The electric vehicle routing problem and its variations: A literature review

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Abstract

Electric vehicle technology is promising to reduce both the costs and environmental impact of logistics operations. Consequently, much research is being carried out in this field. On the operational level, the electric vehicle routing problem (EVRP) has recently been introduced and deals with forming effective route plans for vehicles while satisfying a set of battery-related restrictions. This paper presents a comprehensive literature review on the EVRP and its extensions. In this context, 136 published papers that consider the routing of battery electric vehicles are reviewed. The EVRP is clearly defined, variations on the basic EVRP are discussed, a mathematical formulation, which also models several simple variations of the problem, is given, and developed solution approaches are discussed in detail. In addition, EVRP benchmark sets are presented, and, lastly, interesting future research directions are discussed.

Keywords: Electric vehicles, vehicle routing, research directions, survey, classification

1. Introduction

Electric vehicles are promising to reduce both transportation costs and pollution effects in comparison to fossil-fuel-based engines. However, the limited cruising range, long charging times, and limited availability of charging facilities make the charging operations a more critical issue compared to the refueling operations for fossil-fuel-based vehicles (Jing et al., 2016; Juan et al., 2016; Margaritis et al., 2016; Pelletier et al., 2016). The electric vehicle routing problem (EVRP) is an extension of the traditional vehicle routing problem (VRP) that specifically deals with finding optimized routes for electric vehicles, taking battery constraints and charging operations into account (Keskin & Çatay, 2016; Schiffer & Walther, 2017; Schneider et al., 2014).

Following the increasing interest of the logistics community in incorporating electric vehicles in their fleets, academic studies on the EVRP have been increasing in tandem, as can be seen in Figure 1. This paper presents a comprehensive survey on the EVRP by taking into account 136 journal papers (JP), conference proceedings (CP), theses (TH), and technical reports (TR). Table 1 gives an overview of the journals in which 84 academic papers have been published.

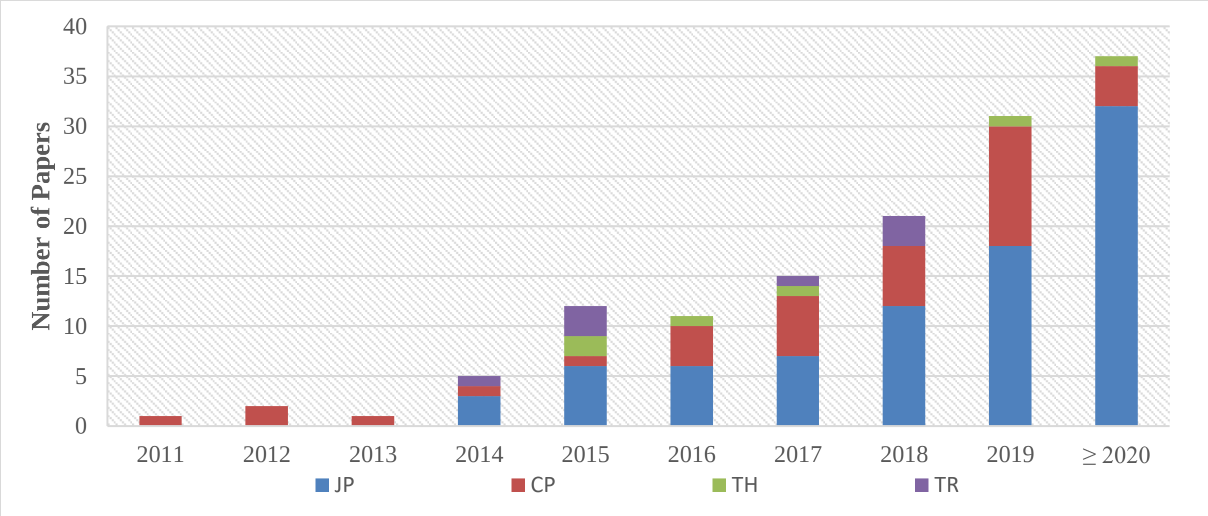

Figure 1. Number of papers published by year

Table 1. Number of papers published in academic journals

Journal	#Papers Published
Advances in Operations Research	1
Algorithms	1
CBU Journal of Science	1
Complex and Intelligent Systems	2
Computers and Industrial Engineering	1
Computers and Operations Research	7
Electronic Notes in Discrete Mathematics	2
EURO Journal on Transportation and Logistics	1
European Journal of Operational Research	6
Expert Systems With Applications	6
IEEE Access	3
IEEE Transactıons on Engıneerıng Management	1
IEEE Transactıons on Smart Grıd	1
IEEE Transactions on Cybernetics	1
IEEE Transactions on Intelligent Transportation Systems	1
IEEE Transactions on Transportation Electrification	1
IET Intelligent Transport Systems	2
International Journal of Advances in Agricultural & Environmental Engg.	1
International Journal of Computer Integrated Manufacturing	1
International Journal of Industrial Engineering Computations	3
International Journal of Production Economics	1
International Transactions in Operational Research	1
Journal of Advanced Transportation	1
Journal of Applied Research on Industrial Engineering	1
Journal of Business Economics	1
Journal of Cleaner Production	3
Journal of Engineering Science and Technology Review	1
Journal of Industrial and Systems Engineering	1
Journal of the Operational Research Society	1
Mathematical Problems in Engineering	4
Networks	1
Omega: The International Journal of Management Science	1
Operations Research	1
Operations Research Forum	1
Statistics and Operations Research Transactions	1
Sustainability	1
Sustainable Cities and Society	1

TecnoLógicas	1
Transport Research Arena	1
Transportation in Developing Economies	1
Transportation Letters	1
Transportation Research Part B: Methodological	5
Transportation Research Part C: Emerging Technologies	2
Transportation Research Part D: Transport and Environment	1
Transportation Research Part E: Logistics and Transportation Review	4
Transportation Science	2
Uludağ University Journal of The Faculty of Engineering	1

The objective of this survey is to provide a comprehensive literature review of the EVRP and its extensions. First, existing studies are classified with respect to four criteria: objective function, energy consumption calculations, additional constraints considered, and fleet type. Following this classification, the mathematical formulations of the EVRP and its basic variations are presented. Finally, the existing solution approaches proposed for the EVRP and useful problem datasets are reviewed and introduced. This paper contributes to the literature as follows:

- A comprehensive and detailed survey is presented by analyzing 136 publications. Until now, a literature review on electric vehicles (in which EVRP is included) or on EVRP was presented by Pelletier et al. (2016), Juan et al. (2016), Dammak and Dhouib (2019), Erdelić and Carić (2019), Ghorbani et al. (2020) and Qin et al. (2021). However, only a few papers on the EVRP were reviewed. Table 2 shows the papers reviewed in this study and points out the overlaps with other review papers. It can be observed from Table 2 that 62 of the analyzed papers are not included in any of the existing literature review studies.
- A systematic classification is introduced.
- Existing solution approaches are summarized, and the performance of seven different solution methodologies is analyzed by comparing the results on a popular dataset.
- Potential research directions are pointed out by discussing the existing research gaps.

Table 2. Papers reviewed in the study

Paper	Type	RP1	RP2	RP3	RP4	RP5	RP6
		Reviewed in					
Abdallah and Adel (2020)	CP						
Abdulaal et al. (2017)	JP						
Afroditi et al. (2014)	CP			✓		✓	✓
Aggoune-Mtalaa et al. (2015)	JP	✓	✓			✓	
Aksoy et al. (2018)	JP						
Almouhanna et al. (2020)	JP						
Arias et al. (2015)	CP						
Arias et al. (2018)	JP						
Barco et al. (2017)	JP	✓			✓	✓	
Basso et al. (2019)	JP				✓	✓	
Basso et al. (2021)	JP						
Basso et al. (2016)	CP						
Booth and Beck (2019)	CP						
Breunig et al. (2018)	TR						
Breunig et al. (2019)	JP				✓	✓	✓
Bruglieri et al. (2017)	JP			✓		✓	
Bruglieri et al. (2015a)	TR			✓	✓		
Bruglieri et al. (2015b)	JP	✓			✓		
Ceselli et al. (2021)	JP						
Chen et al. (2016)	CP					✓	
Conrad and Figliozzi (2011)	CP	✓	✓	✓	✓	✓	
Cortés-Murcia et al. (2018)	CP						
Cortés-Murcia et al. (2019)	JP					✓	✓
Cubides et al. (2019)	JP						
Çatay and Keskin (2017)	CP						
Desaulniers et al. (2016)	JP	✓		✓	✓	✓	✓
Ding et al. (2015)	TR					✓	
Echeverri et al. (2018)	CP						
Erdelić et al. (2019)	CP						✓
Erdem and Koç (2019)	JP					✓	
Erdoğdu and Karabulut (2020)	CP						
Felipe et al. (2014)	JP	✓		✓	✓	✓	✓
Ferro et al. (2018)	CP						
Froger et al. (2018)	CP						
Froger et al. (2019)	JP				✓	✓	✓
Froger et al. (2017)	TR						
Futalef et al. (2020)	CP						
Ge et al. (2020)	JP						
Ghobadi et al. (2021)	JP						
Goeke (2019)	JP					✓	✓
Goeke and Schneider (2015)	JP	✓			✓		✓
Granada-Echeverri et al. (2020)	JP					✓	✓
Hiermann et al. (2014)	TR	✓				✓	
Hiermann et al. (2016)	JP		✓	✓	✓	✓	✓
Hof et al. (2017)	JP				✓	✓	✓
Hulagu and Celikoglu (2020)	JP						

Paper	Type	RP1	RP2	RP3	RP4	RP5	RP6
		Reviewed in					
Hulagu and Çelikoglu (2019)	CP						
Jia et al. (2021)	JP						
Jie et al. (2019)	JP				✓	✓	✓
Kancharla and Ramadurai (2018)	JP					✓	✓
Kancharla and Ramadurai (2020)	JP					✓	
Karakatič (2021)	JP						
Keskin, Akhavan-Tabatabaei, et al. (2019)	CP						
Keskin and Çatay (2016)	JP	✓			✓	✓	✓
Keskin and Çatay (2018)	JP			✓	✓	✓	✓
Keskin et al. (2021)	JP					✓	
Keskin, Laporte, et al. (2019)	JP			✓		✓	
Keskin Özel et al. (2018)	TR				✓		
Koç et al. (2019)	JP					✓	✓
Kopfer and Vornhusen (2019)	JP					✓	
Kouider et al. (2018)	CP			✓		✓	
Kouider et al. (2019a)	CP						
Kouider et al. (2019b)	CP						
Kullman et al. (2017)	CP						
Kullman et al. (2018)	CP				✓	✓	
Küçükoğlu and Cattrysse (2017)	CP						
Küçükoğlu et al. (2019)	JP						✓
Küçükoğlu and Öztürk (2016)	JP						
Lee (2020)	JP					✓	
Li-ying and Yuan-bin (2015)	JP					✓	
B. Li et al. (2019)	CP						
H. Li et al. (2020)	JP						
J. Li et al. (2020)	JP						
L. Li et al. (2019)	CP						
Lin et al. (2021)	JP						
Lin et al. (2016)	CP			✓	✓	✓	✓
Löffler et al. (2020)	JP						
Lu et al. (2020)	JP					✓	
Lu and Wang (2019)	CP						
Mao et al. (2020)	JP					✓	
Mavrovouniotis et al. (2019)	CP						
Mavrovouniotisa et al. (2020)	CP						
Meng and Ma (2020)	JP					✓	
Moghaddam (2015)	TH				✓	✓	
Montoya et al. (2015)	TR					✓	
Montoya et al. (2017)	JP				✓	✓	✓
Montoya (2016)	TH				✓	✓	
Ouahmed et al. (2014)	JP						
Paz et al. (2018)	JP				✓	✓	
Pelletier et al. (2019)	JP					✓	✓
Penna et al. (2016)	CP			✓			
Pierotti (2017)	TH						

Paper	Type	RP1	RP2	RP3	RP4	RP5	RP6
		Reviewed in					
Preis et al. (2012)	CP	✓			✓	✓	
Raeesi and Zografos (2020)	JP					✓	
Rastani (2020)	TH						
Reyes-Rubiano et al. (2019)	JP						
Rezgui et al. (2019)	CP					✓	
Rezgui et al. (2017)	CP						
Roberti and Wen (2016)	JP				✓		✓
Santos (2015)	TH						
Sayarshad et al. (2020)	JP						
Schiffer et al. (2018)	JP					✓	
Schiffer and Walther (2017)	JP				✓	✓	✓
Schiffer and Walther (2018a)	JP				✓	✓	
Schiffer and Walther (2018b)	JP				✓	✓	
Schneider et al. (2014)	JP	✓	✓	✓	✓	✓	✓
Setak and Karimpour (2019)	JP						
Shao et al. (2018)	JP				✓		✓
Shao et al. (2017)	JP			✓	✓	✓	
Soysal et al. (2020)	JP						
Tahami et al. (2020)	JP						
Taş (2021)	JP					✓	
Taweepworadej and Buasri (2016)	JP						
Verma (2018)	JP					✓	✓
Wang et al. (2019)	CP						
Wang and Cheu (2013)	CP						
Wang et al. (2020)	JP						
Worley et al. (2012)	CP					✓	
Wu and Zhang (2021)	JP						
Xiao et al. (2019)	JP					✓	
Yamak (2019)	TH						
Yang et al. (2015)	JP						
Yang and Sun (2015)	JP		✓		✓	✓	✓
Yang et al. (2021)	JP						
R. Zhang et al. (2020)	JP					✓	
S. Zhang et al. (2020)	JP					✓	
S. Zhang et al. (2018)	JP				✓	✓	✓
X. Zhang et al. (2018)	CP					✓	
Zhao and Lu (2019)	JP					✓	✓
Zhao et al. (2020)	JP						
Zhenfeng et al. (2017)	CP						
Zhou and Tan (2018)	JP					✓	
Zhou et al. (2021)	JP						
Zhu et al. (2020)	JP					✓	
Zuo et al. (2019)	JP					✓	✓
Zuo et al. (2017)	CP						

RP1: Review paper of Pelettier et al. (2016)
RP2: Review paper of Juan et al. (2016)
RP3: Review paper of Dammak and Dhouib (2019)
RP4: Review paper of Erdelić and Carić (2019)
RP5: Review paper of Ghorbani et al. (2020)
RP6: Review paper of Qin et al. (2021)

2. Electric Vehicle Routing Problem

The EVRP can be described as finding a set of vehicle routes. Each route services a set of customer nodes and starts and ends at a given depot node. The problem aims to find the best route plan for electric vehicles that minimizes a given cost function while satisfying a number of restrictions and operational procedures for electric vehicles. According to existing studies, the basic assumptions for the EVRP are as follows (Felipe et al., 2014; Lin et al., 2016; Paz et al., 2018):

- Each route starts and ends at the depot node.
- Each customer node is to be serviced by exactly one electric vehicle.
- Electric vehicles can visit a charging station for recharging operations between any two customers.
- Each charging station can be visited by more than one electric vehicle.
- The location of the charging stations and traveling distance from any node to any charging station are known.
- The battery level of an electric vehicle must always be between 0 and its battery capacity.
- A vehicle's battery is always fully charged when visiting a charging station.

