermore, a multi-objective model with the objective of minimizing the total distribution costs while maximizing the average battery utilization was proposed by Zhou and Zhao [92]. The authors introduced the EVRP with battery swap consideration and mixed time-window constraints (EVRP–BS–MTW). To address this problem, a multi-objective whale optimization algorithm strengthened through the integration of particle filter and Levy flights (MWOA-PFLF) was developed. Extended scenario analysis showed that increasing BSS capacity increases total cost yet improves battery utilization. Increasing the number of EVs improved utilization with negligible impact on total cost.

4.1.2. Mobile Battery Swapping Station

Faced with limited coverage of fixed battery swapping facilities for EVs during delivery, the MBS mode has emerged as a key direction for EVRP. Raeesi and Zografos [79] proposed the adoption of MBSs and presented EVRP with time windows and synchronized MBSs (EVRPTW–SMBS). In this scenario, the BSS exists in the form of an MBS vehicle (battery swapping vehicle, BSV) and only provides battery swapping services at the customer nodes. The battery swapping time needs to be coordinated with the EV customer service time and supports multiple rounds for different EVs. The BSV should arrive at the customer node before the EV; otherwise, the swapping is performed after service. To

address these complexities, the authors developed a methodology for the precise evaluation of solutions to the EVRPTW–SMBS. This method was built on a two-stage integration of DP and IP algorithms. The resulting procedure was then positioned as the core component of an intensified LNS algorithm, which was designed to efficiently solve EVRPTW–SMBS instances. The experiments showed that the MBS mode can reduce costs by up to 3.9 times relative to the FCS mode.

By allowing intra-route recharging through FCSs, Raeesi and Zografos [80] extended the EVRPTW–SMBS, presenting EVRP with time windows, recharging stations, and synchronized MBSs (EVRPTW–RS–SMBS). The authors constructed an MILP model to clarify the spatiotemporal synchronization constraints of EVs and BSVs, as well as the charging logic of CSs. A strengthened path planning algorithm based on non-dominated path recognition (NDPI) and a multi-graph DP heuristic algorithm were designed. The authors conducted experiments on the London urban scenario and the regional scenario in southeastern England. Results showed a 33% reduction in fleet size and a 25% reduction in operating cost versus single charging/swapping. However, they assumed that a BSV only serves a single depot and did not consider the collaborative scheduling of multiple depots sharing the BSV. Zhang et al. [83] added multiple prioritized time windows and two modes of charging in FCSs. They proposed collaborative EVRP with multiple prioritized time windows and time-dependent hybrid recharging (CEVRP–PTW–TR). The BSV can provide battery swapping services from any depot and return to different depots. An extended ALNS algorithm with two-dimensional encoding scheme was developed to solve the complex synchronous constraints efficiently. The experiments based on 24 instances showed that the model achieved a cost reduction of 18% on average compared to the EVRPTW model.

Delivery operations utilizing unmanned aerial vehicles (UAVs), commonly referred to as drones, have demonstrated significant potential to meet future customer demands regarding the quality of delivery services. This is attributed to their characteristics as efficient, eco-friendly, and low-maintenance delivery modalities. The adoption of drones as a delivery approach has been used in last-mile delivery. Zhu et al. [78] focused on the distribution scenarios of emergency supplies in rural areas. The authors presented the battery EV traveling salesman problem with drone (BEVTSPD). In this problem, EVs and drones carry out assignment tasks in a collaborative manner, and the EV can serve as a hub for drones. An exact B&P algorithm and a VNS heuristic were developed. Ren et al. [82] considered the MBS and time-dependent speed of EVs and MCSs, presenting the time-dependent EVRP with drones and SMBS (TD–EVRP–DR–SMBS). A mixed-integer programming (MIP) model was constructed to minimize the total operational cost. Additionally, an LNS algorithm based on Q-learning (LNS-QL) was developed. In this algorithm, Q-learning is employed to select combinations of customized destroy and repair operators. Through the verification of real-time traffic data in Xi'an and actual cases of JD logistics, the correctness of LNS-QL's solution in small-scale instances is consistent with Gurobi.

