Sustainable Cities and Society 70 (2021) 102883

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Optimization of electric vehicle recharge schedule and routing problem with time windows and partial recharge: A comparative study for an urban logistics fleet

Ugur Bac [a,*], Mehmet Erdem [b]

[a] Department of Industrial Engineering, Faculty of Engineering, Atilim University, Incek, 06836, Ankara, Turkey
[b] Department of Industrial Engineering, Faculty of Engineering, Ondokuz Mayis University, Samsun, Turkey

ARTICLE INFO

Keywords:
Electric vehicle routing
Electric vehicle recharge scheduling
Urban logistics fleet
Optimization
Heuristics

ABSTRACT

The use of electric vehicles (EVs) is becoming more and more widespread and the interest in these vehicles is increasing each day. EVs promise to emit less air pollution and greenhouse gas (GHG) emissions with lower operational costs when compared to fossil fuel-powered vehicles. However, many factors such as the limited mileage of these vehicles, long recharging times, and the sparseness of available recharging stations adversely affect the preferability of EVs in industrial and commercial logistics. Effective planning of EV routes and recharge schedules is vital for the future of the logistics sector. This paper proposes an electric vehicle routing problem with the time windows (EVRPTW) framework, which is an extension of the well-known vehicle routing problem (VRP). In the proposed model, partial recharging is considered for the EVRPTW with the multiple depots and heterogeneous EV fleet and multiple visits to customers. While routing a set of heterogeneous EVs, their limited ranges, interdependent on the battery capacity, should be taken into consideration and all the customers' deliveries should be completed within the predetermined time windows. To deal with this problem, a series of neighbourhood operators are developed for the local search process in the variable neighbourhood search (VNS) and variable neighbourhood descent (VND) heuristics. The proposed solution algorithms are tested in large-scale instances. Results indicate that the proposed heuristics perform well as to this problem in terms of optimizing recharging times, idle waiting times, overtime of operators, compliance with time windows, number of vehicles, depots, and charging stations used.

1. Introduction

Transportation specifications in a country are highly related to the development level of its economic and social attributes. Although the contribution of transportation to humanity is crucial, its negative effects on human life and the environment cannot be ignored. The majority of the current conventional transportation vehicles are highly dependent on the fossil fuels, which causes an increase in the greenhouse gas (GHG) emissions. Even though there are green transportation alternatives exist, their numbers are still limited especially in developing countries. Not only for the environmental issues such as climate change and pollution, but also for limited fossil fuel dependency concerns lead the governments, officials, and organizations to take precautions to decrease the usage of these fuels or put limits on emissions. The European Commission (European-Commission, 2011) released a bill framing the transportation in 2011 to define their goals for a competitive and efficient energy system by accomplishing emission-free urban freight transportation by 2030. According to this paper, The European Commission's goal is to half the use of conventionally fueled vehicles in the mid-term and phase them out by 2030 in urban freight transportation. EVs are already being favored by shared car services (Melendez, Das, & Kwon, 2020) and public transportation (Yao, Liu, Lu, & Yang, 2020). However,

Abbreviations: ACS, ant colony system; AFV, alternative fuel vehicles; ALNS, adaptive large neighborhood search; BC, branch-and-cut; BPC, branch-price-and-cut; CA, construction algorithm; CVRP, capacitated vehicle routing problem; EV, electric vehicle; EVRPTW, electric vehicle routing problem with time windows; EVRPTW-PR, electric vehicle routing problem with time windows and with partial recharge; GA, genetic algorithm; GHG, greenhouse gas; GVRP, green vehicle routing problem; LB, lower bound; SA, simulated annealing; TS, tabu search; VND, variable neighbourhood descent; VNS, variable neighbourhood search; VRP, vehicle routing problem; VRPTW, vehicle routing problem with time windows.

* Corresponding author.
E-mail address: ugur.bac@atilim.edu.tr (U. Bac).

https://doi.org/10.1016/j.scs.2021.102883
Received 6 October 2020; Received in revised form 20 March 2021; Accepted 22 March 2021
Available online 26 March 2021
2210-6707/

this strategy is not reliable for countries, in which main electricity production methods give rise to intense GHG emissions (Alves, Baptista, Gonçalves, & Duarte, 2016), which brings the problem of efficient usage of these vehicles by planning recharge cycles accurately.

Many studies in the literature are focused on personal EV-usage-related issues; however, focusing on studies aimed at commercial and freight logistics problems is also crucial (Forrest, Kinnon, Tarroja, & Samuelsen, 2020; Mirhedayatian & Yan, 2018). Studies in the literature indicate that the distance covered for the urban deliveries is considerably lower and more suitable for electric vehicles (EVs) and this is an opportunity to support a cleaner transportation system (Afroditi, Boile, Theofanis, Sdoukopoulos, & Margaritis, 2014).

In the USA, many logistic companies such as DHL, UPS, and FedEx have already employed EVs in their fleet for deliveries in urban areas (Schneider, Stenger, & Goeke, 2014). The EVs are more competitive and cheaper than conventional diesel trucks if they are utilized more than 60 miles per day (Feng & Figliozzi, 2013). Moreover, most urban logistics vehicles operate in peak-hours, remain idle for long times, and have more frequent accelerations/decelerations to satisfy deliveries' deadlines, which increases the GHG emissions exponentially (Zhao, Ercan, & Tatari, 2016). More than 50% of the world's population is located in urban areas, and urban freight transportation accounts for 25% of CO_2 emissions and 30–50% of other transport-related pollutants in cities (Muñoz-Villamizar, Santos, Montoya-Torres, & Velázquez-Martínez, 2020). Using EVs in urban transportation can easily help with the solution to these problems and contribute to solving the problem as an eco-efficient solution by decreasing the GHGs. However, the long charging time of EVs is the main drawback of this strategy, the side effects of which can be reduced with effective logistics planning. Logistics planning involves routing and assignment issues, and it is represented as a vehicle routing problem (VRP) (Cordeau, Laporte, Savelsbergh, & Vigo, 2007). An effective routing optimization can increase the efficiency of vehicles used and reduce emissions drastically (Hannan et al., 2020). The capacitated VRP (CVRP) and VRP with time windows (VRPTW) are an extension of the traditional VRP. However, EVs require additional optimization parameters since they need time-consuming recharging cycles (Tu, Gai, Farooq, Posen, & Hatzopoulou, 2020; Zhao, Ma, Zhang, Wang, & Wang, 2019). Logistics planning, especially the planning of EVs' routes and recharge schedules, is the most crucial energy management strategy for companies using EV logistics (Guo, Wang, & Li, 2019). Route and recharge optimizations result in more efficient energy consumption and make these vehicles a more sustainable option for logistics. Erdoğan and Miller-Hooks (2012) derived the green vehicle routing problem (GVRP) from the CVRP perspective, considering the alternative fuel vehicles (AFVs) that can be refueled along their route. Similarly, Schneider et al. (Schneider et al., 2014) defined the electric VRPTW (EVRPTW), in which EVs were utilized instead of AFVs.