Following the assumptions above, Figure 2 presents an illustrative example of a solution to the EVRP involving 15 customer nodes ($C1, \dots, C15$), five charging stations ($S1, \dots, S5$), and the depot node that can also be used as a charging station. Four identical electric vehicles serve customer nodes by starting their tour at the depot node with a full charge. The percentage values on the arcs show the battery level of the electric vehicle when it arrives at a customer location or the depot node. Additionally, since the vehicles are fully charged at stations, battery levels after charging station visits are set to 100%.

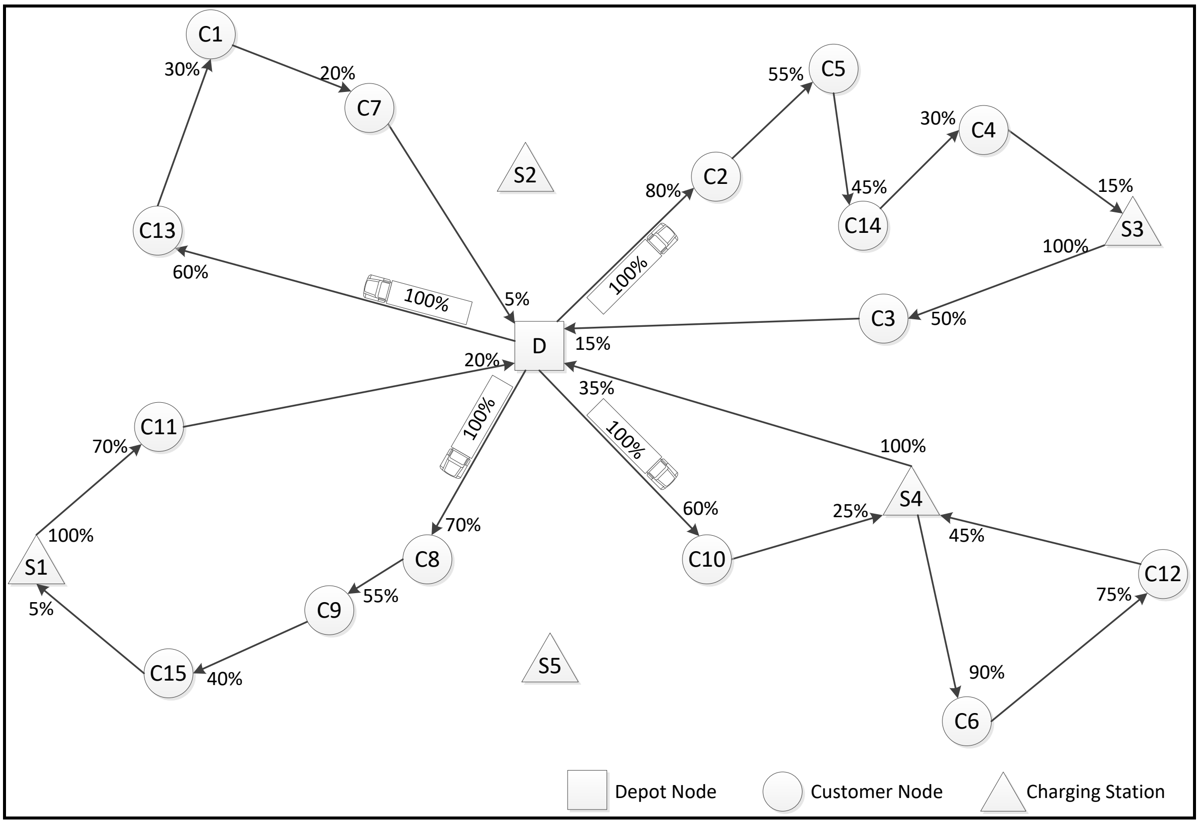

Figure 2. An illustrative example for the EVRP

In addition to the basic EVRP assumptions, other commonly used restrictions come from vehicle capacity constraints and time-related restrictions. Vehicle weight capacity or vehicle volume capacity can be taken into account as a constraint where the total weight or volume of the loads cannot exceed the vehicle's weight or volume capacity, respectively. For the time-related restrictions, there exist several assumptions that can be summarized into two groups: time windows for nodes and duration time limits.

Time window restrictions state that each customer node must be serviced within a given time window, and each route must be completed within a given time window limit of a depot node (Bruglieri et al., 2015a, 2015b; Sassi et al., 2015; Schneider et al., 2014). Time duration constraints state that the total elapsed time for a route cannot exceed the duration time limit (Lin et al., 2016; Montoya et al., 2015). Similar to the vehicle routing problem with time windows (VRPTW), arc travel times, customer service times, and time windows are given beforehand and vehicle travel, waiting, and service times can be determined similarly as in the VRPTW. In addition, the re-charging time at charging stations is computed by using a function or constant value (Goeke & Schneider, 2015; Roberti & Wen, 2016; Schiffer & Walther, 2017). When the time-related constraints are taken into account for the EVRP, the charging operations at stations become more critical. Therefore, partial charging of electric vehicles is also studied in most of the papers.

3. Classifications of the EVRP

This section presents the existing studies on the EVRP and classifies them according to four criteria: objective function types, energy consumption computations, considered constraints in the EVRP, and fleet types.

3.1. Objective Function

Based on the traditional VRP, there exist several objective functions looking at total travel distance, the number of vehicles used for the operations, total travel time, and other operation-dependent objectives (Eksioglu et al., 2009). As in the traditional VRP, some of the existing studies on the EVRP only consider the transportation cost related to the travel time or distance. Others take the cost of recharging and total consumed energy into account. In the EVRP literature, we identified seven different basic objective function components based on:

(1) total number of electric vehicles used
(2) total travel distance
(3) total travel time
(4) total number of used charging stations or station construction cost
(5) total recharging cost or recharging time
(6) total energy consumption
(7) other operational costs

The first three objective function types are typically used in most VRP studies. It follows that these objectives are also considered by most of the researchers of the EVRP. For studies only considering these objectives, the energy consumption and the battery serve as constraints for the route plans. Many papers combine several basic objective function components, both from the original VRP and more energy-related components. An overview is given in Table 3. Additionally, Figure 3 shows the number of times each of the objective function types is used. Similar to most VRP studies, minimization of the total traveled distance is taken into account in most of the papers. It should be noted that most of the studies considered the energy consumption of electric vehicles and their battery capacities. Whether these are taken into account explicitly in the objective function or not, the objective function value is directly impacted whatever the function type is.

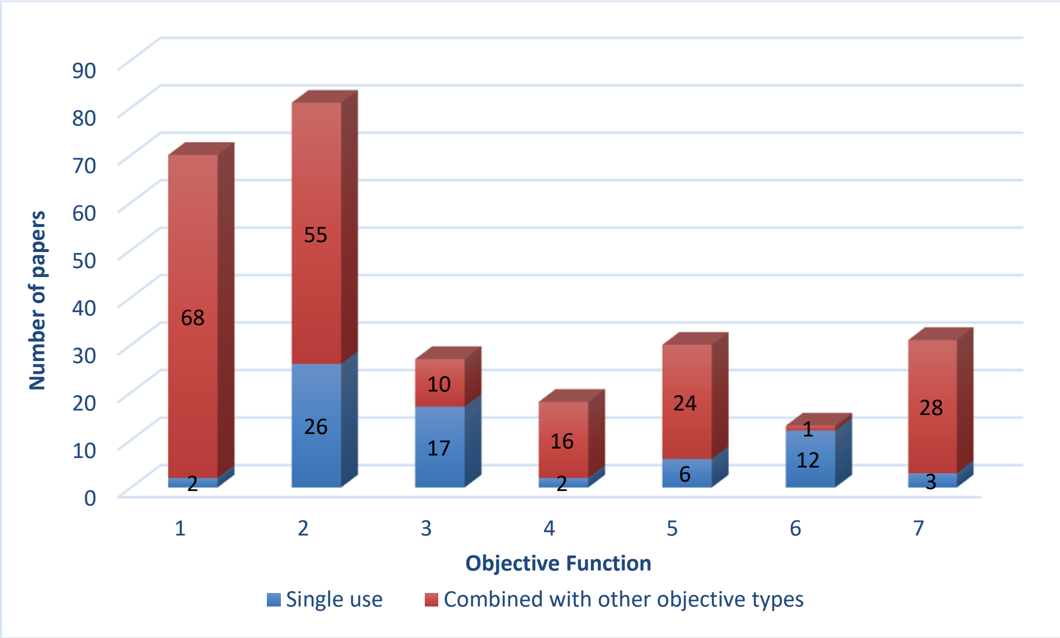

Figure 3. Number of times each of the objective function type is used

Table 3. Classification of the objective functions

	Objective Function							Combination of Objective Functions																											
Paper	1	2	3	4	5	6	7	1-2	1-2-3-6	1-2-4	1-2-4-7	1-2-5	1-2-5-7	1-2-7	1-3	1-3-5-7	1-5	1-5-6-7	1-5-7	1-6	1-6-7	1-7	2-4	2-4-5	2-4-7	2-5	2-5-7	2-6	2-7	3-4	3-5	3-5-7	3-6	4-7	5-7
Abdallah and Adel (2020)						✓																													
Abdulaal et al. (2017)					✓																														
Afroditi et al. (2014)								✓																											
Aggoune-Mtalaa et al. (2015)								✓																											
Aksoy et al. (2018)		✓																																	
Almouhanna et al. (2020)														✓																					
Arias et al. (2015)																							✓												
Arias et al. (2018)																									✓										
Barco et al. (2017)						✓																													
Basso et al. (2019)						✓																													
Basso et al. (2021)						✓																													
Basso et al. (2016)																																	✓		
Booth and Beck (2019)								✓																											
Breunig et al. (2018)								✓																											
Breunig et al. (2019)								✓																											
Bruglieri et al. (2017)																✓																			
Bruglieri et al. (2015a)			✓																																
Bruglieri et al. (2015b)															✓																				
Ceselli et al. (2021)					✓																														
Chen et al. (2016)		✓																																	
Conrad and Figliozzi (2011)	✓																																		
Cortés-Murcia et al. (2018)			✓																																
Cortés-Murcia et al. (2019)						✓																													
Cubides et al. (2019)		✓					✓																												
Çatay and Keskin (2017)		✓																																	
Desaulniers et al. (2016)								✓																											
Ding et al. (2015)		✓																																	
Echeverri et al. (2018)																															✓				
Erdelić et al. (2019)								✓																											
Erdem and Koç (2019)			✓																																
Erdoğdu and Karabulut (2020)																												✓							
Felipe et al. (2014)					✓																														
Ferro et al. (2018)																										✓									
Froger et al. (2018)			✓																																
Froger et al. (2019)			✓																																
Froger et al. (2017)			✓																																
Futalef et al. (2020)																																	✓		
Ge et al. (2020)								✓																											
Ghobadi et al. (2021)																													✓						
Goeke (2019)								✓																											
Goeke and Schneider (2015)		✓			✓		✓																												
Granada-Echeverri et al. (2020)		✓																																	
Hiermann et al. (2014)								✓																											
Hiermann et al. (2016)								✓																											
Hof et al. (2017)																							✓												
Hulagu and Celikoglu (2020)										✓																									
Hulagu and Çelikoglu (2019)											✓																								
Jia et al. (2021)		✓																																	
Jie et al. (2019)																											✓								
Kancharla and Ramadurai (2018)						✓																													