In response to the problems of the insufficient range of EVs, existing research has optimized the system by introducing backup batteries and designing multi-specification BSSs. Cai et al. [81] made use of backup batteries, presenting the EVRP with time windows, backup batteries, and BSSs (EVRPTW–BB–BSS). Backup batteries are limited by load and capacity and cannot support long-distance distribution. The authors proposed an innovative double-assistant evolutionary multitasking algorithm (DAEMTA). This algorithm cleverly combined internal and external knowledge exchange mechanisms to facilitate knowledge transfer between different and similar types of optimization tasks. A population-augmentation strategy deepens the exploration of elite regions while reducing premature convergence. In Xu et al. [104], the BSS was equipped with two specifications

of fully charged batteries: standard and extended-range batteries. A biased randomized-greedy randomized adaptive search procedure (BR-GRASP) algorithm that incorporates geometric distribution was designed. To enhance this algorithm, they integrated local search operators and energy management strategies. For the purpose of achieving efficient iterative optimization, a variable neighborhood descent (VND) mechanism was adopted in this study.

BSSs can be characterized along key operational dimensions: swap time, per-swap cost, inventory of charged batteries, standard compatibility, and recharging turnaround at the station. MBS extends these dimensions with vehicle mobility constraints: onboard battery inventory, service radius, dispatch cost, and synchronization lead time. Table 9 summarizes the main operational and modeling implications that distinguish fixed BSS and mobile MBS solutions.

In summary, fixed BSSs offer higher per-site throughput. They also feature simpler on-site operational processes. Despite higher upfront infrastructure costs and potential queuing risks, fixed BSSs are more preferred in dense urban network scenarios. In contrast, mobile BSSs provide flexible coverage capabilities. They also require lower initial capital expenditure. These attributes make mobile BSSs suitable for sparse traffic areas or emergency situations. However, they demand complex spatio-temporal synchronization. Additionally, mobile BSSs face limitations in onboard battery inventory per dispatch. This characteristic further increases the complexity of both modeling and operational management.

Table 9. Fixed BSS vs. mobile BSS: operational and modeling comparison.

Feature	Fixed BSS	Mobile BSS
Service time	Short, repeatable swap time	Short swap time but includes MBS travel and positioning overhead
Capacity	Stationary inventory	Limited onboard inventory
Spatial coverage	Fixed locations	Flexible coverage
Modeling focus	Facility location, capacity, queuing	Synchronized routing, resource scheduling, SoC of MBS
Typical algorithms	B&P, VNS, ALNS, location-routing heuristics	Heuristics, MILP, synchronized ALNS/DP
Advantages	High throughput per site, simpler operations	Greater flexibility, lower infrastructure CAPEX in sparse areas
Disadvantages	High CAPEX for broad coverage; queuing and peak congestion	Complex spatio-temporal synchronization; limited service episodes

4.2. Battery Swapping Station Location-Routing Problem with Electric Vehicles

The well-planned layout of BSSs is the key to solving the short driving range of EVs and promoting the development of green logistics. The BSS–EV location-routing problem (BSS–EV–LRP) is a composite optimization problem that integrates station siting with vehicle routing. Studies in this area have explored the expansion of decision-making dimensions, algorithm optimization, and scenario adaptation. These contributions provide crucial support for the efficient operation of EV distribution networks.

4.2.1. BSS–EV–LRP

There are four decisions that arise: (i) the location of the BSSs; (ii) the assignment of customers; (iii) the assignment of EVs to BSSs; and (iv) the routes of EVs. Yang and Sun [96] first formulated the BSS–EV–LRP. The authors developed a four-phase heuristic called SIGALNS and a two-phase tabu search-modified Clarke and Wright Savings heuristic (TS-MCWS) to solve the problem. Through instance verification, it has been shown

that BSSs can mitigate the range limitations of EVs, reduce operating costs, and assist green logistics by quickly replenishing energy. Hof et al. [98] proposed an adaptive VNS (AVNS) algorithm for the VRP with intermediate stops (VRPIS). They added neighborhood structures of facility removal, facility replacement, and a dynamic penalty mechanism to synchronously determine the location of BSSs and vehicle routing. They improved the best solutions from Yang and Sun [96] for the large majority of instances.