Efficient use of EVs is vital for their future in the logistics sector to seize energy-saving opportunities (Faria, Moura, Delgado, & de Almeida, 2012), which can be achieved by optimizing EVs' distribution routes by considering recharging constraints. In this study, an extension of the EVRPTW problems, including the partial recharge possibility of EVs – having been developed, and an EVRPTW with partial recharge (EVRPTW-PR) framework is introduced with realistic constraints and novel solution heuristics in the field. The proposed framework takes into account multiple depots, heterogeneous EVs fleet, and multiple visits. In real-life applications, customers are served from any of the geographically located depots in different locations (Desaulniers, Lavigne, & Soumis, 1998; Montoya-Torres, Franco, Isaza, Jiménez, & Herazo-Padilla, 2015). Furthermore, customers also demand a different number of deliveries within different time windows (Brandão & Mercer, 1998; Cattaruzza, Absi, & Feillet, 2016). In this case, vehicles could carry out more than one visit to the same location at different times. In the proposed model, the speeds, load capacities and energy consumptions of different types of EVs are also taken into consideration (Yao et al., 2020) to make the model more real-life compatible as much as possible.

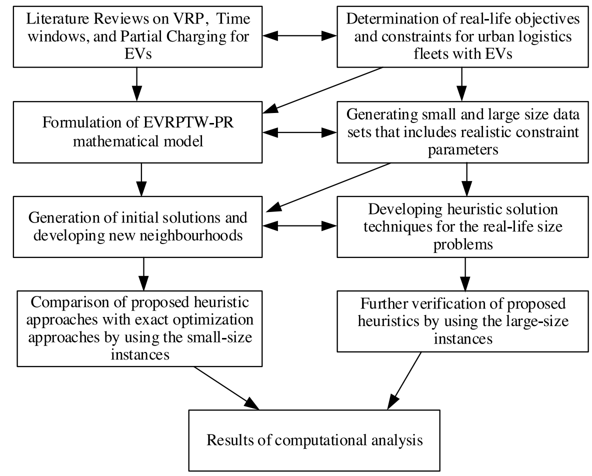

Fig. 1. The framework of the study.

This paper aims to propose different solution approaches to the EVRPTW-PR based on variable neighbourhood search (VNS) and variable neighbourhood descent (VND) algorithms. The proposed solution in the EVRPTW field involves a series of newly developed neighbourhood structures that offers a higher diversification capacity. Moreover, it was evaluated on randomly generated small, medium, and large-size instances by carrying out comparisons through exact global optimal solutions in each instance to validate the efficiency and effectiveness of proposed algorithms. The framework of the study is summarized in Fig. 1.

The rest of the paper is organized as follows: first, the relevant literature review is presented in Section 2; then, the proposed mathematical model is introduced in Section 3; next, the solution approaches based on the VNS and VND are explained with their proposed neighbourhood structures in Section 4; thereafter, computational results are presented in Section 5; finally, conclusions and suggestions for future work are presented in Section 6.

2. Literature review

Conrad and Figliozzi (Conrad and Figliozzi (2011)) studied a VRP based recharging formulation model. The EVs are recharged at the locations of customers by allowing a specified partial charge level. Their hierarchical objective is to minimize the number of routes (vehicles) and total costs consisting of distance, duration, and recharging. Erdoğan and Miller-Hooks (Erdoğan & Miller-Hooks, 2012) formulated the GVRP with AFVs such as biodiesel, hydrogen, natural gas, and electricity. These vehicles have limited ranges and must be refueled on alternative fuel stations to satisfy customers' demands on time. They aim to minimize total traveling distance. Koç and Karaoğlan (2016) proposed an approach based on simulated annealing (SA) and branch-and-cut (BC) algorithms. SA is a heuristic technique used for optimization problems based upon the process of physical annealing. Its main feature is accepting worse solutions to escape local traps in the search solution space. Zhang, Gajpal, and Appadoo (2017) applied two solution methods for the problem; a two-phase heuristic and ant colony system (ACS) algorithm for the capacitated GVRP. ACS is a probabilistic technique and inspired by the behavior of ants. Employing their pheromone-based communication, ants can find the shortest path between their home and their food sources. Hence, this nature-inspired algorithm is used to tackle with the combinatorial optimization problems. Schneider et al. (2014) proposed a hybrid solution approach covering the VNS and tabu search (TS) algorithms for the EVRPTW. Among these methods, VNS depends on the systematic change of neighbourhood amongst the descent to local minima and the escape from the traps. On the other hand, TS is one of the most popular local search techniques, and it allows to accept worse solutions to escape from being trapped in a local optimum solution similar to SA. The authors consider that EVs are fully charged in the initial state and the time when vehicles visit the charging station in their problem. The final charge level of vehicles is not considered since, at this point, all routes are completed. Their solution approach is also accepting worse solutions by employing the Metropolis probability function. While the shaking procedure was achieved by a cyclic-exchange operator in the VNS algorithm, the local search was achieved by 2-opt, exchange, swap, and charge station insertion operators in the TS. Keskin and Çatay (2016) developed an adaptive large neighbourhood search (ALNS) heuristic for the same problem. ALNS covers a series of destroy and repair heuristics. In each iteration, their weights are updated dynamically in terms of the contribution to the objective. In addition, it allows using multiple neighbourhoods in the improvement phase. A set of homogenous fleets with fixed loading capacities, fixed ranges, and one depot are considered in the problem. Although their model was based on the single EV, they defined a set of constraints for allowing a partial recharging strategy instead of a full recharging strategy.