Kancharla and Ramadurai (2020)			✓																				
Karakatič (2021)			✓																				
Keskin, Akhavan-Tabatabaei, et al. (2019)																✓							
Keskin and Çatay (2016)		✓																					
Keskin and Çatay (2018)													✓										
Keskin et al. (2021)																✓							
Keskin, Laporte, et al. (2019)																✓							
Keskin Özel et al. (2018)																✓							
Koç et al. (2019)																					✓		
Kopfer and Vornhusen (2019)						✓																	
Kouider et al. (2018)																		✓					
Kouider et al. (2019a)																		✓					
Kouider et al. (2019b)																		✓					
Kullman et al. (2017)			✓																				
Kullman et al. (2018)			✓																				
Küçükoğlu and Cattrysse (2017)		✓																					
Küçükoğlu et al. (2019)		✓																					
Küçükoğlu and Öztürk (2016)		✓																					
Lee (2020)			✓																				
Li-ying and Yuan-bin (2015)																							✓
B. Li et al. (2019)			✓																				
H. Li et al. (2020)														✓									
J. Li et al. (2020)															✓								
L. Li et al. (2019)		✓																					
Lin et al. (2021)					✓																		
Lin et al. (2016)																						✓	
Löffler et al. (2020)								✓															
Lu et al. (2020)																✓							
Lu and Wang (2019)		✓																					
Mao et al. (2020)											✓												
Mavrovouniotis et al. (2019)			✓																				
Mavrovouniotisa et al. (2020)		✓																					
Meng and Ma (2020)											✓												
Moghaddam (2015)				✓								✓											
Montoya et al. (2015)			✓																				
Montoya et al. (2017)			✓																				
Montoya (2016)			✓																				
Ouahmed et al. (2014)								✓															
Paz et al. (2018)		✓																					
Pelletier et al. (2019)																	✓						
Penna et al. (2016)								✓															
Pierotti (2017)																			✓				
Preis et al. (2012)						✓																	
Raeesi and Zografos (2020)								✓															
Rastani (2020)						✓									✓								
Reyes-Rubiano et al. (2019)			✓																				
Rezgui et al. (2019)										✓													
Rezgui et al. (2017)																				✓			
Roberti and Wen (2016)		✓																					
Santos (2015)							✓																
Sayarshad et al. (2020)		✓																					
Schiffer et al. (2018)	✓	✓		✓					✓*														
Schiffer and Walther (2017)									✓														
Schiffer and Walther (2018a)									✓*														
Schiffer and Walther (2018b)									✓														

Schneider et al. (2014)				✓													
Setak and Karimpour (2019)													✓				
Shao et al. (2018)						✓											
Shao et al. (2017)						✓											
Soysal et al. (2020)			✓														
Tahami et al. (2020)	✓																
Taş (2021)								✓									
Taweepworadej and Buasri (2016)	✓																
Verma (2018)							✓										
Wang et al. (2019)							✓										
Wang and Cheu (2013)	✓																
Wang et al. (2020)														✓			
Worley et al. (2012)												✓					
Wu and Zhang (2021)				✓													
Xiao et al. (2019)										✓							
Yamak (2019)			✓														
Yang et al. (2015)											✓						
Yang and Sun (2015)		✓															
Yang et al. (2021)	✓																
R. Zhang et al. (2020)																✓	
S. Zhang et al. (2020)	✓																
S. Zhang et al. (2018)			✓														
X. Zhang et al. (2018)							✓										
Zhao and Lu (2019)							✓										
Zhao et al. (2020)									✓								
Zhenfeng et al. (2017)															✓		
Zhou and Tan (2018)																	✓
Zhou et al. (2021)							✓										
Zhu et al. (2020)	✓																
Zuo et al. (2019)					✓												
Zuo et al. (2017)	✓																

[*]In addition to the charging station construction cost, investment cost for freight replenishment facilities is taken into account

3.2. Energy Consumption Calculation

The energy consumption calculation of the electric vehicles is one of the essential issues for the EVRP since it directly affects the route plans, computation times, required data, and, most importantly, the capability to execute it in practice. To obtain results that are more realistic for the EVRP, the energy consumption calculation needs to take into account several aspects, such as road conditions, technical features of the vehicle, vehicle load, and environmental conditions. However, each additional aspect makes the computations for energy consumption more complex. Therefore, choosing which aspects to take into account is a critical trade-off between acceptable computation times and the degree to which the solution can be executed in practice. In the existing studies, the energy consumption calculations can be categorized into three groups: linear deterministic functions, non-linear deterministic functions, and stochastic functions. The linear deterministic functions can be categorized into five subgroups based on the used equation parameters. Table 4 groups the existing studies according to the chosen energy consumption functions.

The linear deterministic functions determine the energy consumption of an electric vehicle by using a constant parameter value for a given metric. For example, the distance-based equation determines the energy consumption by scaling an energy consumption rate for a given distance. Similarly, other linear functions use a set of parameters to compute the energy consumption. On the other hand, non-linear deterministic functions are considered to obtain more realistic results for the energy consumption of electric vehicles (Murakami, 2017). Goeke and Schneider (2015) introduced a comprehensive approach to determine the energy consumption in which air resistance force (F_a), rolling resistance force (F_r), and gravitational force (F_g) factors were taken into account and converted to mechanical (P_M) power using the following formulations:

$$P_M = F_a + F_r + F_g$$

$$P_M = \left(m \cdot a + \frac{1}{2} \cdot c_d \cdot \rho \cdot A \cdot v^2 + m \cdot g \cdot sin(\alpha) + c_r \cdot m \cdot g \cdot cos(\alpha) \right) \cdot v$$

where m denotes the total weight (vehicle plus current load), a the acceleration, c_d the aerodynamic drag coefficient, ρ the air density, A the frontal area of the electric vehicle, v the speed, g the gravitational constant, c_r the rolling friction coefficient, and α the gradient angle.

Table 4. Classification of the energy consumption computations

Paper	Linear Deterministic Functions					Non-Linear Deterministic Functions	Stochastic Functions
	Traveled Distance	Vehicle Speed	Vehicle Load	Road Gradient	Time		
Abdallah and Adel (2020)	✓	✓					
Abdulaal et al. (2017)	✓		✓				
Afroditi et al. (2014)						✓	
Aggoune-Mtalaa et al. (2015)	✓						
Aksoy et al. (2018)	✓		✓				
Almouhanna et al. (2020)	✓						
Arias et al. (2015)	✓						
Arias et al. (2018)	✓						
Barco et al. (2017)						✓	
Basso et al. (2019)	✓	✓	✓	✓			
Basso et al. (2021)							✓
Basso et al. (2016)	✓	✓	✓	✓			
Booth and Beck (2019)	✓						
Breunig et al. (2018)	✓						
Breunig et al. (2019)	✓						
Bruglieri et al. (2017)	✓						
Bruglieri et al. (2015a)	✓						
Bruglieri et al. (2015b)	✓						
Ceselli et al. (2021)	✓						
Chen et al. (2016)	✓						
Conrad and Figliozzi (2011)	✓						
Cortés-Murcia et al. (2018)	✓						
Cortés-Murcia et al. (2019)	✓						
Cubides et al. (2019)	✓						
Çatay and Keskin (2017)	✓						
Desaulniers et al. (2016)	✓						
Ding et al. (2015)	✓						
Echeverri et al. (2018)	✓						
Erdelić et al. (2019)	✓						
Erdem and Koç (2019)	✓						
Erdoğdu and Karabulut (2020)	✓						
Felipe et al. (2014)	✓						
Ferro et al. (2018)						✓	
Froger et al. (2018)	✓						
Froger et al. (2019)	✓						
Froger et al. (2017)	✓						
Futalef et al. (2020)	✓		✓				
Ge et al. (2020)	✓						
Ghobadi et al. (2021)	✓						
Goeke (2019)	✓						
Goeke and Schneider (2015)						✓	
Granada-Echeverri et al. (2020)	✓						
Hiermann et al. (2014)	✓						
Hiermann et al. (2016)	✓						
Hof et al. (2017)	✓						
Hulagu and Celikoglu (2020)	✓						
Hulagu and Çelikoglu (2019)	✓						
Jia et al. (2021)	✓						
Jie et al. (2019)	✓						
Kancharla and Ramadurai (2018)	✓		✓				
Kancharla and Ramadurai (2020)			✓				
Keskin, Akhavan-Tabatabaei, et al. (2019)	✓						
Keskin and Çatay (2016)	✓						
Keskin and Çatay (2018)	✓						
Keskin et al. (2021)	✓						
Keskin, Laporte, et al. (2019)	✓						
Keskin Özel et al. (2018)	✓						
Koç et al. (2019)	✓						
Kopfer and Vornhusen (2019)	✓		✓				
Kouider et al. (2018)	✓						
Kouider et al. (2019a)	✓						
Kouider et al. (2019b)	✓						
Kullman et al. (2017)	✓						
Kullman et al. (2018)	✓						
Küçükoğlu and Cattrysse (2017)	✓						
Küçükoğlu et al. (2019)	✓						

Küçükoğlu and Öztürk (2016)	✓						
Lee (2020)	✓						
Li-ying and Yuan-bin (2015)	✓						
B. Li et al. (2019)	✓						
J. Li et al. (2020)						✓	
L. Li et al. (2019)						✓	
Lin et al. (2021)	✓						
Lin et al. (2016)						✓	
Löffler et al. (2020)	✓						
Lu et al. (2020)			✓		✓		
Lu and Wang (2019)						✓	
Mao et al. (2020)	✓						
Mavrovouniotis et al. (2019)						✓	
Mavrovouniotisa et al. (2020)						✓	
Meng and Ma (2020)	✓						
Moghaddam (2015)	✓						
Montoya et al. (2015)	✓						
Montoya et al. (2017)	✓						
Montoya (2016)	✓						
Ouahmed et al. (2014)	✓						
Paz et al. (2018)	✓						
Pelletier et al. (2019)							✓
Penna et al. (2016)	✓						
Pierotti (2017)	✓						
Preis et al. (2012)						✓	
Raeesi and Zografos (2020)	✓						
Rastani (2020)	✓		✓	✓			
Reyes-Rubiano et al. (2019)							✓
Rezgui et al. (2019)	✓						
Rezgui et al. (2017)	✓						
Roberti and Wen (2016)	✓						
Santos (2015)	✓		✓				
Sayarshad et al. (2020)	✓						
Schiffer et al. (2018)	✓						
Schiffer and Walther (2017)	✓						
Schiffer and Walther (2018a)	✓						
Schiffer and Walther (2018b)	✓						
Schneider et al. (2014)	✓						
Setak and Karimpour (2019)	✓						
Shao et al. (2018)						✓	
Shao et al. (2017)	✓						
Soysal et al. (2020)							✓
Tahami et al. (2020)	✓						
Taş (2021)	✓						
Taweepworadej and Buasri (2016)						✓	
Verma (2018)	✓						
Wang et al. (2019)					✓		
Wang and Cheu (2013)					✓		
Wang et al. (2020)						✓	
Worley et al. (2012)	✓						
Wu and Zhang (2021)							
Xiao et al. (2019)	✓	✓	✓				
Yamak (2019)						✓	
Yang et al. (2015)	✓						
Yang and Sun (2015)						✓	
Yang et al. (2021)					✓		
R. Zhang et al. (2020)	✓						
S. Zhang et al. (2020)							✓
S. Zhang et al. (2018)						✓	
X. Zhang et al. (2018)	✓						
Zhao and Lu (2019)	✓						
Zhao et al. (2020)	✓	✓	✓				
Zhenfeng et al. (2017)	✓	✓					
Zhou and Tan (2018)	✓						
Zhou et al. (2021)	✓						
Zhu et al. (2020)	✓						
Zuo et al. (2019)	✓						
Zuo et al. (2017)	✓						

Based on the deterministic equations, it should be concluded from Table 4 that the linear equations are mostly preferred by researchers to formulate the EVRP as a Mixed Integer Programming (MIP) model. On the other hand, non-linear deterministic functions can be incorporated within heuristic approaches to simulate energy consumption more realistically. In this context, Goeke and Schneider (2015) introduced an adaptive large neighborhood search algorithm that uses non-linear formulations to determine the energy consumption amounts. The authors tested the performance of the algorithm on a benchmark dataset where the problem sizes vary from 10 to 100 customer nodes. Similarly, Preis et al. (2012) proposed an adaptive tabu search algorithm for the EVRP, which considers non-linear equations. The results of the studies show that the non-linear equations can be applied effectively for real-life EVRP applications using a heuristic approach. S. Zhang et al. (2018) introduced an ant colony optimization approach considering non-linear objective function equations in the algorithm. The authors compared the performance of their algorithm to an adaptive large neighborhood search proposed by Goeke and Schneider (2015). Their results show that the ant colony optimization algorithm is capable of finding better results for the EVRP in shorter computational times. In more recent studies, the non-linear deterministic functions are used in variable neighborhood search algorithm introduced by L. Li et al. (2019) and Wang et al. (2020), adaptive genetic algorithm introduced by J. Li et al. (2020), and bi-strategy based optimization algorithm introduced by Lu and Wang (2019). In addition to the deterministic functions, Pelletier et al. (2019), Reyes-Rubiano et al. (2019), Soysal et al. (2020), S. Zhang et al. (2020), and Basso et al. (2021) used stochastic approaches to estimate energy consumption amounts of the electric vehicles.

3.3. Constraints

In most of the studies related to the EVRP, the battery capacity of the electric vehicles and recharging policies are considered under different assumptions and formulated as such in the mathematical models. Conductive charging is the most common method of recharging electric vehicles. Recharging procedures can be categorized into two major policies: full charging and partial charging. In the full charging policy, a vehicle’s battery is always fully charged when visiting a charging station. In the partial charging policy, an electric vehicle can leave from a charging station at any charge level depending on the time spent charging. In addition to the recharging policy, the studies can be classified based on the charging technology used. In practice, there exist different types of available charging technologies depending on the vehicle type. Each of these has different construction costs, operational costs, charging times, and capacities. Some of the studies considered different charging technologies that allow slow, normal, or fast charging with different operational costs.

An overview of the charging policies used in the reviewed papers is given in Table 5. Here, it should be noted that the column labeled N/A in Table 5 presents the papers in which recharging operations are not considered in the route plans. For these studies, commonly, it is assumed that the electric vehicle leaves the depot with a fully charged battery and completes its tour according to the battery limit restriction. Based on the conductive charging systems, full and partial charging strategies with identical charging technologies were investigated most often. Furthermore, some of the papers considered both strategies and ran computational experiments to compare their performance. In addition to charging stations with identical charging technologies, different types of charging technologies were considered mostly for the partial charging policy, where the full charging policy with different charging technologies is considered in a few studies.