Zhang et al. [95] considered stochastic demands in the BSS–EV–LRP. The author extended the preventive replenishment policy and classic recourse policy by simultaneously considering the impact of battery and EV capacity. They applied the concept of Pareto optimality to accelerate the selection of BSS sequences. A hybrid VNS (HVNS) algorithm was proposed. This algorithm incorporates binary PSO and VNS, enabling the interactive solution of the location and routing problems. Souza et al. [100] presented a flexible VNS-based (Flexi-VNS) algorithm to tackle both the EVRP and the BSS–EV–LRP. Multiple benchmark instance validations have shown that the algorithm can optimize 90.38% of EVRP instances and 75% of BSS–EV–LRP instances. Li et al. [97] introduced a cooperative business model into BSS–LRP. Firms may co-invest or outsource BSS construction to minimize facility capital and EV travel costs. A hybrid heuristic incorporating SA, K-Means, and ACO was derived. The BSS–LRP under joint distribution and cost allocation was studied by Zhang et al. [99]. They designed a bi-level programming model to solve it, and employed Shapley value to allocate the cost among enterprises. However, most of these studies omitted customer time windows.

4.2.2. BSS–EV–LRP with Time Window

Customer service time windows are a common requirement in logistics distribution. Portela et al. [101] took multi-depot and time windows into account, presenting the multi-depot EV location-routing problem with time windows and battery swapping (MDEVLRPTW-BS). They proposed two constructive methods to be used with GRASP and random variable neighborhood descent (RVND), which show high efficiency in solving the problem.

Taking mixed fleet into account in BSS–EV–LRP, Chen et al. [102] introduced BSS location and routing problem with time windows and a mixed fleet of electric and conventional vehicles (BSS–MF–LRPTW). The author proposed a heuristic B&P algorithm with adaptive selection mechanism (HBP-ASS). This algorithm incorporated the heuristic policy and exact algorithm. They designed seven heuristic operators, combined with efficient screening operators using adaptive selection mechanism to optimize the label extension and dominance rules of DP. The experiments showed that the time for HBP-ASS to solve small- and medium-sized instances is only 1.02% of CPLEX. Chen et al. [103] developed an improved B&P algorithm enhanced with adaptive heuristic–exact labeling (IBP-HL) and a robust arc-based branching scheme. The proposed algorithm reduces the average computation time by 80% compared to Gurobi on small-scale instances. The efficiency improved by 35% compared to the benchmark B&P algorithm on instances with 30 customers.

Table 10 compares the key characteristics of EVRP–BSS and BSS–EV–LRP scenarios. It reports decision dimensions, objectives, algorithmic challenges, and planning phases for both scenarios. AVNS is currently among the more efficient BSS–EV–LRP algorithms. Relative to SIGALNS [96], AVNS [98] improved large-scale solutions in up to 85% of instances.

Notably, a battery swapping strategy is not competitive with a charging strategy in reality. The main reason is that the battery standardization level is low, which makes the battery swapping operation difficult to carry out on a large scale [105]. However, with the advancement of battery technology and the promotion of industry standards, battery swapping is expected to become an important solution to the EV range anxiety problem.

For example, NIO, a Chinese EV manufacturer, has built over 1000 BSSs in China by 2025. At the same time, the CATL in China and Ample in America are promoting BSSs.

Table 10. Key characteristics of EVRP–BSS and BSS–EV–LRP scenarios.