Hiermann, Puchinger, Ropke, and Hartl (2016) formulated the electric fleet size and mix VRPTW, in which vehicles have a different battery and load capacities and different acquisition costs. The objective of the proposed model is to minimize total distance and acquisition cost. The authors consider the full charge approach of vehicles as in the study of Schneider et al. (2014). A hybrid approach is developed based on ALNS with a labeling procedure and a local search for the problem. Moreover, the electric and conventional vehicles were also considered in the same problem (Goeke & Schneider, 2015). Moreover, energy consumptions of these vehicles were calculated by regarding speed, load, and gradient factors instead of employing a linear function. In contrast to the existing works in the literature which employed linear recharging function, Montoya, Guéret, Mendoza, and Villegas (2017) considered the nonlinear recharging for the EVRP. This was achieved by using a piecewise linear approximation.

Another type of EV-related problem is the location selection of charging stations. There are a variety of studies in the literature for the solution of this problem utilizing different approaches from multi-criteria decision making models (Feng, Xu, & Li, 2021; Wang, Li, Xu, & Li, 2020) to genetic algorithm (GA) applications (Pan, Yao, Yang, & Zhang, 2020). GA is a population-based meta-heuristic and reflects the process of natural selection. It aims to yield better solutions to optimization problems based on crossover, mutation, and selection operators. Schiffer and Walther (2017) proposed a model for routing EVs and deciding on the locations of charging stations. Their model considered time windows, demand, and capacity as constraints. Moreover, partial recharging and recharging at the location of customers were also taken into consideration. Desaulniers, Errico, Irnich, and Schneider (2016) defined four different strategies: single-full, single-partial, multiple-full, and multiple-partial recharging for the EVs in the EVRPTW literature, which were solved by branch-price-and-cut (BPC) algorithms. Li, Huang, and Mason (2016) proposed a multi-period recharging station location model for EVs. The objective is to minimize recharging stations' total cost and relocate recharging stations for a predefined period. Felipe, Ortuño, Righini, and Tirado (2014) formulated a mathematical model for the GVRP with different partial recharging strategies employing series of technologies. The objective is to minimize recharging costs consisting of variable and fixed components. A greedy generation method based constructive algorithm was used for the initial feasible solutions. Deterministic local search, which covers series of operators such as recharge relocation, 2-opt, reinsertion and combination of these three operators, is used in the SA. It is reported that partial strategies and recharging technologies provides efficiency not only about energy, but also the cost. The authors also found that the location of the depot is important. On the other hand, the number of recharging stations has limited effect on the results.

Optimization problems in the field of EVRP deal with the decisions taken, such as energy consumption, recharging strategies, battery capacity, and the charging infrastructure. In most of the studies, it is considered that there is a linear relationship between energy consumption and traveled distance. The battery capacity is a crucial component that restricts the range of EVs. Moreover, the number of recharging stations is limited and is scattered in different geographical locations. Also, it is assumed that recharging stations' capacity is unlimited in most of the existing studies in the literature. In addition, the customer sites are considered as recharging stations in some studies (Montoya et al., 2017). In the EVRP literature, there are two types of recharging policies: full and partial recharging. Charging infrastructures, on the other hand, categorized as traditional charging infrastructures, fast-charging stations, and battery swapping stations (Sachan, Deb, & Singh, 2020). However, battery swapping solution also causes additional problems such as the transportation of batteries between the charging station and swapping stations and their charging schedules (Sayarshad & Mahmoodian, 2021). After visiting the recharging stations, the battery capacity is assumed to be complete in full recharging policy, which is not the case in real-life. This assumption is widespread in studies focusing on home charging of personal use EVs (Duman, Erden, Gönül, & Güler, 2021). In the full recharging policy, some of the authors consider that recharging time is fixed (Conrad & Figliozzi, 2011; Erdoğan & Miller-Hooks, 2012; Montoya, Guéret, Mendoza, & Villegas, 2016; Sayarshad, Mahmoodian, & Gao, 2020) because the depleted battery is allowed to be swapped with a full one. Furthermore, the rest of the authors (Desaulniers et al., 2016; Goeke & Schneider, 2015; Hiermann et al., 2016; Schneider et al., 2014) assume that the recharging time depends on the battery level and recharging technology. The battery swapping approach is not suitable to be employed in commercial or industrial fleet logistics cases for the time being because of the installation space requirements of this alternative recharging strategy (Zhang et al., 2020). In partial recharging policy, the charge level is determined by the aforementioned model. Hence, the recharging time is decided by the model above (Desaulniers et al., 2016; Felipe et al., 2014; Keskin & Çatay, 2016; Škugor & Deur, 2016). Allowing partial recharging also proved to have a profitable effect on the number of charging stations needed to supply the demand (Sa'adati, Jafari-Nokandi, & Saebi, 2021).

This study's contribution to the field of EVRPTW-PR can be summarized as follows: The proposed framework carries out some of the extensions of current studies for considering real-world applications. In the proposed EVRPTW-PR model, a customer can be visited multiple times. In other words, a customer may request more than one visit. The heterogeneous fleet can also be distributed across multiple depots, and the EVs have different load capacities, cruising ranges, speeds, and recharging times. It is evident that the number of recharging stations is limited in real-life. Thus, each EV is allowed to visit more than one recharging station if needed, which means different partial recharging levels are allowed for each EV. This kind of approach is also efficient to prevent inducing an overload on the city's power grid at peak hours (Brinkel, Schram, AlSkaif, Lampropoulos, & van Sark, 2020; Gong, Cao, Liu, & Zhao, 2020) by distributing the fleet's recharging schedule throughout different hours of the day. Instead of considering only total traveled distance as an objective function, as many studies do, a multi-objective function is developed in this study based on unit-times as in the work of Gao, Zhou, Amir, Rosyidah, and Lee (2018). The deviation from the predetermined time windows of customers and the EV drivers' overtime work are also taken into consideration in the proposed model. Besides, the objective function involves minimizing the total time of the EVs and minimizing the number of unscheduled visits. Furthermore, the EVs' traveling times have been generated randomly considering traffic conditions and other realistic delay assumptions. Likewise, demands of customers, duration of services, and time windows were generated in similar ways.