Table 5. Classification of the charging policies

		Full Charging Policy		Partial Charging Policy		
Paper	**N/A**	**Using Identical Technology**	**Using Different Technology**	**Using Identical Technology**	**Using Different Technology**	**Battery Swapping**
Abdallah and Adel (2020)	✓					
Abdulaal et al. (2017)		✓				
Afroditi et al. (2014)		✓				
Aggoune-Mtalaa et al. (2015)		✓				
Aksoy et al. (2018)	✓					
Almouhanna et al. (2020)	✓					
Arias et al. (2015)						✓
Arias et al. (2018)		✓				
Barco et al. (2017)			✓			
Basso et al. (2019)			✓			
Basso et al. (2021)				✓		
Basso et al. (2016)			✓			
Booth and Beck (2019)		✓				
Breunig et al. (2018)		✓				
Breunig et al. (2019)		✓				
Bruglieri et al. (2017)				✓		
Bruglieri et al. (2015a)				✓		
Bruglieri et al. (2015b)				✓		
Ceselli et al. (2021)					✓	
Chen et al. (2016)						✓
Conrad and Figliozzi (2011)			✓			
Cortés-Murcia et al. (2018)		✓				
Cortés-Murcia et al. (2019)				✓		
Cubides et al. (2019)		✓				
Çatay and Keskin (2017)				✓	✓	
Desaulniers et al. (2016)		✓		✓		
Ding et al. (2015)				✓		
Echeverri et al. (2018)					✓	
Erdelić et al. (2019)		✓				
Erdem and Koç (2019)				✓		
Erdoğdu and Karabulut (2020)	✓					
Felipe et al. (2014)					✓	

Ferro et al. (2018)					✓	
Froger et al. (2018)					✓	
Froger et al. (2019)					✓	
Froger et al. (2017)					✓	
Futalef et al. (2020)				✓		
Ge et al. (2020)						✓
Ghobadi et al. (2021)		✓				
Goeke (2019)				✓		
Goeke and Schneider (2015)		✓				
Granada-Echeverri et al. (2020)		✓				
Hiermann et al. (2014)		✓				
Hiermann et al. (2016)		✓				
Hof et al. (2017)						✓
Hulagu and Celikoglu (2020)				✓		
Hulagu and Çelikoglu (2019)					✓	
Jia et al. (2021)		✓				
Jie et al. (2019)						✓
Kancharla and Ramadurai (2018)		✓				
Kancharla and Ramadurai (2020)					✓	
Karakatič (2021)				✓		
Keskin, Akhavan-Tabatabaei, et al. (2019)				✓		
Keskin and Çatay (2016)		✓				
Keskin and Çatay (2018)					✓	
Keskin et al. (2021)				✓		
Keskin, Laporte, et al. (2019)				✓		
Keskin Özel et al. (2018)		✓				
Koç et al. (2019)					✓	
Kopfer and Vornhusen (2019)		✓				
Kouider et al. (2018)				✓		
Kouider et al. (2019a)				✓		
Kouider et al. (2019b)				✓		
Kullman et al. (2017)					✓	
Kullman et al. (2018)					✓	
Küçükoğlu and Cattrysse (2017)		✓				
Küçükoğlu et al. (2019)			✓			
Küçükoğlu and Öztürk (2016)		✓				
Lee (2020)				✓		
Li-ying and Yuan-bin (2015)			✓			
B. Li et al. (2019)		✓				
H. Li et al. (2020)		✓				
J. Li et al. (2020)						✓
L. Li et al. (2019)		✓				
Lin et al. (2021)				✓		
Lin et al. (2016)		✓				
Löffler et al. (2020)		✓		✓		
Lu et al. (2020)		✓				
Lu and Wang (2019)	✓					
Mao et al. (2020)				✓		✓
Mavrovouniotis et al. (2019)		✓				
Mavrovouniotisa et al. (2020)		✓				
Meng and Ma (2020)		✓				✓
Moghaddam (2015)				✓		
Montoya et al. (2015)					✓	
Montoya et al. (2017)					✓	
Montoya (2016)					✓	
Ouahmed et al. (2014)		✓				
Paz et al. (2018)				✓		✓
Pelletier et al. (2019)				✓		
Penna et al. (2016)		✓				
Pierotti (2017)			✓		✓	
Preis et al. (2012)		✓				
Raeesi and Zografos (2020)		✓				✓
Rastani (2020)				✓		
Reyes-Rubiano et al. (2019)	✓					
Rezgui et al. (2019)				✓		
Rezgui et al. (2017)		✓				
Roberti and Wen (2016)		✓		✓		
Santos (2015)		✓				
Sayarshad et al. (2020)						✓
Schiffer et al. (2018)				✓		
Schiffer and Walther (2017)		✓		✓		

Schiffer and Walther (2018a)			✓		
Schiffer and Walther (2018b)			✓		
Schneider et al. (2014)		✓			
Setak and Karimpour (2019)		✓			
Shao et al. (2018)		✓			
Shao et al. (2017)		✓			
Soysal et al. (2020)					✓
Tahami et al. (2020)		✓			
Taş (2021)		✓			
Taweepworadej and Buasri (2016)	✓				
Verma (2018)		✓			✓
Wang et al. (2019)					✓
Wang and Cheu (2013)		✓			
Wang et al. (2020)		✓			
Worley et al. (2012)		✓			
Wu and Zhang (2021)	✓				
Xiao et al. (2019)	✓				
Yamak (2019)	✓				
Yang et al. (2015)				✓	
Yang and Sun (2015)					✓
Yang et al. (2021)				✓	
R. Zhang et al. (2020)				✓	
S. Zhang et al. (2020)			✓		
S. Zhang et al. (2018)		✓			
X. Zhang et al. (2018)				✓	
Zhao and Lu (2019)		✓			
Zhao et al. (2020)		✓			
Zhenfeng et al. (2017)		✓			
Zhou and Tan (2018)					✓
Zhou et al. (2021)				✓	
Zhu et al. (2020)		✓			
Zuo et al. (2019)		✓			
Zuo et al. (2017)		✓			

Another method presented in Table 5 for charging electric vehicles is battery swapping. In battery swapping stations, the current battery in the electric vehicle is replaced with a fully charged one. The advantage is that swapping batteries requires only a small amount of time compared to recharging operations (Pelletier et al., 2016). A swapping operation can be executed in less than 10 minutes, which is similar to going to a fuel station for conventional vehicles (Yang & Sun, 2015). Yang and Sun (2015), Arias et al. (2015), and Hof et al. (2017) studied simultaneously siting the battery swap station locations and routing the electric vehicles. A similar problem is also considered by Zhou and Tan (2018), where battery swap station locations and electric vehicle routing problems are simultaneously optimized for planning material handling operations at automotive assembly plants. Chen et al. (2016) proposed a mixed-integer mathematical model formulation for the EVRP with battery swapping operations for a given number of uncapacitated battery swapping stations. Paz et al. (2018) studied both the conductive charging and battery swapping methods for electric vehicles. The authors introduced three different mathematical formulations regarding three strategies: one for conductive charging in which electric vehicles are recharged at customer locations or conventional charging stations, one for battery swapping in which the electric vehicles can be recharged at conventional charging stations, and lastly, one for both conductive charging and battery swapping possibilities in which the conventional charging stations are used for battery swapping while customer locations are used for conductive charging. Multiple recharging options are also taken into account by Mao et al. (2020), Meng and Ma (2020), Raeesi and Zografos (2020), and Verma (2018). Jie et al. (2019) considered battery swapping operations for a two-echelon capacitated EVRP in which different battery capacitated electric vehicles are taken into account in each echelon. Another related study is introduced by Sayarshad et al. (2020), in which the dynamic routing problem of electric taxis with battery swapping stations is solved using a Markov decision process.

In addition to the battery capacity-related restrictions, most of the studies on the EVRP also consider the most commonly used VRP restrictions. Table 6 gives an overview of constraints considered in the reviewed papers, excluding the studies of Lee (2020), Taweepworadej and Buasri (2016), and Yamak (2019), in which only battery capacity restrictions are considered. Most papers consider volume or weight capacity constraints as encountered in the capacitated VRP. In addition to the vehicle capacity, some of the papers considered a special station capacity constraint, which limits the number of vehicles allowed to be present simultaneously at a charging station. Other frequently used constraints for the EVRP are time window constraints, which significantly affect the route plans if the charging operations are very time-consuming. A time limit is often enforced on a vehicle's tour duration. This is usually the result of the maximum timespan that the driver is allowed to work that day. The duration time limit is also used in multi-period EVRP by Echeverri et al. (2018), Kouider et al. (2018), Kouider et al. (2019a), and Kouider et al. (2019b). In multi-period EVRP, electric vehicles are allowed to service all customer nodes in a number of periods, where each time period has a duration time limit. Time-related constraints in the reviewed papers are limited to these time windows and duration time constraints. However, the break times of the drivers should also be integrated with the EVRP to make route plans more applicable in practice (Coelho et al., 2016; Kopfer et al., 2016; Sahoo et al., 2005). Interestingly, break times are also not often investigated in the VRP literature. However, for the daily plans, the legal breaks of the drivers have to be taken into account in real-life applications. The break times of the drivers should take the charging plans into account since the drivers are often waiting a considerable time during charging in the EVRP. In addition, the EVRP has also been extended with the following restrictions:

- EVRP with Pickup and Delivery: Each customer has three demand options (pickup, delivery, or both pickup and delivery), where the pickup and delivery requests have to be satisfied in a single visit.
- EVRP with Backhauls: The customers are divided into two groups. The first group contains the linehaul customers, each requiring a given quantity of products to be delivered. The second group contains the backhaul customers, where a given quantity of products is transported to the depot node.
- EVRP with Simultaneously Routing and Siting: The problem considers the routing of electric vehicles and siting decisions for charging stations simultaneously.
- EVRP with Simultaneously Vehicle Recharging and Customer Service: Customer service is provided while the electric vehicle is recharged at a public charging station or private charging station established at the customer location.
- EVRP with Multiple Depots: Customer demands are satisfied through more than one depot, where each depot has its own fleet consisting of electric vehicles. Each electric vehicle starts and finishes its tour at its home depot.
- Time/Speed Dependent EVRP: Discharging amount of the electric vehicle is variable according to the speed of the vehicle or the travel speed is dependent on the current time.

Table 6. Considered additional restrictions for the EVRP

Paper	Constraint Type									
	Vehicle Weight Capacity	Station Capacity	Time Windows	Duration Time	Pickup and Delivery	Backhauls	Simultaneously Routing and Siting	Simultaneously Vehicle Recharging and Customer Service	Multiple Depots	Time/Speed Dependency
Abdallah and Adel (2020)	✓		✓							✓
Abdulaal et al. (2017)	✓		✓		✓					
Afroditi et al. (2014)	✓		✓							
Aggoune-Mtalaa et al. (2015)	✓		✓							
Aksoy et al. (2018)	✓									
Almouhanna et al. (2020)	✓								✓	
Arias et al. (2015)	✓						✓			
Arias et al. (2018)	✓						✓			
Barco et al. (2017)	✓		✓							
Basso et al. (2019)	✓		✓							
Basso et al. (2021)	✓									
Basso et al. (2016)	✓		✓							
Booth and Beck (2019)	✓		✓							
Breunig et al. (2018)	✓								✓	
Breunig et al. (2019)	✓									
Bruglieri et al. (2017)	✓		✓							
Bruglieri et al. (2015a)	✓		✓							
Bruglieri et al. (2015b)	✓		✓							
Ceselli et al. (2021)	✓			✓						
Chen et al. (2016)	✓		✓							
Conrad and Figliozzi (2011)	✓		✓							
Cortés-Murcia et al. (2018)	✓		✓							
Cortés-Murcia et al. (2019)	✓		✓					✓		
Cubides et al. (2019)	✓					✓				
Çatay and Keskin (2017)	✓		✓							
Desaulniers et al. (2016)	✓		✓							
Ding et al. (2015)	✓	✓	✓							
Echeverri et al. (2018)		✓		✓						
Erdelić et al. (2019)	✓		✓							
Erdem and Koç (2019)			✓	✓					✓	
Erdoğdu and Karabulut (2020)			✓							
Felipe et al. (2014)	✓		✓							
Ferro et al. (2018)	✓		✓							
Froger et al. (2018)		✓		✓						
Froger et al. (2019)				✓						
Froger et al. (2017)				✓						
Futalef et al. (2020)	✓	✓	✓	✓						
Ge et al. (2020)	✓									
Ghobadi et al. (2021)	✓		✓		✓				✓	
Goeke (2019)	✓		✓		✓					
Goeke and Schneider (2015)	✓		✓							
Granada-Echeverri et al. (2020)	✓					✓				
Hiermann et al. (2014)	✓		✓							
Hiermann et al. (2016)	✓		✓							
Hof et al. (2017)	✓						✓			
Hulagu and Celikoglu (2020)	✓			✓			✓			
Hulagu and Çelikoglu (2019)			✓	✓						