Scenario	Decision Dimensions	Objectives	Challenges	Applicable Phase
EVRP–BSS	Visit timing, swaps counts	Minimize travel cost, battery swapping cost	Coordination between swapping time and customer time windows	Operational
BSS–EV–LRP	BSS location selection, customer assignment, EV routing	Minimize facility construction cost, operational cost	Coupled optimization of location and routing	Strategic

5. Discussion and Future Research Directions

5.1. Algorithmic Comparisons

Table 11 presents a comprehensive comparison of major algorithms applied to EVRP variants. Exact methods, such as MILP (implemented via CPLEX/Gurobi), offer provably optimal or near-optimal solutions. However, their scalability is limited. Consequently, applicability is restricted to small–moderate instance sizes. The BP&C algorithm is effective for path-based formulations. It provides strong dual bounds and tight integrality gaps. Implementation is comparatively complex due to specialized pricing and branching design. DP enables exact multi-resource state management. Nevertheless, label explosion arises under multiple simultaneous resource dimensions. LNS and ALNS offer high flexibility and scalability. They consistently yield high-quality solutions in large-scale instances. Solution quality is maintained within practical runtimes. GAs are proficient in addressing multi-objective optimization problems. However, convergence is typically slower than ALNS owing to weaker intensification. The hybrid method (heuristic + exact) balances solution quality and computational effort. It leverages the advantages of both heuristic and exact paradigms. This balance comes at the cost of higher implementation complexity and tuning overhead. Finally, combining simulation with optimization can effectively capture stochastic dynamics and operational realism. They are suitable for modeling queuing, stochastic demand, and failure-risk scenarios. However, computational cost is high due to repeated scenario sampling. In summary, algorithm selection is contingent on interacting problem features. Key determinants include instance scale, structural complexity, the requirement for solution precision, and the trade-off between solution quality and computational efficiency.

Table 11. Algorithmic comparison for EVRP variants (charging/swapping aware).

Algorithm	Typical Application	Complexity	Efficiency	Strengths/Limitations
Exact MILP (CPLEX/Gurobi)	Small–moderate instances	Worst-case exponential	Time consuming	Precise; poor scalability with nonlinear or synchronized formulations
BP&C	Path-based formulations, high-quality benchmarks	Exponential in pricing and branching	Better than monolithic MILP	Strong bounds; complex implementation

Table 11. *Cont.*

Algorithm	Typical Application	Complexity	Efficiency	Strengths/Limitations
DP	Column generation	Label explosion with many resources	Sensitive to pruning quality	Exact resource handling; needs aggressive dominance/pruning
LNS/ALNS	Large instances	Runtime scales with neighborhoods and iterations	High-quality solutions within practical time limits	Flexible and scalable; requires careful operator design and multi-run statistics
GAs	Multi-objective	Moderate to high	Slower convergence than ALNS	Flexible objective handling; needs designed encoding for EV constraints
Heuristic + exact	Medium instances	Moderate	Competitive quality/time trade-off	Leverages strengths of exact and heuristic methods; higher implementation complexity
Simulation + optimization	Stochastic demand; queuing	Computationally expensive	Expensive for wide scenario sweeps	Captures stochastic/operational realism; high computational cost

5.2. Challenges

Although existing EVRP research has advanced along multiple dimensions, persistent gaps remain in practical applicability and theoretical rigor.

First, balancing modeling fidelity and efficiency remains difficult. Nonlinear charging functions more accurately represent the charging dynamic. However, the computational complexity increases sharply due to segmented approximation or exponential relationships, which limits scalability on large fleets and complex networks [8]. Moreover, most models decouple battery degradation effects from dynamic energy consumption factors, resulting in deviations between optimization results and actual operations [106,107].

Secondly, scenario coverage is limited. Existing research mainly focuses on ordinary urban distribution, and there is insufficient exploration of special scenarios such as cold chain logistics and cross-border distribution [4]. At the same time, the collaborative model between mobile charging/swapping and emerging vehicles such as drones and autonomous driving is still in its preliminary stage [108].

Thirdly, technological integration is shallow; real-time V2X data and AI predictive models are weakly embedded in EVRP formulations [109]. Dynamic path adjustment still relies predominantly on static historical data. Consequently, models struggle with order surges and sudden CS failures, lacking real-time adaptive capability.