In order to solve the problem, many of the authors developed metaheuristic solution procedures. The population-based algorithms are GA (Li et al., 2016) and ACS (Zhang et al., 2017). Local search-based algorithms are as follows SA (Felipe et al., 2014; Koç & Karaoğlan, 2016), VNS and TS (Schneider et al., 2014), ALNS (Hiermann et al., 2016; Keskin & Çatay, 2016). When we consider the exact solution procedure, we observe that BC (Koç & Karaoğlan, 2016) and BPC (Desaulniers et al., 2016) are employed. These methods involve series of different relaxation procedures used to solve combinatorial optimization problems. The combination of exact solution procedures and heuristics are also applied in some studies (Hiermann et al., 2016).

Proposed solution approaches in this study are based upon the VNS and VND algorithms, evaluated by using a set of small, medium, and large-size instances (up to 750 EVs and 4,000 visits) with a varying number of depots and recharge stations. Within the algorithms, the proposed new neighbourhood structures, which have not been used in the field of the EVRPTW, not only provide the improvement of objectives but also minimize the total number of EVs at the same time. The proposed local search process covers dynamic neighbourhood change (Prandtstetter, Raidl, & Misar, 2009), which means that neighbourhood routes change dynamically according to the improvement made in the objective. Furthermore, during the local search process, infeasible solutions are also accepted. The maximum number of iterations is the only parameter of the VNS algorithm, and this makes the proposed approach free from the parameter selection process.

3. Problem definition and mathematical model

The EVRPTW-PR framework involves routing the EV to satisfy the customers' demands within specific time windows while minimizing the total time, overtime, deviation from time windows, and the number of unscheduled visits. The mathematical formulation is based on Schneider et al. (2014) for the EVRPTW, and Keskin et al. (Keskin & Çatay, 2016) for the EVRPTW-PR. Since available studies are an extension of VRP, costs of vehicles, total traveling time, and its related costs are the major foci of these studies. Moreover, energy-related considerations such as fuel costs, recharge costs, battery swap costs, and station-visiting costs are considered as the objective function components. On the other hand, customers' waiting times and delays due to long recharging times are not considered. In real-life, companies run their operations with a limited number of vehicles. In addition, the fact that the possibility of some visits not being performed with a limited number of EVs has been ignored in the literature. In terms of constraints, current studies cover a series of routing and time-related constraints and charging constraints.

On the other hand, available studies ignore real-life circumstances such as; multiple depots as route starting points and multiple visits to customers, in addition to the heterogeneous fleet structure. To the best of our knowledge, EVRPTW-PR problem defined in our study, which covers all of these mentioned missing features, has not been addressed in the literature before. Furthermore, we developed a set of problem-specific neighbourhoods for the local search process used in heuristics.

One of aforementioned novel features of this study is the consideration of heterogeneous fleet structure. In our proposed framework, the demands of the customers are supplied by a heterogeneous fleet of EVs with different battery and load capacities. Hence, the EVs have different ranges and speeds and can visit recharging stations to be recharged partially. Besides, different partial recharging levels are allowed for each EV in our study, which is another novel approach when combined with a heterogeneous fleet structure. Moreover, it is assumed that the charging duration depends on the EVs battery capacity. For a feasible solution, we considered the following real-life assumptions, which contribute to the originality of our study, such:

- Each customer can be visited multiple times;
- If the EV reaches a customer before the starting (job) time window, it must wait there, which may create an idle time penalty;
- The EV cannot work before its time windows, and if it arrives at the depot after ending time windows, then overtime work is calculated;
- The load capacity of the vehicle cannot exceed;
- The EVs depart from their own depot with a full charge; they have the opportunity to recharge partially in any recharge station. However, EVs must return to their own depot at the end of the day;
- The load level of battery must always be positive and overcharging the battery is not allowed.

Table 1
Notations of the model.

Notation	Definition
Sets	
$SC=\{1,2,\ldots,C\}$	Set of customers
$SV=\{1,2,\ldots,V\}$	Set of visits
$SE=\{1,2,\ldots,E\}$	Set of EVs
$SS=\{1,2,\ldots,S\}$	Set of recharging stations
$SS'=\{1,2,\ldots,S'\}$	Set of dummy nodes indicating the multiple visits of SS
$SD=\{1,2,\ldots,D\}$	Set of depots
$VA_k=\{1,2,\ldots,V\}\bigcup SS'$	Set of all possible visits for EV k
$VA'_k=\{1,2,\ldots,V\}\bigcup\{l_k\}$	Set of all possible visits included start node of depot for EV k
$VA''_k=\{1,2,\ldots,V\}\bigcup\{l'_k\}$	Set of all possible visits included end node of depot for EV k
Parameters	
l_k, l'_k	Start and end nodes of depot k
s_{ijk}	Travelling time from visit i to visit j by EV k
a'_k, b'_k	Starting and ending time windows of EV k
a_i, b_i	Starting and ending time windows of EV i
d_i	Duration of visit i
r_k	Partial recharging rate of EV k
cr_k	Consumption rate of EV k based on travelling time
Y_k	Battery capacity of EV k
Q_k	Capacity of EV k
p_i	Demand of the visit i
S'	A large number
α_1, α_2	Scalarization parameters
Variables	
x_{ijk}	Binary variables, 1 if EV k moves to visit j after fulfilling visit i; 0 otherwise
us_i	Binary variables, 1 if a visit is unscheduled; 0 otherwise
c_{ijk}	Time between visit i and visit j by EV k including duration of visit i and waiting time
t_{ik}	EV k's actual starting time at the visit i
t_k	The depot's arrival time of EV k
o_k	Overtime work of EV k
Θ_i	Deviation from the predetermined time windows of visit i
dc_{ik}	Recharge duration at recharging station i of EV k
v_{ik}	Arrival time of EV k to visit i
e_{ik}	Waiting time of EV k before visit i
y_{ik}	Battery state of EV k in visit i
yp_{ik}	Battery state of EV k after visiting recharging station i
q_{ik}	Current load of EV k in visit i

Definitions of the sets, decision variables, and parameters used in the formulation are represented in Table 1. Let SC be a set of customers and SV be a set of requested visits of the customers. While SS denotes a set of recharging stations, SS' refers to a set of dummy nodes indicating the multiple visits of SS. There are different depots available and denoted as SD.

Let VA_k be the set of all possible visits for the vehicle k, and VA_k is defined as the SV and SS' union. l_k and l'_k represent the start and end depot nodes for vehicle k. While VA'_k represents the set of all possible visits with the start depot node, VA''_k denotes the set of all possible visits with the end depot node for vehicle k.