Jia et al. (2021)	✓								
Jie et al. (2019)	✓							✓	
Kancharla and Ramadurai (2018)	✓		✓						
Kancharla and Ramadurai (2020)		✓		✓					
Karakatič (2021)	✓		✓	✓				✓	
Keskin, Akhavan-Tabatabaei, et al. (2019)	✓	✓	✓						
Keskin and Çatay (2016)	✓		✓						
Keskin and Çatay (2018)	✓		✓						
Keskin et al. (2021)	✓	✓	✓						
Keskin, Laporte, et al. (2019)	✓	✓	✓						
Keskin Özel et al. (2018)	✓	✓	✓						
Koç et al. (2019)				✓		✓		✓	
Kopfer and Vornhusen (2019)	✓		✓						
Kouider et al. (2018)	✓			✓					
Kouider et al. (2019a)	✓			✓					
Kouider et al. (2019b)	✓			✓					
Kullman et al. (2017)		✓							
Kullman et al. (2018)		✓							
Küçükoğlu and Cattrysse (2017)	✓		✓						
Küçükoğlu et al. (2019)			✓				✓		
Küçükoğlu and Öztürk (2016)	✓		✓						
Li-ying and Yuan-bin (2015)	✓		✓			✓			
B. Li et al. (2019)	✓	✓		✓					
H. Li et al. (2020)	✓		✓						
J. Li et al. (2020)	✓								
L. Li et al. (2019)	✓		✓		✓				
Lin et al. (2021)	✓		✓						
Lin et al. (2016)	✓			✓	✓				
Löffler et al. (2020)	✓		✓						
Lu et al. (2020)	✓		✓						✓
Lu and Wang (2019)	✓								
Mao et al. (2020)	✓		✓						
Mavrovouniotis et al. (2019)	✓			✓					
Mavrovouniotisa et al. (2020)	✓		✓						
Meng and Ma (2020)	✓		✓						
Moghaddam (2015)			✓						
Montoya et al. (2015)				✓					
Montoya et al. (2017)				✓					
Montoya (2016)				✓					
Ouahmed et al. (2014)	✓		✓						
Paz et al. (2018)	✓		✓			✓		✓	
Pelletier et al. (2019)	✓								
Penna et al. (2016)	✓		✓						
Pierotti (2017)	✓		✓						
Preis et al. (2012)	✓		✓						
Raeesi and Zografos (2020)	✓		✓						
Rastani (2020)	✓		✓						
Reyes-Rubiano et al. (2019)	✓								
Rezgui et al. (2019)	✓		✓						
Rezgui et al. (2017)	✓		✓						
Roberti and Wen (2016)			✓						
Santos (2015)	✓								
Sayarshad et al. (2020)	✓				✓				

Schiffer et al. (2018)	✓		✓					
Schiffer and Walther (2017)	✓		✓			✓		
Schiffer and Walther (2018a)	✓		✓			✓		
Schiffer and Walther (2018b)	✓		✓			✓		
Schneider et al. (2014)	✓		✓					
Setak and Karimpour (2019)	✓	✓	✓					
Shao et al. (2018)	✓		✓					
Shao et al. (2017)	✓		✓					
Soysal et al. (2020)	✓				✓			
Tahami et al. (2020)	✓							
Taş (2021)	✓		✓					
Verma (2018)	✓		✓					
Wang et al. (2019)	✓		✓					
Wang and Cheu (2013)			✓					
Wang et al. (2020)	✓		✓					
Worley et al. (2012)	✓					✓		
Wu and Zhang (2021)	✓							
Xiao et al. (2019)	✓		✓					
Yang et al. (2015)	✓							
Yang and Sun (2015)		✓				✓		
Yang et al. (2021)	✓	✓	✓	✓				
R. Zhang et al. (2020)	✓		✓					✓
S. Zhang et al. (2020)	✓		✓					
S. Zhang et al. (2018)	✓							
X. Zhang et al. (2018)	✓		✓					
Zhao and Lu (2019)	✓		✓		✓			
Zhao et al. (2020)	✓		✓					✓
Zhenfeng et al. (2017)	✓		✓					
Zhou and Tan (2018)	✓			✓				
Zhou et al. (2021)	✓		✓					
Zhu et al. (2020)	✓						✓	
Zuo et al. (2019)	✓		✓					
Zuo et al. (2017)	✓							

3.4. Fleet Type

In the EVRP, similar to the VRP or its extensions, one can consider a homogeneous fleet or a heterogeneous fleet (Eksioglu et al., 2009; Lin et al., 2014). Simply put, a homogeneous fleet consists of vehicles that are all identical, while the heterogeneous fleet includes different types of vehicles with regards to their capacity, operating cost, environmental impact, charging technology, battery capacity, energy consumption per distance unit, etc.

Most of the reviewed papers consider a homogeneous fleet, while only 16 of 136 papers deal with a heterogeneous fleet (see, e.g., Arias et al. (2018), Breunig et al. (2018), Erdem and Koç (2019), Futalef et al. (2020), Hiermann et al. (2016), Jie et al. (2019), Lin et al. (2016), Kopfer and Vornhusen (2019), or Penna et al. (2016)). It should be stated for both the VRP and EVRP that heterogeneous fleets increase the problem complexity for both exact solvers and heuristics. The selection of a vehicle type for a route directly affects the traveling cost/time or may cause a violation of a constraint such as capacity or other related restrictions (Jiang et al., 2014). On the other hand, a heterogeneous fleet has the potential to decrease total transportation cost or energy consumption by selecting more appropriate vehicles for the routes (Küçükoğlu & Öztürk, 2016).

4. Mathematical model of the EVRP and its basic variations

As indicated in the previous sections, there are many considerations influencing the exact nature of the EVRP. This section presents a mathematical formulation of the EVRP and its commonly used variations in the literature. The following mathematical models are derived from the work of Schneider et al. (2014), Keskin and Çatay (2016), Roberti and Wen (2016), Hiermann et al. (2016), and Schiffer and Walther (2017).

A mathematical formulation of the basic EVRP that only considers battery capacity as a constraint can be stated as follows.

<u>Notations</u>

$0, N+1$	Depot nodes
F	Set of charging stations
F'	Set of dummy nodes required to allow multiple visits to a charging station in the set F
V	Set of customers; $V = \{1,2,\dots,N\}$

V_0, V_{N+1}	Set of customers and depot node; $V_0 = V \cup \{0\}$, $V_{\mathrm{N+1}} = V \cup \{N+1\}$
V'	Set of customers and charging stations; $V' = V \cup F'$
$V'_0, V'_{N+1}, V'_{0,N+1}$	Set of customers, charging stations, and depot node; $V'_0 = V' \cup \{0\}$, $V'_{\mathrm{N+1}} = V' \cup \{N+1\}$, $V'_{0,\mathrm{N+1}} = V' \cup \{0\} \cup \{N+1\}$
K	Set of vehicles
d_{ij}	Traveling distance from node *i* to node *j*; $\forall i, j \in V'_{0,N+1}$
h	Energy consumption rate of the vehicles per unit distance
Q	Battery capacity of the vehicles

<u>Decision Variables</u>

x_{ij}^k	Binary variable and equal to 1 if vehicle *k* travels from node *i* to node *j*, 0 otherwise; $\forall i, j \in V'_{0,N+1},\ i \neq j,\ \ d_{ij} > 0,\ \ \forall k \in K$
y_i^k	Decision variable to track the battery level of vehicle *k* on arriving at node *i*; $\forall i \in V'_0,\ \ \forall k \in K$

<u>Objective Function</u>

$$Min\ z = \sum_{i \in V'_0} \sum_{j \in V'_{N+1}} \sum_{k \in K} d_{ij} x_{ij}^k \tag{1}$$

Subject to

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

$$\sum_{j \in V'_{N+1}} \sum_{k \in K} x_{ij}^k \leq 1 \qquad \forall i \in F' \tag{3}$$

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

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

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

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

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

The objective function (1) aims to minimize the total distance of electric vehicles. Constraints (2) handle the connectivity of the customer nodes. Constraints (3) ensure that each dummy charging station can be visited at most once. Constraints (4) make sure that each electric vehicle can be used only in one route plan. Constraints (5) ensure that the total number of outgoing arcs is equal to the total number of incoming arcs at customer and charging station nodes, which provide continuity in the routes. Constraints (6)-(8) track the battery level of the electric vehicles and battery state after the recharging operations at the charging stations following a full charging policy.

In case of a partial charging policy, constraints (7)-(8) should be replaced by constraints (9)-(10) by defining a new decision variable Y_i that represents the battery level of the vehicle before departure from node i where $i \in F' \cup \{0\}$.

$$y_j^k \leq Y_i - \left(h \cdot d_{ij}\right)x_{ij}^k + Q\left(1 - x_{ij}^k\right) \qquad \forall i \in F' \cup \{0\}, \quad \forall j \in V'_{N+1}, \quad \forall k \in K \tag{9}$$

$$y_i^k \leq Y_i \leq Q \qquad \forall i \in F' \cup \{0\} \tag{10}$$

In the case of a capacitated EVRP, constraints (11) should be added to the model where C is the weight/load capacity of the vehicles and q_i is the demand amount of customer i, where $\forall i \in V$. These constraints guarantee that the total amount of goods in a vehicle cannot exceed the vehicle load capacity.

$$\sum_{i \in V} \sum_{j \in V'_{N+1}} q_i x_{ij}^k \leq C \qquad \forall k \in K \tag{11}$$

The electric vehicle routing problem with time windows (EVRPTW) is a common variation of the EVRP, and the above formulation can be turned into a formulation for the EVRPTW by defining the following new parameters and decision variables.

t_{ij} Travel time from node i to node j; $\forall i, j \in V'_{0,N+1}$

e_i Earliest time to start service allowed at node i; $\forall i \in V'_{0,N+1}$

l_i Latest time to start service allowed at node i; $\forall i \in V'_{0,N+1}$

s_i Service time at node i; $\forall i \in V_0$

g Recharging rate of the electric vehicles

p_i Decision variable to track service start time at node i; $\forall i \in V'_{0,N+1}$

Using the parameters and decision variables defined above, the EVRPTW can be formulated by adding constraints (12)-(14) to the EVRP formulation. Constraints (12)-(14) track the times between the nodes, determine the charging times at charging stations following a full charging policy and ensure feasibility with regard to the time windows. In particular, constraints (12) and (13) ensure the time feasibility of the arcs leaving from the customers (and depot node) and the charging stations, respectively. Constraints (14) enforce the time windows of the nodes.

$$p_i + (t_{ij} + s_i) \sum_{k \in K} x_{ij}^k \leq p_j + l_0 \left(1 - \sum_{k \in K} x_{ij}^k\right) \qquad \forall i \in V_0, \quad \forall j \in V'_{N+1} \tag{12}$$

$$p_i + t_{ij} x_{ij}^k + g(Q - y_i^k) \leq p_j + (l_0 + g \cdot Q)(1 - x_{ij}^k) \quad \forall i \in F', \quad \forall j \in V'_{N+1}, \quad \forall k \in K \tag{13}$$

$$e_i \leq p_i \leq l_i \qquad \forall i \in V'_{0,N+1} \tag{14}$$

Constraints (13) determine the time of the electric vehicles before leaving the charging stations considering the full charging policy. In the case of a partial charging policy, constraints (13) should be replaced by constraints (15), in which the charging time of vehicle k at station i is determined using the decision variables Y_i and y_i^k.

$$p_i + t_{ij} x_{ij}^k + g(Y_i - y_i^k) \leq p_j + (l_0 + g \cdot Q)(1 - x_{ij}^k) \quad \forall i \in F', \quad \forall j \in V'_{N+1}, \quad \forall k \in K \tag{15}$$

To consider a heterogeneous fleet, parameters Q, C, h, and g should be modified to allow different technical specifications per vehicle: Q^k, C^k, h^k, and g^k. Constraints (16)-(18), (19)-(20), (21), (22), and (23) should be used in the case of a heterogeneous fleet instead of constraints (6)-(8), (9)-(10), (11), (13) and (15), respectively.

$$y_j^k \leq y_i^k - (h^k \cdot d_{ij}) x_{ij}^k + Q^k (1 - x_{ij}^k) \quad \forall i \in V, \quad \forall j \in V'_{N+1}, \quad \forall k \in K \tag{16}$$

$$y_j^k \leq Q^k - (h^k \cdot d_{ij}) x_{ij}^k \quad \forall i \in F' \cup \{0\}, \quad \forall j \in V'_{N+1}, \quad \forall k \in K \tag{17}$$

$$y_0^k \leq Q^k \quad \forall k \in K \tag{18}$$

$$y_j^k \leq Y_i - (h^k \cdot d_{ij}) x_{ij}^k + Q^k (1 - x_{ij}^k) \quad \forall i \in F' \cup \{0\}, \quad \forall j \in V'_{N+1}, \quad \forall k \in K \tag{19}$$

$$y_i^k \leq Y_i \leq Q^k \quad \forall i \in F' \cup \{0\} \tag{20}$$

$$\sum_{i \in V} \sum_{j \in V'_{N+1}} q_i x_{ij}^k \leq C^k \qquad \forall k \in K \tag{21}$$

$$p_i + t_{ij}x_{ij}^k + g^k\left(Q^k - y_i^k\right) \le p_j + (l_0 + g^kQ^k)\left(1 - x_{ij}^k\right)$$

$$\forall i \in F', \quad \forall j \in V'_{N+1}, \quad \forall k \in K \qquad (22)$$

$$p_i + t_{ij}x_{ij}^k + g^k\left(Y_i - y_i^k\right) \le p_j + (l_0 + g^kQ^k)\left(1 - x_{ij}^k\right)$$

$$\forall i \in F', \quad \forall j \in V'_{N+1}, \quad \forall k \in K \qquad (23)$$

5. Solution Approaches

As an extension of the well-known VRP, the EVRP additionally deals with planning the charging station visits while determining the customer orders in a route. Since the VRP is an NP-hard problem and the EVRP is a generalization of the VRP, the EVRP can equally be considered NP-hard in the strong sense (Desaulniers et al., 2016; Ferro et al., 2018; Roberti & Wen, 2016; S. Zhang et al., 2018). Furthermore, adding the restrictions described in the previous sections makes the problem considerably more complex to solve (Afroditi et al., 2014; Desaulniers et al., 2016; Goeke & Schneider, 2015). Solution methodologies proposed in the literature can be classified into either exact or heuristic approaches. However, due to the complexity of the problem, the number of studies in which exact approaches are used as solution approach is very small. Tahami et al. (2020) proposed a branch-and-cut algorithm to solve well-known EVRP. Desaulniers et al. (2016) introduced an exact branch-price-and-cut algorithm to solve four variants of the EVRP: at most a single recharge per route with a full charging policy, multiple recharges per route with a full charging policy, at most a single recharge per route with a partial charging policy, and multiple recharges per route with a partial charging policy. Similarly, a branch-price-and-cut algorithm was used by Pierotti (2017) to solve the EVRPTW with heterogeneous recharging stations. Ceselli et al. (2021) provided a branch-and-cut-and-price algorithm for the EVRP with multiple charging technologies, where the proposed algorithm relies upon a path-based formulation. Lee (2020) introduced a branch-and-price method to optimally solve an extended version of the EVRP with non-linear charging time. The branh-and-price method is also considered by Wu and Zhang (2021) to solve two-echelon EVRP. Besides these methods, commercial solvers are commonly employed to find the optimal solution for the EVRP and its extensions. Paz et al. (2018) and Küçükoğlu and Öztürk (2016) extended the EVRPTW with different assumptions and solved their small-sized problems (including 5, 10, and 15 customer nodes) using CPLEX, a commercial solver. CPLEX was also used to solve different EVRP variations (see, e.g., Hulagu and Çelikoglu (2019), Keskin, Akhavan-Tabatabaei, et al. (2019), Lin et al. (2016)). GUROBI, another commercial solver, was used for the EVRP by Aksoy et al. (2018), Chen et al. (2016), Cubides et al. (2019), Froger et al. (2017), Froger et al. (2018), Froger et al. (2019), Granada-Echeverri et al. (2020), Moghaddam (2015), Montoya et al. (2015), Schiffer and Walther (2017), and Wang et al. (2019).