Fourthly, multi-party collaborative perspectives are underdeveloped [110]. BSS siting and charging resource allocation are typically optimized from a single-enterprise cost viewpoint. Incorporating cross-enterprise resource sharing and policy constraints enables network-level (global) optimization [9,111].

5.3. Future Research Directions

The core challenge of EVRP stems from its limited driving range and time-consuming energy replenishment. As pointed out in the relevant academic literature, this has shifted the research focus from simple path optimization to the integrated optimization of routing and energy replenishment. Future research will no longer be limited to single-cost minimization, but will systematically construct a more intelligent, resilient, and collaborative

logistics energy decision-making system from the three levels of technology advancement, operational optimization, and policy and economic considerations.

5.3.1. Technological Advancement

Technological advancement is a key driver of future EVRP research. It reshapes the problem along two axes. First, hardware and infrastructure innovations reduce physical constraints (e.g., batteries, power electronics). Second, software and algorithmic advances improve decision making (e.g., predictive models, AI).

There is an urgent need to refine energy replenishment models. A significant challenge in the current literature is the trade-off between model fidelity and computational tractability. Many models rely on oversimplified linear charging functions, which fail to capture the physical, nonlinear dynamics of the constant current–constant voltage (CC–CV) charging process. Consequently, we recommend two priorities: (i) tractable methods for nonlinear charging models; (ii) integration of battery-health (SoH) costs. This will enable the joint optimization of routing, charging, and battery longevity Martin et al. [6].

The energy-consumption framework in Xiao et al. [8] can be extended. Useful augmentations include turn-induced kinetic losses, congestion-driven speed variability (and its effect on recuperation), and thermal-management power draw at low ambient temperatures. We note that Section 2.2 does not explicitly model regenerative braking (recuperation). A focused literature search found few routing studies that endogenize recuperation at the arc level. Two practical reasons explain this gap. First, recuperation can produce negative net arc energy on downhill or heavy-braking segments, which complicates SoC accounting and standard MILP constraints [112]. Second, high-fidelity recuperation models require speed and elevation profiles or rich telemetry data, which are often unavailable in public instances [113]. Accordingly, we recommend the following pragmatic research paths: (i) Precompute arc energies from elevation and representative speed profiles and use these values as exogenous inputs [114]; (ii) Train calibrated surrogate models (e.g., GBRT or small neural nets) to predict recoverable energy from sparse features such as grade statistics and stop-frequency [115]; (iii) Adopt MILP-compatible treatments for negative arc energy, for example, by allowing bounded negative credits, applying conservative clipping, or aggregating arcs into speed/grade classes with class-specific w_{ij}; (iv) When endogenous modeling is required, explore bilevel or scenario-based formulations that couple physics simulation with optimization. Empirical validation with vehicle telemetry is essential to assess the impact on SoC margins and routing decisions.

The convergence of autonomous driving and EVRP is unlocking new paradigms in collaborative delivery [4]. Examples include EVs serving as mobile UAV hubs. Another example is autonomous mobile charging platforms. In such models, EVs serve as launch, landing, and recharging platforms for drones, facilitating last-mile logistics. Simultaneously, robotic charging systems can offer on-demand energy services, mitigating range anxiety. Future research directions in this field will include developing collaborative EV-drone delivery models and analyzing the autonomous decision-making of SAEVs. The latter focuses on how these vehicles, under full autonomy, can optimally balance the competing needs of energy replenishment and new order fulfillment.

The V2G model transforms EVs into active grid participants by enabling bi-directional energy flow. Under TOU tariffs, fleets can arbitrage price differences. They charge off-peak and discharge during peaks. Benefits include lower operational costs and the provision of ancillary services (e.g., peak shaving, frequency support). Consequently, integrating V2G charging and discharging decisions into EVRP models is a promising research direction [9]. Such formulations co-optimize logistics and grid participation, subject to battery-wear constraints.

Solid-state batteries (SSBs), as a disruptive technology, will profoundly impact the EVRP due to their extended range and rapid charging characteristics. In last-mile settings, SSBs can reduce recharging frequency. EVRP may then approach classical VRP regimes. For long-haul use, high asset cost remains a barrier. Research must then address battery longevity and the planning of high-power corridors. This promotes the logistics industry's development in a more efficient and sustainable direction.