For each visit (a_i, b_i) and EV (a'_k, b'_k) are defined as time windows. There are two types of EV employed and different recharging rates (r_k), consumption rates (cr_k), and capacities (Q_k) are defined for each vehicle type. Moreover, the requested demand of each visit is defined as p_i. Two different types of EV have different speeds. Hence, the traveling time (s_{ijk}) depends on the speed of EVs. In addition, the maximum load and battery capacity of EV k are represented by Q_k and Yk, respectively.

The binary routing decision variable x_{ijk} is equal to 1 if the EV k moves to node j after visiting node i, and 0 otherwise. Similarly, if visit i cannot be covered, then a binary coverage variable us_i takes the values 1 and 0 otherwise.

For each EV, the starting time at the visit i and the depot's arrival time are calculated by t_{ik} and t_k, respectively. The arrival time of EV k to visit i is defined by the variable v_{ik}. Furthermore, the waiting time of EV k before visit i is stored in positive variable e_{ik} that is calculated by the difference between the actual starting time and the arrival time of EV k (t_{ik} - v_{ik}). The time cost (c_{ijk}) of EVs consists of traveling time (s_{ijk}) between two locations by vehicle k, including the duration of visit i (d_i) and waiting time (e_{ik}). If an EV arrives at the depot after covering all the assigned tasks later than their ending times (b'_k,), overtime occurs. The variables o_k hold the overtime work of a driver of vehicle k.

Customers desire to take the service at the beginning time of the time window. It is also considered a favored starting time. If an EV arrives late, the customer waiting duration is penalized, as in real-life, to consider customer satisfaction. The penalty for this waiting time for each late visit should be calculated in the objective. For this purpose, we used the positive variable Θ_i in the objective function. It represents the deviation from the predetermined customer time window of visit i.

The battery state of EV k in visit i and its battery state after visiting recharging station i are denoted as y_{ik} and yp_{ik}, respectively. Variable dc_{ik} is the recharge duration at recharging station i of EV k. The variable q_{ik} is the current load of EV k in visit i.

Mathematical model is given as follows:

$$Min \overbrace{\sum_{k\in SE, i\in VA'_k, j\in VA''_k, i\neq j} c_{ijk}x_{ijk} + \sum_{i\in SS', k\in SE} dc_{ik}}^{\text{Total time}} + \overbrace{\sum_{i\in SV}\theta_i}^{\substack{\text{Time windows}\\ \text{Deviation}}} + \overbrace{\alpha_1\sum_{i\in SV} us_i}^{\text{Unscheduled jobs}} + \overbrace{\alpha_2\sum_{k\in SE} o_k}^{\text{Overtime}} \quad (1)$$

$$\text{st.} \sum_{k\in SE}\sum_{j\in VA_k, i\neq j} x_{ijk} + us_i = 1 \quad \forall \mathrm{i} \in SV \quad (2)$$

$$\sum_{j\in VA_k, l_k\neq j} x_{l_k jk} = 1 \quad \forall \mathrm{k} \in SE \quad (3)$$

$$\sum_{i\in VA_k, i\neq l'_k} x_{il'_k k} = 1 \quad \forall k \in SE \quad (4)$$

$$\sum_{i\in VA'_k, i\neq j} x_{ijk} = \sum_{i\in VA''_k, i\neq j} x_{ijk} \quad \forall k \in SE, \forall j \in VA \quad (5)$$

$$a'_k \leq t_{ik} \leq b'_k \quad \forall k \in SE,\ \forall i \in VA'_k \quad (6)$$

$$a_j \leq t_{jk} \leq b_j \quad \forall k \in SE, \forall j \in VA_k \cup \{l_k, l'_k\} \quad (7)$$

$$t_{ik} + (s_{ijk} + d_i)x_{ijk} \leq t_{jk} + b_i(1 - x_{ijk}) \quad \forall k \in SE,\ \forall i,j \in VA_k \quad (8)$$

$$t_{ik} + s_{ijk}x_{ijk} + r_k(yp_{ik} - y_{ik}) \leq t_{jk} + (b_i + r_kY_k)(1 - x_{ijk}) \quad \forall k \in SE,\ \forall i \in SS',\ \forall j \in VA''_k, i\neq j \quad (9)$$

$$0 \leq y_{jk} \leq y_{ik} - s_{ijk}cr_kx_{ijk} + Y_k(1 - x_{ijk}) \quad \forall k \in SE,\ \forall i \in SV,\ \forall j \in VA''_k, i\neq j \quad (10)$$

$$0 \leq y_{jk} \leq yp_{ik} - s_{ijk}cr_kx_{ijk} + Y_k(1 - x_{ijk}) \quad \forall k \in SE,\ \forall i \in SS' \cup \{l_k\},\ \forall j \in VA''_k, i\neq j \quad (11)$$

$$y_{jk} \leq yp_{jk} \leq Y_k \quad \forall k \in SE, \forall j \in SS' \cup \{l_k\} \quad (12)$$

$$dc_{ik} \geq r_k(yp_{ik} - y_{ik}) \quad \forall k \in SE,\ \forall i \in SS' \quad (13)$$

$$q_{jk} \leq q_{ik} - p_ix_{ijk} + Q_k(1 - x_{ijk}) \quad \forall k \in SE, \forall i \in VA'_k, \forall j \in VA''_k, i\neq j \quad (14)$$

$$0 \leq q_{jk} \leq Q_k \quad \forall k \in SE, \forall j \in VA_k \cup \{l_k, l'_k\} \quad (15)$$

$$\left(\sum_{k\in SE} t_{ik} - a_i\right) \leq \theta_i \quad \forall i \in SV \quad (16)$$

$$o_k \geq t_k - b'_k \quad \forall k \in SE \quad (17)$$

$$v_{ik} = t_{mk} + d_m + s_{mik} \quad \forall k \in SE,\ \forall i \in VA_k,\ \forall m \in VA''_k \quad (18)$$

$$e_{ik} \geq t_{ik} - v_{ik} \quad \forall k \in SE, \forall i \in VA_k \quad (19)$$

$$c_{ijk} = d_i + s_{ijk} + e_{ik} \quad \forall k \in SE, \forall i \in VA'_k, j \in VA''_k, i\neq j \quad (20)$$