In addition to exact solution approaches, meta-heuristic algorithms are widely used as a solution approach for the EVRP. Table 7 gives an overview of the meta-heuristic algorithms used in the reviewed papers: ant colony optimization (ACO), cuckoo search (CS), differential evolution algorithm (DEA), genetic algorithm (GA), iterated local search (ILS), large neighborhood search/adaptive large neighborhood search (LNS/ALNS), memetic algorithm (MA), simulated annealing (SA), tabu search/adaptive tabu search/granular tabu search (TS/ATS/GTS) algorithm, and variable neighborhood search/adaptive variable neighborhood search (VNS/AVNS). The last column of Table 7 also presents the additional procedures integrated with the meta-heuristic algorithms. Additionally, a pair of meta-heuristic algorithms marked in a row in Table 7 denotes the hybrid structure of the two algorithms. Based on the algorithms given in Table 7, Figure 4 presents the relative occurrence of these approaches. From Table 7 and Figure 4, it can be observed that LNS/ALNS, VNS/AVNS, GA, and TS/ATS/GTS are the most common metaheuristics for the EVRP.

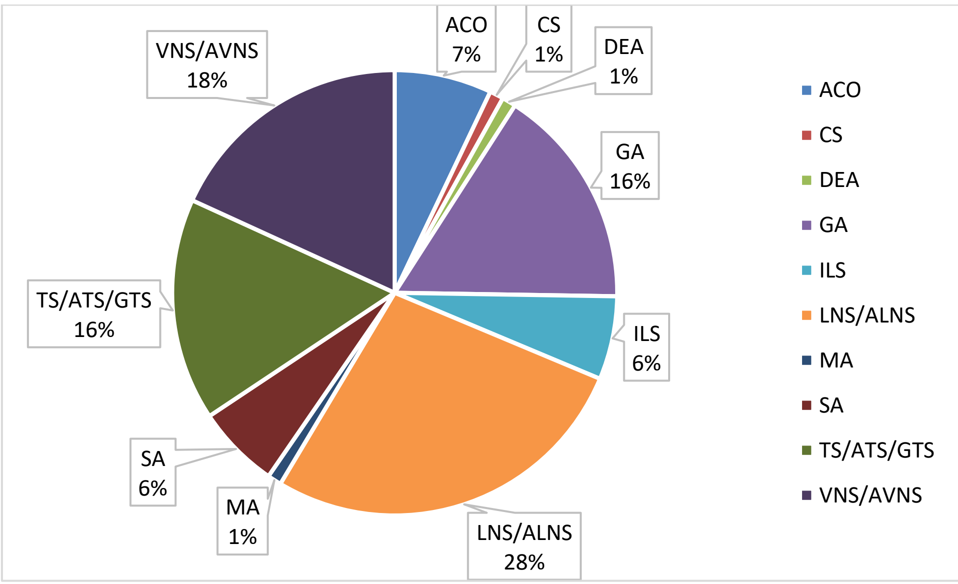

Figure 4. The usage rates of the ten principal algorithms for the EVRP

Table 7. Meta-heuristic solution approaches used for the EVRP

Paper	ACO	CS	DEA	GA	ILS	LNS/ALNS	MA	SA	TS/ATS/GTS	VNS/AVNS	Integrated with
Abdallah and Adel (2020)				✓							
Abdulaal et al. (2017)				✓							Markov Decision Process
Aggoune-Mtalaa et al. (2015)				✓					✓		
Almouhanna et al. (2020)										✓	Biased Randomization
Barco et al. (2017)			✓								
Breunig et al. (2018)						✓					
Breunig et al. (2019)						✓					Local Search
Bruglieri et al. (2017)										✓	Matheuristic
Bruglieri et al. (2015a)										✓	Matheuristic
Bruglieri et al. (2015b)										✓	Matheuristic
Cortés-Murcia et al. (2019)					✓						Local Search and Set Partitioning
Ding et al. (2015)									✓	✓	
Erdelić et al. (2019)						✓					
Erdem and Koç (2019)				✓							Local Search and Set Partitioning
Erdoğdu and Karabulut (2020)								✓			Local Search
Felipe et al. (2014)									✓		
Futalef et al. (2020)				✓							
Ge et al. (2020)									✓		Clarke and Wright's Saving Method
Ghobadi et al. (2021)								✓		✓	
Goeke (2019)									✓		
Goeke and Schneider (2015)						✓					Local Search
Granada-Echeverri et al. (2020)					✓						
Hiermann et al. (2014)						✓					Dynamic Programming
Hiermann et al. (2016)						✓					Dynamic Programming
Hof et al. (2017)										✓	
Jia et al. (2021)	✓										
Jie et al. (2019)						✓					Column Generation
Kancharla and Ramadurai (2018)						✓					
Kancharla and Ramadurai (2020)										✓	
Karakatič (2021)				✓							
Keskin and Çatay (2016)						✓					
Keskin and Çatay (2018)						✓					Matheuristic
Keskin et al. (2021)						✓					
Keskin, Laporte, et al. (2019)						✓					Matheuristic
Keskin Özel et al. (2018)						✓					Matheuristic
Koç et al. (2019)						✓					Matheuristic
Kouider et al. (2019a)						✓					
Kouider et al. (2019b)						✓					
Küçükoğlu and Cattrysse (2017)								✓			Branch-and-Bound
Küçükoğlu et al. (2019)								✓	✓		Dynamic Programming
Li-ying and Yuan-bin (2015)									✓	✓	
B. Li et al. (2019)				✓							Constraint Programming
H. Li et al. (2020)											
J. Li et al. (2020)				✓							Hill Climbing Search
L. Li et al. (2019)										✓	
Lin et al. (2021)									✓	✓	
Löffler et al. (2020)						✓			✓		
Lu et al. (2020)										✓	Local Search
Lu and Wang (2019)										✓	*k*NN-based Heuristic
Mao et al. (2020)	✓										Local Search

Mavrovouniotis et al. (2019)	✓									
Mavrovouniotisa et al. (2020)	✓									
Meng and Ma (2020)	✓									
Montoya et al. (2017)				✓						Local Search and Set Partitioning
Montoya (2016)				✓						Local Search and Set Partitioning
Ouahmed et al. (2014)			✓					✓		
Pelletier et al. (2019)					✓					Local Search and Set Partitioning
Penna et al. (2016)				✓						Local Search and Set Partitioning
Preis et al. (2012)								✓		
Raeesi and Zografos (2020)					✓					Dynamic Programming
Rastani (2020)					✓					
Reyes-Rubiano et al. (2019)										
Rezgui et al. (2019)			✓							Local Search
Rezgui et al. (2017)			✓			✓				Local Search
Roberti and Wen (2016)									✓	Dynamic Programming
Schiffer et al. (2018)					✓					Local Search
Schiffer and Walther (2018a)					✓					Dynamic Programming
Schiffer and Walther (2018b)					✓					Dynamic Programming
Schneider et al. (2014)								✓	✓	
Setak and Karimpour (2019)							✓			
Shao et al. (2018)			✓							Dynamic Dijkstra
Shao et al. (2017)			✓							Dynamic Dijkstra
Verma (2018)			✓							Local Search
Wang and Cheu (2013)								✓		
Wang et al. (2020)									✓	
Yamak (2019)							✓			
Yang et al. (2015)			✓					✓		
Yang and Sun (2015)					✓			✓		
R. Zhang et al. (2020)					✓					
S. Zhang et al. (2020)					✓					Local Search
S. Zhang et al. (2018)	✓			✓						
X. Zhang et al. (2018)								✓		
Zhao and Lu (2019)					✓					
Zhao et al. (2020)	✓									
Zhenfeng et al. (2017)			✓							
Zhou and Tan (2018)		✓								
Zhou et al. (2021)									✓	Dynamic Programming
Zhu et al. (2020)									✓	Space Saving Heuristic

For the heuristic-based solution methodologies, one of the essential issues that directly affects the search performance is the solution representation. As in the classical VRP, the permutation ordered integer array is commonly employed in the existing solution approaches to represent a solution (Goeke & Schneider, 2015; Küçükoğlu & Öztürk, 2016; Roberti & Wen, 2016; Schiffer & Walther, 2018a; Schneider et al., 2014). For VRPs, an integer array consisting of customer locations enriched with the earliest arrival, earliest departure, latest arrival, and latest departure times enables the development of efficient local search algorithms (Mitrović-Minić & Laporte, 2004). However, a solution for the EVRP additionally requires charging station visits in the route plans. Since the number of visits to charging stations is not restricted for a route, a vehicle can make none, one or more visits to charging stations. Furthermore, it is even possible to make multiple charging station visits between a single pair of customer nodes. Moreover, if a partial charging policy is followed, the recharge amount at the charging stations is another critical decision. Especially for the EVRP with time windows constraints, recharging times at the charging stations need to be well planned to meet the time window restrictions of the customers. Therefore, a feasible route construction is considerably more difficult for the EVRP than for the VRP. To make a feasible route plan with respect to battery capacity, there exist two main approaches in the literature: heuristic and optimal charging station insertion approaches.

Heuristic charging station insertion approaches search the solution space for insertions in a straightforward way. The most common approach is consecutively applying a removal and insertion procedure for the charging stations. This is successfully applied to the EVRP in a number of studies (Felipe et al., 2014; Goeke & Schneider, 2015; Keskin & Çatay, 2015, 2016; Schiffer & Walther, 2018a; Schneider et al., 2014). This procedure requires a solution representation consisting of both customer and charging stations. For the removal operations, a number of stations are removed from the route according to heuristic rules such as random selection, selecting the station that causes a high travel distance, selecting the station that causes a high battery usage, etc. Similarly, the charging stations are inserted into the routes to restore battery feasibility.

As an alternative to the heuristic charging station insertion approaches, a forward labeling algorithm on the basis of dynamic programming was applied in a number of studies (see, e.g., Hiermann et al. (2014), Hiermann et al. (2016), Jie et al. (2019), Küçükoğlu et al. (2019) Pierotti (2017), and Roberti and Wen (2016)). The labeling algorithm works through a solution consisting of only customer locations and tries to insert the charging stations into the route in an optimal way while maintaining feasibility with regard to battery capacity or other constraints such as time windows. The algorithm starts with an initial label at the depot node (with a full battery level) and creates a set of feasible labels at each step by inserting possible charging stations between the customer nodes. The algorithm provides an optimal set of charging station insertions for a given route of customers nodes (Roberti & Wen, 2016). When compared to heuristic charging station insertion approaches, the labeling algorithm is much more time-consuming. However, if sufficient computational time is available, solutions generated by this labeling algorithm typically generate better solutions than using the heuristic approaches. Similar to the study of Roberti and Wen (2016), Kullman et al. (2017), and Kullman et al. (2018) introduced a dynamic decision-making procedure for the single electric vehicle routing problem with uncertain charging station availability. The computational complexity of the charging station insertion for a given customer-only route has not been identified before. However, it is highly likely that the problem is NP-hard in the strong sense since the insertion problem is similar to the resource-constrained shortest path problem, which aims to find a minimum cost-directed path from a source to a destination while satisfying the resource constraints (Horváth & Kis, 2016; Strehler et al., 2017).

6. Problem Datasets

The most widely used EVRP dataset is introduced by Schneider et al. (2014) and consists of small and large-sized instances with up to 100 customer locations. All these instances are generated based on the benchmark dataset for the VRPTW of Solomon (1987). The VRPTW dataset is divided into three classes based on geographical distribution: random customer distribution (R), clustered customer distribution (C), and a mixture of both R and C classes (RC). Moreover, these classes are divided into two groups with respect to the scheduling horizon where R1, C1, and RC1 form the first group with a short scheduling horizon while R2, C2, and RC2 form the second group with a long scheduling horizon. Based on the VRPTW instances, Schneider et al. (2014) propose a set of 56 large-sized instances consisting of 100 customer locations and 21 charging stations, and a set of 36 small-sized instances consisting of 5, 10, and 15 customer locations. The charging stations in each instance are determined as follows: One of the charging stations is located at the depot node. The remaining charging stations are located randomly with the assumption that each customer can be reached from the depot using at most two charging stations. On the other hand, the battery capacity of the electric vehicles is determined by considering the maximum of the following two values: the charge needed to travel 60% of the average route length of the best-known VRPTW solution for the instance and twice the charge required for the longest arc distance between a customer and a station. Finally, the time window data is re-generated to obtain feasible instances using a procedure as described in Solomon (1987).