Large language models (LLMs) and machine learning (ML) modules can support EVRP workflows. They can parse unstructured inputs (reports, advisories) into structured parameters. They can also provide natural-language explanations of plans. Interactive interfaces enable rapid scenario edits. Any ML or LLM component must include validation layers. These layers should enforce feasibility, check constraints, and trigger retraining when data drift occurs.

5.3.2. Operational Optimization

In real-world EVRP implementations, operational-level optimization is vital for addressing highly dynamic and complex scenarios. It directly determines logistical efficiency, cost-effectiveness, and service quality, making it a critical component for achieving sustainable EVRP operations.

EVRP is inherently complex due to intertwined uncertainties in factors like demand, transportation, and charging, which significantly challenges distribution planning. The stochastic nature of charging station operations is a prime example: variable arrival times and service durations often lead to vehicular queuing. This congestion not only increases vehicle waiting times but also jeopardizes the timeliness of the entire delivery schedule. To quantify and mitigate this specific uncertainty, the M/M/1 queuing model provides an effective analytical framework. Assuming exponential distributions for both customer arrival and service times, this model analyzes arrival and service rates to calculate key metrics, such as average waiting time and queue length. These indicators enable the system to proactively schedule charging, thereby minimizing congestion and enhancing delivery efficiency. Furthermore, this model can be integrated with other stochastic variables (e.g., demand fluctuations, traffic congestion) to develop more comprehensive and robust delivery plans [106].

Resource sharing models are increasingly prevalent in logistics. The gig economy, for instance, enhances resource utilization by integrating idle social transportation capacity. Platforms often leverage part-time delivery personnel to augment capacity and meet demand surges during peak periods. Concurrently, B2B collaboration, particularly cross-enterprise resource sharing, is another vital model [9]. This approach allows different logistics firms to share assets—such as vehicles, warehouses, and personnel—to achieve operational synergies and complementary advantages. Building on this collaborative concept, the development of a shared BSS model for multiple logistics companies represents a significant future direction. This model entails the joint use of BSS infrastructure, including batteries and facilities. However, its viability hinges on resolving complex challenges related to collaborative algorithms and cost allocation. Effective algorithms are essential to orchestrate orderly battery swapping and prevent congestion. Simultaneously, a fair and equitable cost-sharing mechanism, likely based on usage and revenue, is crucial to ensure that participants bear appropriate costs and to promote the long-term sustainability of the shared model.

The static assumptions limit the practical applicability of EVRP solutions [107]. A real-time response layer is needed to fuse short-term prediction with adaptive routing. For instance, LSTM models can forecast traffic density and the probability of emergency orders over a 1–2 h horizon. These forecasts feed a dynamic shortest-path routine to update routes and avoid stale plans. A complementary module is required to manage charging-

facility uncertainty. For example, M/M/1 queuing models can estimate real-time charger availability and maintain an alternative charging station set. If a primary charger fails or the predicted queue time exceeds a threshold, EVs are redirected to alternatives to mitigate interruption risk. Robustness to joint uncertainty in demand, traffic, and charging should be addressed via scenario trees and robust optimization. This ensures route plans satisfy constraints under adverse scenarios, improving operational resilience.

5.3.3. Policy and Economic Implications

Policy and economic factors are central to EVRP development. They affect firm costs, economic viability, societal sustainability, and resource allocation. Integrating these external factors into EVRP models is essential for grounding the research in reality. This yields targeted, actionable recommendations for policymakers and managers. Such recommendations support wider adoption and sustainable deployment.

From a policy perspective, government agendas should prioritize three areas: (i) quantitative policy design; (ii) full life-cycle cost accounting; (iii) post-subsidy market mechanisms. We further recommend focusing research on two linked themes: refinement of policy tools and comprehensive life-cycle economic accounting.