$$\theta_i \geq 0 \quad \forall i \in SV \quad (21)$$

$$o_k \geq 0 \quad \forall k \in SE \quad (22)$$

$$dc_{ik} \geq 0 \quad \forall k \in SE, \forall i \in SS' \quad (23)$$

$$e_{ik} \geq 0 \quad \forall k \in SE, \forall i \in VA_k \quad (24)$$

$$x_{ijk} \in \{0,1\} \quad \forall k \in SE, \forall i \in VA'_k, j \in VA''_k, i\neq j \quad (25)$$

$$us_i \in \{0,1\} \quad \forall i \in VA_k \quad (26)$$

Our aim is to find a good feasible solution that is convenient for customers, employees, and employers at the same time. Therefore, the objective function is developed in line with the demands and expectations of each party. The model's objective function is to minimize the total time (that involves travelling time, waiting time, and the durations of visit and recharging), the deviation from the time windows, unscheduled visits, and overtime works as given in Eq. (1). The total time consists of travelling time, waiting time, duration of visits and recharging time spent at stations. The travelling time is calculated according to the distance traveled between nodes. If the EV arrives at the customer location before the visit, it must wait until the starting time and a waiting time are recalculated. If the EV needs recharging, the time it waits at the recharging station is to be computed. Consideration of deviation from time intervals is defined as starting at the preferred starting time. In this way, it is ensured that customers receive service(s) with minimum delay in the time window they prefer. In other words, considering both EVs and customers' waiting times, the idleness of the vehicle and the minimization of customer dissatisfaction are taken into consideration. We aim to cover as many visits as possible; hence the number of uncovered visits is penalized as the fourth component of the objective. The last component counts the number of working times outside predefined time windows. All components of the objective function are measured in time units. Moreover, scalarization parameters (α_1 and α_2) are defined for the unscheduled visits and overtime works to obtain these components in the same units (in time units). Here, α_1 and α_2 are equal to the number of visits and the number of EVs, respectively.

Eqs. (2)–(4) cover connectivity constraints. Eq. (2) guarantees that each visit is covered by any EV or left unassigned, and the number of unscheduled visits is computed via this constraint. As mentioned before, unscheduled visits are penalized in the objective. Eq. (3) and Eq. (4) enforce each EV to start its own route from the depot, and after covering all assigned tasks, each EV returns back to its own depot. Eqs (3)–(4) keep track of departures from and arrivals at depots. Flow conservation is established by Eq. (5).

Eqs (6)–(9) cover the time constraints. Eq. (6) and Eq. (7) ensure that each EV can work in its own working time window, and each visit is performed within its predefined time window. Constraint (8) ensures the time feasibility for each EV k; in other words, it guarantees that starting time of node j (t_{jk}) has to consider the starting time of node i (t_{ik}), the duration of visit i (d_i), and travelling time between nodes i and j (s_{ijk}). If node i is a recharging station, Eq. (9) takes the recharge time into account.

Eqs (10)–(13) define charge constraints. In order to keep track of the battery charge level at each node, Eq. (10) and Eq. (11) are defined. The energy consumption is also considered with these when departing from any node. Additionally, consideration of maximum battery capacity and preventing overcharging are satisfied via Eq. (12). The energy consumption rate is a function of traveling time units (between two locations) that is dependent on the type of the EV. Traveling times and average consumptions of vehicles are calculated by considering the distances, speeds, and capacities of vehicles during the data generation phase of the study. Constraint 13 determines the duration of recharging in terms of recharging rate.

Eqs. (14)–(15) are related to capacity constraints of the heterogeneous fleet. Demands of customers are satisfied by employing Eq. (14). In other words, the load of the EV in the node q_{jk} is based upon the load of the previous node q_{ik} and the demand of the visit p_i. Eq. (15) ensures that the EVs' load capacity must not exceed their capacities of Q_k. As mentioned earlier, each visit has a time window, and one of the objective components is to satisfy the customer with a minimum delay/waiting time. Hence, we aim to visit customers after their earliest starting time. Because many customers regard the beginning time of the time window of a visit as a favored starting time. If an EV arrives late, the customer waits at a cost. In order to compute potential delays, we employ variable θ_i and constraint defined in Eq. (16) to ensure that each visit is achieved at the beginning of the time window. Variable θ_i is equal to the difference between the actual starting time of EV k at visit i (t_{ik}) and starting time of the visit i (a_i).

Overtime, arriving time, waiting time and time between two nodes are defined by Eqs (16)–(20). If an EV arrives at its own depot at the end of its route after ending time, overtime occurs. We introduced the positive variable o_k and defined it as the difference between arriving time and ending time window of vehicle k as shown in Eq. (17). The arriving time of EV k to node i is defined by the positive variable v_{ik}. Constraint defined in Eq. (18) ensures that the arriving time of EV k to node i has to cover the start time of previous node t_{mk} plus the duration of previous visit d_m in addition to the traveling time s_{mik} for EV k. Furthermore, if an EV arrives earlier, it must wait, and the waiting time of vehicle k before visit i is calculated with Eq. (19). The constraint stated in Eq. (20) ensures the time between two nodes (i, j) by vehicle k includes both duration of the visit (i) and waiting time. Therefore, it defines the cost coefficients of binary routing variables. Finally, nonnegativity constraints and the domains of the variables are defined by Eqs. (21–26).

4. Proposed heuristic EVRPTW-PR solution framework

Solution approaches developed for the EVRPTW-PR framework are based on the VNS and VND algorithms to solve a series of large-scale instances. The application of these heuristic approaches is a novel approach for EVRPs. While the VND algorithm involves deterministic neighbourhood change in the local search procedure, the VNS algorithm covers dynamic neighbourhood change along with changing the order of the neighbourhood according to the improvements in the objective function. First, the algorithms that are employed for the construction are presented. Then local search procedure with the newly developed neighbourhood (operators) is described. Finally, the shaking operators that are used in the VNS will be introduced.

Table 2
Cross, vertical, and horizontal neighbourhoods (operators) with its sequence in the local search.