Many solution procedures make use of the EVRPTW dataset introduced by Schneider et al. (2014). Therefore, this section also presents the best-found solutions for the instances in the existing studies and compares the solution quality of the different solution approaches. Table 8 shows the existing results for the small-sized instances based on the studies of Schneider et al. (2014), Küçükoğlu and Öztürk (2016), and Schiffer and Walther (2017). Schneider et al. (2014) compare their proposed VNS/TS algorithm with exact solutions obtained by CPLEX in a two-hour time limitation. The other two studies proposed by Küçükoğlu and Öztürk (2016) and Schiffer and Walther (2017) introduce optimal solutions obtained by both the CPLEX and GUROBI solvers, respectively. According to the exact solver results shown in Table 8, each study finds the same solution for most of the instances. However, the results presented by Küçükoğlu and Öztürk (2016) obtain the minimum average objective function values with much shorter CPU times by using a better formulation. On the other hand, the VNS/TS is able to obtain the same results as the optimal solutions or better than the best-bound integer solutions of the exact solver in even shorter processing times.

Table 8. Results of the small-sized EVRPTW instances

		CPLEX[1]		CPLEX[2]		GUROBI		VNS/TS	
Inst.	**Best Solution**	**OFV**	**CPU Time (s)**	**OFV**	**CPU Time (s)**	**OFV**	**CPU Time (s)**	**OFV**	**CPU Time (s)**
c101_5	257.75	257.75	81.00	257.75	0.98	257.75	0.29	257.75	0.21
c103_5	176.05	176.05	5.00	176.05	0.18	176.05	0.11	176.05	0.12
c206_5	242.55	242.55	518.00	242.55	1.15	242.55	0.90	242.55	0.14
c208_5	158.48	158.48	15.00	158.48	1.57	158.48	0.24	158.48	0.11
r104_5	136.69	136.69	1.00	136.69	0.79	136.69	0.07	136.69	0.13
r105_5	156.08	156.08	3.00	156.08	0.62	156.08	0.09	156.08	0.11
r202_5	128.78	128.78	1.00	128.78	0.34	128.78	0.11	128.78	0.11
r203_5	179.06	179.06	5.00	179.06	0.42	179.06	0.29	179.06	0.15
rc105_5	241.30	241.30	764.00	241.30	1.60	241.30	1.07	241.30	0.14
rc108_5	253.93	253.93	311.00	253.93	0.88	253.93	1.55	253.93	0.17
rc204_5	176.39	176.39	54.00	176.39	1.74	176.39	0.27	176.39	0.15
rc208_5	167.98	167.98	21.00	167.98	0.72	167.98	0.27	167.98	0.13
c101_10	393.76	393.76	171.00	393.76	8.09	393.76	11.60	393.76	0.77
c104_10	273.93	273.93	360.00	273.93	2.60	273.93	6.31	273.93	0.95
c202_10	304.06	304.06	300.00	304.06	1.07	304.06	85.90	304.06	0.71
c205_10	228.28	228.28	4.00	228.28	0.16	228.28	0.35	228.28	0.49
r102_10	249.19	249.19	389.00	249.19	0.61	249.19	7.76	249.19	0.65
r103_10	207.05	207.05	119.00	207.05	4.80	207.05	1382.00	207.05	0.72
r201_10	241.51	241.51	177.00	241.51	3.34	241.51	39.30	241.51	0.78
r203_10	218.21	218.21	573.00	218.21	2.07	218.21	4.59	218.21	0.71
rc102_10	423.51	423.51	810.00	423.51	0.66	423.51	0.94	423.51	0.69
rc108_10	345.93	345.93	39.00	345.93	0.48	345.93	4.48	345.93	0.90
rc201_10	412.86	412.86	7200.00	412.86	69.00	412.86	4661.00	412.86	0.90
rc205_10	325.98	325.98	399.00	325.98	0.50	325.98	0.60	325.98	0.81
c103_15	384.29	384.29	7200.00	384.79	7200.00	384.29	7200.00	384.29	15.37
c106_15	275.13	275.13	17.00	275.13	23.74	275.13	1.52	275.13	14.94

c202_15	383.61	383.62	7200.00	383.62	2384.00	383.62	955.00	383.61	13.41
c208_15	300.55	300.55	5060.00	300.55	153.00	300.55	11.50	300.55	11.08
r102_15	413.93	413.93	7200.00	413.93	7200.00	413.93	7200.00	413.93	19.55
r105_15	336.15	336.15	7200.00	336.15	10.09	336.15	27.80	336.15	13.35
r202_15	358.00	358.00	7200.00	358.00	7200.00	358.00	740.00	358.00	13.17
r209_15	313.24	313.24	7200.00	313.24	39.54	313.24	2254.00	313.24	13.73
rc103_15	397.67	397.67	7200.00	397.67	4456.00	397.67	7200.00	397.67	14.62
rc108_15	370.25	370.25	7200.00	370.25	7200.00	370.25	7200.00	370.25	12.92
rc202_15	394.39	394.39	7200.00	394.39	640.00	394.39	116.00	394.39	12.74
rc204_15	384.86	407.45	7200.00	384.86	7200.00	394.47	7203.00	384.86	15.57
Avg.	283.65	284.28	2483.25	283.66	1216.97	283.92	1286.64	283.65	5.03

Note: CPLEX[1] and VNS/TS results are introduced by Schneider et al. (2014). CPLEX[2] and GUROBI solutions are introduced by Küçükoğlu and Öztürk (2016) and Schiffer and Walther (2017), respectively.
OFV: Objective Function Value

For the large-sized instances, Table 9 shows the results of seven different solution approaches and presents the best-found solution for each instance. It should be noted that for this table, the first objective of the EVRPTW proposed by Schneider et al. (2014) is to minimize the total number of electric vehicles used for the routes. The secondary objective is to minimize the total travel distance of electric vehicles. Therefore, a solution, which has a smaller number of routes, can be identified as a better solution than another solution with a smaller total travel distance. With regards to solution quality, the ALNS algorithm proposed by Goeke and Schneider (2015) is the best algorithm compared to the other six solution approaches. In addition to the results shown in Table 9, shorter distances are established for the EVRPTW by Schiffer and Walther (2018a) and Kancharla and Ramadurai (2018). However, these results are not taken into account in this study because the total number of electric vehicles used for the routes is not given by the authors.

Table 9. Comparison of different solution approaches on the large-sized EVRPTW instances

	Best Solution		**VNS/TS[1]**		**VNS/TS[2]**		**TS**		**ALNS[1]**		**ALNS[2]**		**Branch-and-Price**		**ALNS[3]**	
Inst.	**NV**	**OFV**	**NV**	**OFV**	**NV**	**OFV**	**NV**	**OFV**	**NV**	**OFV**	**NV**	**OFV**	**NV**	**OFV**	**NV**	**OFV**
c101	12	1053.83	**12**	**1053.83**	**12**	**1053.83**	**12**	**1053.83**	**12**	**1053.83**	**12**	**1053.83**	**12**	**1053.83**	**12**	**1053.83**
c102	11	1051.38	11	1057.16	11	1056.47	11	1069.35	**11**	**1051.38**	11	1057.16	**11**	**1051.38**	11	1056.12
c103	10	1034.86	10	1041.55	11	1002.03	10	1134.36	**10**	**1034.86**	10	1044.15	-	-	11	1001.81
c104	10	951.57	10	980.82	10	988.77	10	979.63	10	961.88	10	984.61	-	-	**10**	**951.57**
c105	11	1075.37	**11**	**1075.37**	**11**	**1075.37**	11	1079.69	**11**	**1075.37**	**11**	**1075.37**	**11**	**1075.37**	**11**	**1075.37**
c106	11	1057.65	11	1057.87	11	1057.87	11	1057.87	**11**	**1057.65**	**11**	**1057.65**	11	1063.11	**11**	**1057.65**
c107	11	1031.56	**11**	**1031.56**	**11**	**1031.56**	11	1033.08	**11**	**1031.56**	**11**	**1031.56**	11	1083.12	**11**	**1031.56**
c108	10	1095.66	10	1100.32	11	1015.73	11	1015.73	**10**	**1095.66**	10	1109.45	11	1150.51	11	1015.68
c109	10	1033.67	10	1051.84	10	1036.64	10	1051.36	**10**	**1033.67**	10	1051.50	-	-	10	1069.16
c201	4	645.16	**4**	**645.16**	**4**	**645.16**	**4**	**645.16**	**4**	**645.16**	**4**	**645.16**	-	-	**4**	**645.16**
c202	4	645.16	**4**	**645.16**	**4**	**645.16**	**4**	**645.16**	**4**	**645.16**	4	646.52	-	-	**4**	**645.16**
c203	4	644.98	**4**	**644.98**	**4**	**644.98**	**4**	**644.98**	**4**	**644.98**	**4**	**644.98**	-	-	**4**	**644.98**
c204	4	636.43	**4**	**636.43**	**4**	**636.43**	**4**	**636.43**	**4**	**636.43**	4	638.32	-	-	**4**	**636.43**
c205	4	641.13	**4**	**641.13**	**4**	**641.13**	**4**	**641.13**	**4**	**641.13**	**4**	**641.13**	-	-	**4**	**641.13**
c206	4	638.17	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	-	-	**4**	**638.17**
c207	4	638.17	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	-	-	**4**	**638.17**
c208	4	638.17	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	**4**	**638.17**	-	-	**4**	**638.17**
r101	17	1859.51	18	1672.55	18	1673.12	18	1670.80	18	1665.62	18	1663.04	**17**	**1859.51**	18	1679.06
r102	15	1659.87	16	1535.81	16	1522.84	16	1495.31	16	1487.41	16	1488.97	**15**	**1659.87**	16	1519.80
r103	13	1267.35	13	1299.64	13	1299.17	13	1348.25	13	1271.35	13	1285.96	**13**	**1267.35**	13	1312.50
r104	11	1088.43	**11**	**1088.43**	11	1143.69	11	1097.09	**11**	**1088.43**	11	1097.82	-	-	12	1071.89
r105	14	1442.35	14	1473.59	15	1401.24	14	1514.36	**14**	**1442.35**	15	1433.92	14	1471.98	15	1383.29
r106	13	1321.08	13	1344.66	13	1395.18	13	1369.55	13	1324.10	13	1363.25	**13**	**1321.08**	14	1276.15
r107	12	1148.43	12	1154.52	12	1158.13	12	1162.90	12	1150.95	12	1165.33	12	1170.87	**12**	**1148.43**

r108	11	1050.04	11	1065.89	11	1061.91	11	1056.84	**11**	**1050.04**	11	1067.43	-	-	11	1051.59
r109	12	1261.31	12	1294.05	12	1341.01	12	1308.62	**12**	**1261.31**	13	1245.89	13	1311.19	13	1214.72
r110	11	1119.50	11	1143.52	11	1141.90	11	1126.74	**11**	**1119.50**	11	1155.64	-	-	12	1097.89
r111	12	1106.19	12	1124.06	12	1107.52	12	1123.96	**12**	**1106.19**	12	1120.48	12	1145.34	12	1109.14
r112	11	1016.63	11	1026.52	11	1033.97	11	1047.92	**11**	**1016.63**	11	1043.79	-	-	11	1038.74
r201	3	1264.82	**3**	**1264.82**	**3**	**1264.82**	3	1266.26	**3**	**1264.82**	3	1269.52	-	-	3	1265.67
r202	3	1052.32	**3**	**1052.32**	3	1053.11	3	1052.65	**3**	**1052.32**	3	1053.93	-	-	**3**	**1052.32**
r203	3	895.54	3	912.86	3	914.68	3	914.10	**3**	**895.54**	3	897.12	-	-	**3**	**895.54**
r204	2	779.49	2	790.57	2	801.56	2	790.68	**2**	**779.49**	2	788.67	-	-	2	780.98
r205	3	987.36	3	988.67	3	1000.96	3	997.15	**3**	**987.36**	3	1002.00	-	-	**3**	**987.36**
r206	3	922.19	3	925.20	3	926.94	3	928.26	**3**	**922.19**	3	922.70	-	-	3	922.70
r207	2	845.26	2	852.73	2	848.53	2	855.99	**2**	**845.26**	2	859.78	-	-	2	847.14
r208	2	736.12	2	736.60	2	737.05	2	741.44	**2**	**736.12**	2	740.24	-	-	**2**	**736.12**
r209	3	867.05	3	872.36	3	877.40	3	874.74	**3**	**867.05**	3	890.69	-	-	3	871.22
r210	3	843.65	3	847.06	3	850.41	3	848.44	3	846.20	3	863.53	-	-	**3**	**843.65**
r211	2	827.89	2	866.21	2	860.32	2	861.17	**2**	**827.89**	2	873.67	-	-	3	761.56
rc101	15	1823.23	16	1731.07	16	1766.44	16	1753.35	16	1726.91	16	1726.91	**15**	**1823.23**	16	1731.07
rc102	14	1659.53	15	1554.61	15	1556.08	15	1559.95	15	1552.08	**14**	**1659.53**	14	1661.76	15	1551.69
rc103	13	1350.09	13	1353.55	13	1351.15	13	1355.36	**13**	**1350.09**	13	1369.34	13	1366.96	13	1351.73
rc104	11	1227.25	11	1249.23	11	1267.55	11	1280.82	**11**	**1227.25**	11	1229.82	-	-	11	1232.45
rc105	14	1473.24	14	1483.38	14	1475.31	14	1479.56	14	1475.31	14	1478.67	14	1502.65	**14**	**1473.24**
rc106	13	1425.70	13	1440.19	13	1469.99	13	1437.96	13	1427.21	13	1436.61	**13**	**1425.70**	14	1414.99
rc107	12	1274.89	12	1275.89	12	1280.44	12	1284.47	**12**	**1274.89**	12	1283.52	13	1431.56	12	1283.05
rc108	11	1197.83	11	1238.81	11	1227.88	11	1209.61	**11**	**1197.83**	11	1204.87	-	-	11	1209.11
rc201	4	1444.94	4	1447.20	**4**	**1444.94**	4	1446.03	**4**	**1444.94**	4	1464.33	-	-	4	1446.84
rc202	3	1410.74	3	1412.91	3	1418.79	3	1425.17	**3**	**1410.74**	3	1437.02	-	-	3	1450.34
rc203	3	1055.19	3	1078.28	3	1077.16	3	1084.66	**3**	**1055.19**	3	1084.71	-	-	3	1069.27
rc204	3	884.80	3	889.22	3	886.03	3	889.22	**3**	**884.80**	3	902.69	-	-	3	887.45
rc205	3	1273.55	3	1321.75	3	1353.54	3	1360.39	**3**	**1273.55**	3	1282.58	-	-	3	1277.60
rc206	3	1188.63	3	1191.13	3	1204.93	3	1207.77	**3**	**1188.63**	3	1218.79	-	-	3	1207.64
rc207	3	985.03	3	995.52	3	1015.60	3	1010.66	**3**	**985.03**	3	1016.12	-	-	3	994.48
rc208	3	836.23	3	838.03	3	838.41	3	838.03	**3**	**836.23**	3	847.89	-	-	3	841.34
Avg.	7.80	1078.32	7.88	1078.77	7.93	1080.27	7.89	1083.54	7.88	1068.61	7.89	1080.94	12.90	1344.82	8.04	1066.60