Regarding policy tool design, existing instruments such as carbon taxes and subsidies are often one-size-fits-all and fail to reflect differences between urban last-mile delivery and long-haul logistics [111]. Current instruments (such as carbon taxes, subsidies) are often uniform and do not distinguish last-mile from long-haul logistics. Future research should build dynamic models that link carbon prices to routing and fleet investment decisions. Such models can identify EV replacement thresholds and quantify the sensitivity of routing costs to carbon prices. The resulting outputs can inform graduated carbon tax schemes and guide targeted allowance or credit allocation policies. Likewise, EVRP models can test linkage schemes between allowances and operational benchmarks to align incentives with real deployment conditions.

For full-life-cycle accounting and post-subsidy incentives, research should develop a unified life-cycle cost framework. The framework should integrate purchase cost, operating cost, battery replacement, charger depreciation, and renewable investments. It enables scenario comparisons between EV and ICE fleets and quantifies threshold conditions for EV cost advantage [116]. For example, it can evaluate the trade-offs between BSS capital expenditure and time saving from accelerated swap operations. Dynamic pricing for charging and swapping should be co-simulated with routing. This allows assessment of temporal arbitrage and peak-load mitigation.

6. Conclusions

This conclusion summarizes key insights, practical implications, and recommendations, emphasizing modeling choices and solution approaches. The literature centers on two dominant replenishment approaches—charging and battery swapping—each requiring distinct modeling decisions: (i) battery charging formulations must explicitly account for SoC-dependent charging time and per-arc energy consumption, and (ii) battery swapping formulations trade capital and infrastructure design for rapid service and simpler temporal dynamics. Model fidelity, such as nonlinear charging, queuing, and battery degradation, enhances realism but increases computational burden. Method selection must therefore balance accuracy and tractability. For small-to-moderate instances or benchmarking, exact MILP and B&P methods remain practical for obtaining optimality certificates. For large-scale instances, tailored heuristics/metaheuristics, such as ALNS or VNS, with problem-specific neighborhoods and preprocessing (precomputed w_{ij}) are preferable. Time-expanded occupancy formulations and integrated MCS/MBS scheduling should be reserved for capacity stress or peak-period studies due to model size growth.

Overall, the energy replenishment strategy driven classification framework established in this review provides an intuitive reference dimension for scenario adaptation and modeling in EVRP research. By systematically analyzing the modeling logic and progress of charging and swapping strategies, the review offers actionable guidance for future EVRP modeling and solution design.

Author Contributions: Conceptualization, Y.Z. and Q.L.; methodology, Q.L. and L.L.; software, Y.Z., Q.L. and L.L.; validation, Y.Z.; formal analysis, Y.Z. and L.L.; investigation, Y.Z.; data curation, Q.L.; writing—original draft preparation, Q.L. and L.L.; writing—review and editing, Y.Z. and Z.W.; visualization, Y.Z., Q.L. and L.L.; supervision, Z.W.; project administration, Z.W.; funding acquisition, Z.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number 72371175 and 71971148.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors wish to thank two anonymous reviewers and the area editor, whose insightful comments helped to improve the paper.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
VRP	Vehicle Routing Problem
EVRP	Electric Vehicle Routing Problem
SoC	State of Charge
CS	Charging Station
FCS	Fixed Charging Station
MCS	Mobile Charging Station
BSS	Battery Swapping Station
MBS	Mobile Battery Swapping
DCFC	DC Fast Charging
CC	Constant Current (charging stage)
CV	Constant Voltage (charging stage)
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
LNS	Large Neighborhood Search
ALNS	Adaptive LNS
B&P	Branch-and-Price
BP&C	Branch-Price-and-Cut
VNS	Variable Neighborhood Search
DP	Dynamic Programming
OBD	On-Board Diagnostics
GIS	Geographic Information System
V2X	Vehicle-to-Everything
V2G	Vehicle-to-Grid
TOU	Time-of-Use
SAEV	Shared Autonomous Electric Vehicle
UAV	Unmanned Aerial Vehicle
DWC	Dynamic Wireless Charging
CAPEX	Capital Expenditure

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