Group	Operator	Sequence
Vertical	Swap of the EVs	1
Cross	Re-assignment of the recharge station	2
Cross	Re-assignment of the free EV	3
Cross	Insertion of the unscheduled visit	4
Cross	Destruction of the one-visit route	5
Cross	Insertion of the recharge station	6
Cross	Remove of the recharge station	7
Vertical	Swap of the visits	8
Vertical	Insertion of the visit	9
Horizontal	Swap of the visits	10
Horizontal	Shift of the visit	11

4.1. Variable neighbourhood search - variable neighbourhood descent

The EVRPTW-PR problem in this study is solved by using the VNS heuristic, which was introduced by Mladenović and Hansen (1997) as a local search algorithm. The procedure of the VNS is shown in Pseudocode A.1. in Appendix A. The systematic change of neighbourhood is the principal of the VNS algorithm. By employing a descend method, the VNS move to a local minimum, and by applying a shaking method the VNS escape from being trapped in a local minimum (Hansen & Mladenović, 2001; Hansen, Mladenović, Brimberg, & Pérez, 2010). The deterministic version of VNS is the VND that is also used for the improvement phase (or the local search procedure). The VND algorithm does not involve a shaking procedure as the VNS. The applications of the VNS can be found in a variety of fields, such as routing (Bräysy & Gendreau, 2005; Hansen et al., 2010; Jarboui, Derbel, Hanafi, & Mladenović, 2013), graph theory (Belhaiza, de Abreu, Hansen, & Oliveira, 2005), and scheduling (Aloise et al., 2006). In our implementation of VND and VNS, a series of different neighbourhood structures (N_k, $k = 1,2,\ldots,k_{max}$) are employed. Many of the applications in the literature consider only simple operators such as insert/remove recharging stations and swap/relocate customers. On the other hand, these structures provide a higher diversification capability when compared with the basic and simple operators in the available publications. The first step of the procedure involves generating a solution by using one of the construction algorithms, defining neighbourhood structures and the stopping condition (Pseudocode A.1). In the second step, a local search starts to improve the solution utilizing perturbation of the neighbourhood. VND takes initial solution x' and yields a local optimum (solution) x'' utilizing the nested neighbourhood strategy. If the value of x'' is better than the incumbent, the search continues with the same neighbourhood; otherwise, the search starts with the next neighbourhood. A random point is chosen from this structure in the shaking to avoid cycling. If the stopping condition is met, the search automatically stops. Furthermore, the procedure of VND is represented in Pseudocode A.2. in Appendix A. The deterministic neighbourhood change is achieved by means of the VND.

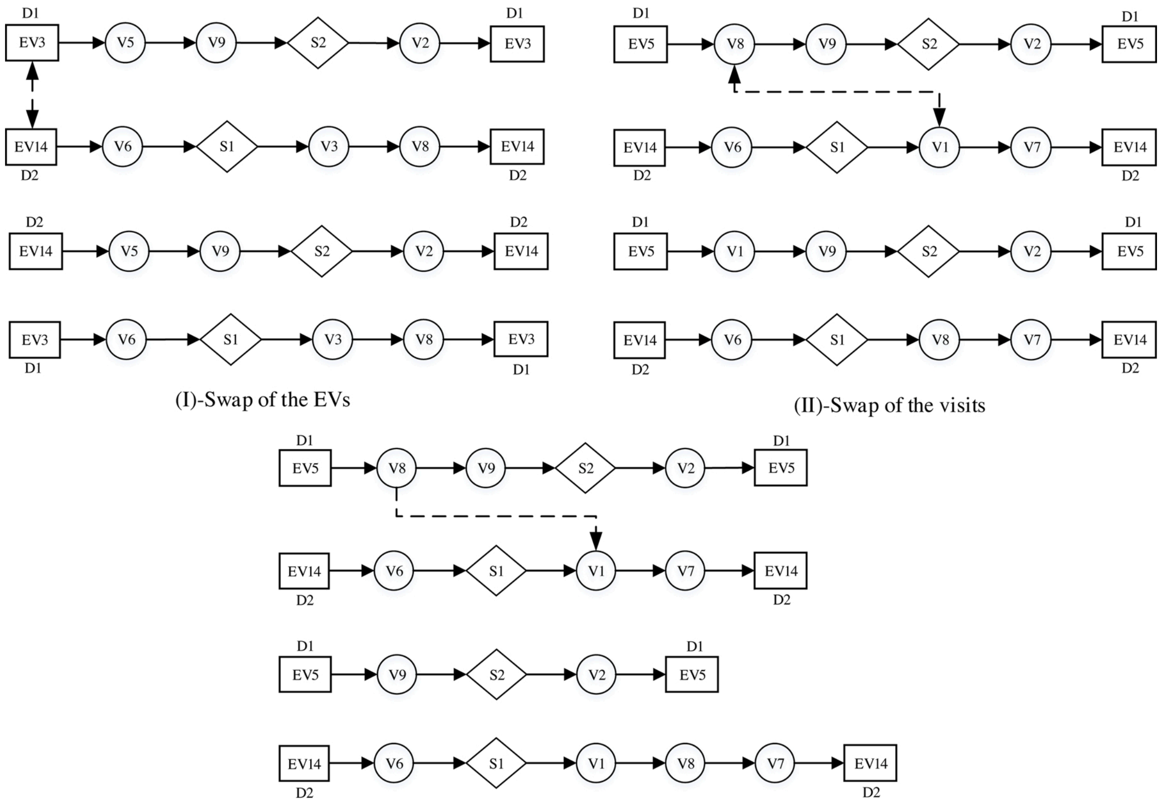

Fig. 2. Vertical operators.

4.2. Construction algorithms

Our solution approach starts with the generation of the initial solution, and then a heuristic initiates the improvement process. Thus, two types of construction algorithms (CAs) are proposed for finding the initial solution. The first one is the deterministic route construction heuristic (CA1) that starts routing with free minimum-indexed EV and tries to allocate the unscheduled minimum-indexed visit to this EV. The second one is the random route construction heuristic (CA2), which chooses EVs and visits randomly and assigns random visits to the randomly selected EVs. Both of the CAs do not necessarily allocate all the visits at the beginning; in other words, the improvement phase can start with the unscheduled visits. While the exact solution based on the initial solution covers all the visits, our heuristic solution approach can start with a more relaxed solution.