Notes: VNS/TS[1], VNS/TS[2], and TS algorithms are proposed by Schneider et al. (2014). ALNS[1], ALNS[2], Branch-and-Price, and ALNS[3] algorithms are proposed by Goeke and Schneider (2015), Hiermann et al. (2014), Hiermann et al. (2016), and Keskin and Çatay (2016), respectively. VNS/TS[1] uses a SA solution acceptance procedure, and VNS/TS[2] accepts only improved solutions.
OFV: Objective Function Value, **NV:** Number of Vehicles

With regard to CPU times, it is difficult to make a fair comparison between the algorithms since the computations are performed on different technological environments given in Table 10. The computations for the branch-and-price algorithm proposed by Hiermann et al. (2016) are performed with an eight-hour time limitation, and, for most of the instances, the results are obtained at the end of the time limit. For the other algorithms, the average CPU times are similar except for the ALNS algorithm proposed by Goeke and Schneider (2015), which outperforms the algorithms proposed by Schneider et al. (2014), Hiermann et al. (2014), Hiermann et al. (2016), and Keskin and Çatay (2016).

Table 10. Technological environments used in the EVRP studies

Algorithm	Processor	Memory	Operating System	Average Time (min)
VNS/TS with SA Acceptance Schneider et al. (2014)	Intel Core i5 750 with 2.67 GHz	4 GB	Windows 7 Professional	15.34
VNS/TS Schneider et al. (2014)	Intel Core i5 750 with 2.67 GHz	4 GB	Windows 7 Professional	16.22
TS Schneider et al. (2014)	Intel Core i5 750 with 2.67 GHz	4 GB	Windows 7 Professional	16.01
ALNS Goeke and Schneider (2015)	Intel Core i7 with 2.8 GHz	8 GB	Windows 7 Enterprise	2.78 (on a single core)
ALNS Hiermann et al. (2014)	Intel Core2 Quad CPU Q6600 with 2.4 GHz	4 GB	64-bit Linux	15.92 (shared between 4 cores)

Branch-and-Price Hiermann et al. (2016)	Intel Xeon 2643 with 3.3 GHz	Up to 7 GB	Linux	360.73 (on a single core)
ALNS Keskin and Çatay (2016)	Intel Xeon E5 with 3.3 GHz	32 GB	64-bit Windows 7	12.26

The computations and their results mentioned above for the EVRPTW all consider a full charge policy for the charging operations at stations. Some of the papers address a partial charge policy applied on the problem dataset of Schneider et al. (2014) to test their methodology. Since partial charging requires less operational time for the electric vehicles with respect to full charging, the problem dataset for the EVRPTW can be used without any issue. Following a partial charging policy, Keskin and Çatay (2016) proposed 33 optimal solutions for the small-sized EVRPTW instances by using CPLEX with a two-hour time limitation. Furthermore, the authors applied their ALNS algorithm on small and large-sized instances and reported average savings on the total distance of up to 1.64% with respect to the EVRPTW solutions. In addition, a reduction in the number of used electric vehicles is observed for some of the instances. Similar results for the small-sized EVRPTW with partial charge are found by Schiffer and Walther (2017). However, they were able to obtain the optimal solution for 32 instances, albeit with a higher average CPU time. The authors also extended the dataset of Schneider et al. (2014) for another extended version of the EVRP called robust electric location-routing problem with time windows and partial recharging (Schiffer & Walther, 2018a, 2018b). This dataset is used in another study by Schiffer et al. (2018) to test an ALNS introduced for the location-routing problem with intra-route facilities.

The dataset of Schneider et al. (2014) is also used for the EVRPTW with a heterogeneous fleet. For this extension, Hiermann et al. (2014) and Hiermann et al. (2016) modified the original instance by adopting different electric vehicle types into the problem data by using the instance set defined by Liu and Shen (1999) for mixed vehicle routing problem with time windows. The same extension is taken into account by Küçükoğlu and Öztürk (2016). The authors modified the original small-sized EVRPTW dataset by using the real-life technical information of eight different electric vehicles. According to their computational results obtained with CPLEX, a 5.55% average reduction on total distance can be obtained by using a heterogeneous fleet. Desaulniers et al. (2016) modified the dataset of Schneider et al. (2014) for their proposed four variants of the EVRPTW that are described in the previous section. The authors introduced detailed solutions to the problems solved by a branch-price-and-cut algorithm.

Distinct from the EVRPTW dataset of Schneider et al. (2014), some of the researchers formed their own dataset for the considered EVRP problems. For instance, Felipe et al. (2014) generated a new problem set consisting of 60 instances for the EVRP with multiple technologies and partial charging, where the number of customers varies between 100 and 400 and are randomly located with uniform geographical distribution. Goeke and Schneider (2015) adapted the dataset proposed by Demir et al. (2012) for the pollution routing problem to the routing problem of a mixed fleet of electric and conventional vehicles. The modified dataset consists of nine instance sets grouped according to the problem size varying between 10 and 200 customers, where each set contains 20 instances. S. Zhang et al. (2018) introduced 40 instances for the EVRP where the objective of the study is the energy minimization of the electric vehicles instead of distance minimization. Yang and Sun (2015) used four well-known capacitated vehicle routing problem datasets for the battery swap station location and routing problem by assuming that all nodes are candidate battery swap stations. These problems are also used by Hof et al. (2017). Based on the battery swapping technology, Jie et al. (2019) introduced a new dataset for the two-echelon capacitated electric vehicle routing problem. Another useful dataset is introduced by Roberti and Wen (2016) for the electric traveling salesman problem with time windows to test their GVNS algorithm. The authors generated two sets of test problems where the first group consists of 50 small-sized instances with 20 customer locations, and the second group consists of 50 large-sized instances with 150 and 200 customer locations. Moreover, each group is divided into two subsets with respect to the number of charging stations (5 and 10) in the problems. The small and large-sized instances are derived from the traveling salesman problem with time window instances proposed by Gendreau et al. (1998) and Ohlmann and Thomas (2007), respectively. The proposed GVNS is tested on the dataset both with a full and a partial charge policy. Hof et al. (2017) and Montoya et al. (2017) introduced different kinds of datasets for their more specific problems: the battery swap station location-routing problem with capacitated electric vehicles and the electric vehicle routing problem with non-linear charging functions, respectively. As one of the more recent studies, Karakatič (2021) extended the dataset proposed by the Cordeau et al. (2001) for the multi-depot EVRPTW with addition of charging stations for each instance, where each charging station has same charging speed.

7. Conclusions and Future Research Directions

In this study, we have presented a comprehensive and up-to-date review of existing studies on the EVRP. Looking just at electric vehicle routing, we have analyzed 136 different papers consisting of journal papers, conference proceedings, technical reports, and theses. We have discussed these studies on the basis of different aspects. The mathematical formulations of the EVRP and its basic variations are given, the most successful solution approaches are presented, useful problem datasets for the EVRP are summarized, and computational tests comparing several successful approaches are discussed. Considering current studies on the EVRP, the following conclusions and future research directions can be expressed:

- As in the traditional vehicle routing problems, most of the researches related with EVRP aim to minimize distance-based performance metrics while a few of them take into account the total consumed energy or the number of used charging stations. With growing interest in green logistics concepts, the objective functions more related to the consumed energy or charging operations are of interest to be studied in the EVRP. However, in practice, a logistics company is primarily concerned with the bottom line. Therefore, the real-life objective in most applications is to minimize the total cost, which consists of the energy usage, driver cost, and vehicle cost. Energy usage is a function of distance, speed, vehicle load, and vehicle type. Driver cost is dependent on the total route duration, and special attention should be given to possible overtime costs. Vehicle cost can be addressed in a primary objective that minimizes the number of vehicles or minimizes the weighted number of vehicles of a given type. Alternatively, vehicle cost can be expressed as depreciation which is a function of distance and vehicle type. These objectives can be combined in a single objective expressed in monetary terms.
- In almost all works, the amount of energy consumed by an electric vehicle for a given distance is determined by using a constant energy usage per distance unit. However, in real-life driving conditions, the energy consumption amount of an electric vehicle is affected by different conditions, such as road conditions, traffic conditions, weather conditions, driver performance, and topography, and vehicle load. Therefore, these conditions should be taken into account to obtain more realistic results for the route plans. Furthermore, regeneration of the energy while going downhill or braking is possible and should be taken into account. Moreover, the energy usage of heating or air conditioning systems of the electric vehicles with respect to weather conditions can be analyzed. Since optimization algorithms will optimize to the limit, some routes will have battery levels nearing zero when arriving at a charging station or depot. Therefore, disregarding or oversimplifying energy consumption aspects has a large probability of resulting in routes that are infeasible to execute in practice. Since it is impractical to model energy usage exactly in large-scale applications, it might be interesting to

investigate when such infeasibilities appear when simplifying some aspects. This can then be used to determine a safety buffer on the battery dependent on the EVRP instance type or even route characteristics.

- Heterogeneous fleets consisting of different types of pure electric vehicles should be analyzed by taking different technical details of electric vehicles into account. Moreover, a mixed fleet of conventional and pure electric vehicles is a relevant research topic since it seems more applicable for the logistics companies in the coming years, considering that any shift to electric vehicles will be gradual. Additionally, as several cities in Europe are introducing low-emission zones, additional benchmark instances are required where certain (geographically clustered) customers are allowed to be served only by electric vehicles.
- As in the energy consumption computations, the charging amounts or times at the charging stations are computed by using a constant rate in most of the papers. Yet, the charging amount of the electric vehicle is not linearly proportional to the charged battery level (Margaritis et al., 2016; Rahman et al., 2016). Non-linear formulations for the charging operations at stations should be adopted to better approach reality.
- In addition to the computations for the charging operations, different charging technologies can be considered for the charging plans. Depending on the charging power, charging technologies are divided into three levels: Level I-III (Awasthi et al., 2017). Level I and Level 2 are referred to as slow or normal charging modes, while Level III is a fast charging mode, and its usage is typically limited to public charging stations (Xu et al., 2017). Regarding the different charging technologies, charging operations at customer locations should be studied more comprehensively by analyzing their limitations, required investments, and efficiency.
- Using non-linear calculations for the energy consumption amounts or charging times considerably increases the computation times of the algorithms. Especially for large-sized instances, long computational times are required to achieve a satisfactory result. To reduce redundant computations, heuristic solution approaches should be enriched by preprocessing steps. Providing an efficient preprocessing, some non-linear calculations can be avoided during optimization but retrieved from a “distance” matrix.
- Besides the battery capacity of the electric vehicles, vehicle capacities and time windows of the customer nodes are typically considered in the EVRP. Station capacity, duration time of the vehicles, and simultaneous routing and siting are investigated in a

limited number of works. However, other real-life constraints for the EVRP pose interesting research challenges. Investigating the synergy of abiding by legal break time rules for the drivers and scheduling charging operations during such breaks could yield interesting insights. Furthermore, allowing charging operations before, during, or after service can be another future research topic. Of course, considering such additional decisions requires more realistic benchmark instances, and providing such (large-scale) benchmarks can be a valuable contribution to the literature by itself.

- It should be noted that LNS/ALNS, VNS/AVNS, GA, and TS/ATS/GTS based heuristic approaches are capable of finding high-quality solutions for the existing EVRP problems in computational times acceptable in practice. As the problems get larger or more complex, improving these algorithms or devising new schemes remain worthwhile research endeavors. Additionally, existing local search or station insertion procedures should be studied to improve their efficiency. As parallel computing becomes ever cheaper and easier, research in effectively parallelizing EVRP local search algorithm is warranted.

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