4.3. Neighbourhoods (operators) and local search procedure

The neighbourhoods (operators) applied for local search are designed for the VNS and VND algorithms. The definitions of the local search strategies are divided into three groups: vertical, cross, and horizontal operators, which will be later explained in detail, respectively. The sequence of these operators, which is determined according to the initial runs, is presented in Table 2. This initial sequence is also the same for the VNS and VND. As mentioned before, the VNS has a different local search procedure, in which the sequence of operators changes dynamically according to the improvement made in the objective function. The first improvement strategy is employed in the local search procedure.

4.3.1. Vertical operators

This group consists of three operators, *swap of the EVs*, *swap of the visits*, and the *insertion of the visit*. These legends are illustrated in Fig. 2. Here, rectangle, circular, and rhombus nodes represent EV, visit, and recharging stations, respectively. The name of the depot to which the vehicle belongs is indicated on the rectangle. Two different EVs are exchanged in the swap of the EVs (in Fig. 2-I). The swap of the EVs provides improvement by changing the routes of different vehicles. The swap of the visits changes the position of the assigned visits of different vehicles and assigns them by considering the load capacities of vehicles (in Fig. 2-II). This operator also takes into account the improvement of the objective function. The insertion of the visit is the last member of this group (Fig. 2-III). In this operator, any job assigned to any vehicle is selected and allocated to another vehicle. All these operators select vehicles and visits randomly.

4.3.2. Cross operators

This group consists of 6 operators, as illustrated in Fig. 3. After running either any of the CAs or any operators, some of the visits may be uncovered. Then *insertion of the unscheduled visit* becomes active so as to assign these visits to randomly selected vehicles (Fig. 3-I). This operator makes the unscheduled visits be a part of the solution. If the idle vehicle list has an element, *re-assignment of the free EV* (Fig. 3-II) operator initializes and selects an EV from the free vehicle list randomly. Then, it tries to swap all assigned visits to a selected working vehicle with the idle EV if there is an improvement on objective value. If the number of jobs assigned to the EV is only one, then *destruction of the one-visit route* (Fig. 3-III) tries to assign this visit by allocating another working EV. Attempts are made to improve the objective function by reducing the number of vehicles. This also contributes to the improvement of vehicle utilization by decreasing their numbers and indirectly improving cost efficiency, which encourages the logistics sector to utilize more EVs in their urban logistics operations.

Furthermore, a series of operators have been developed to arrange the EVs' charging status at any stage of the solution or to bring the EVs back to the depot after satisfying all demands with a minimum (battery) charge level. *Re-assignment of the recharge station* operator switches to the existing remote charging station by selecting the nearest charging

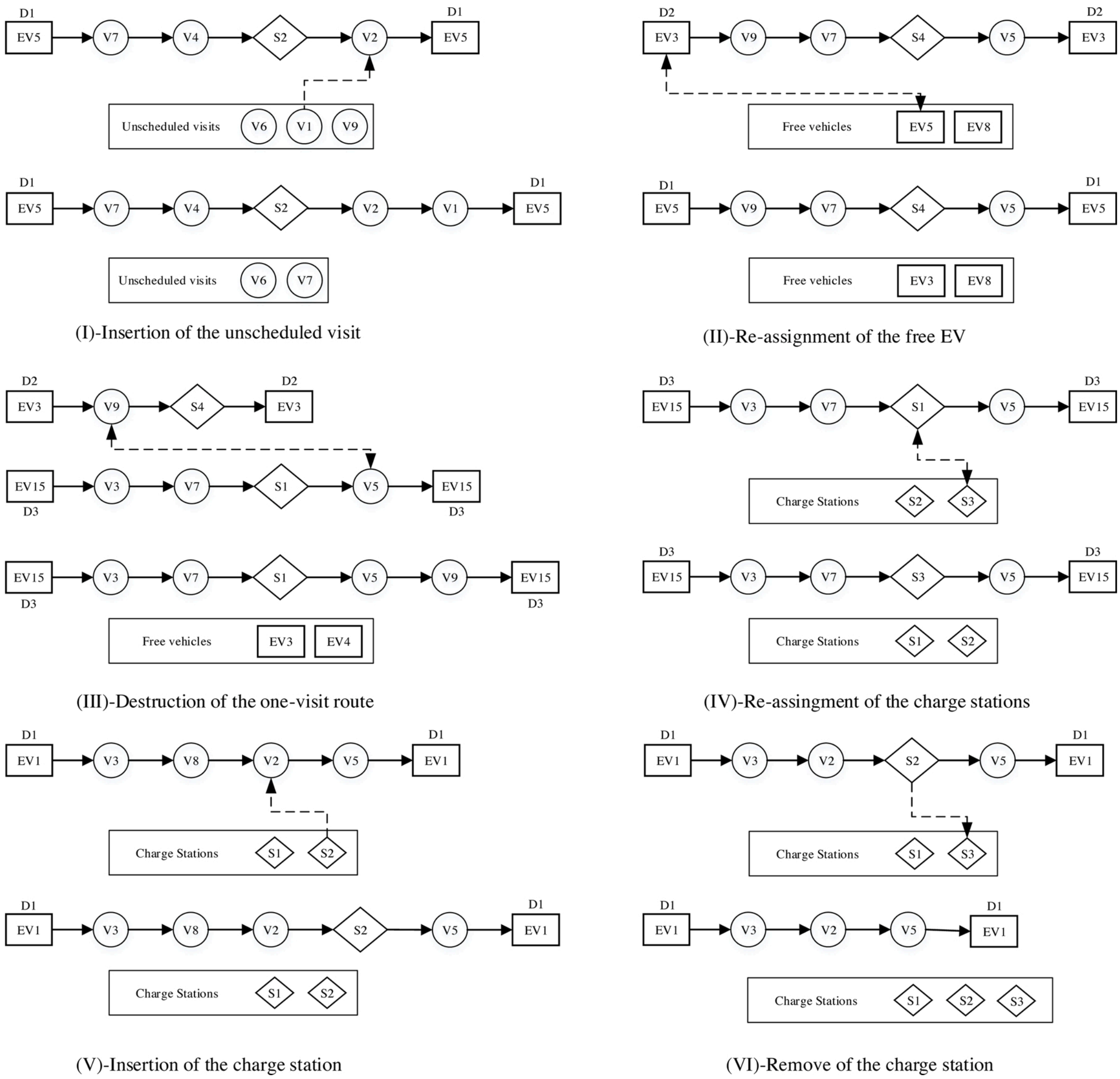

Fig. 3. Cross operators.

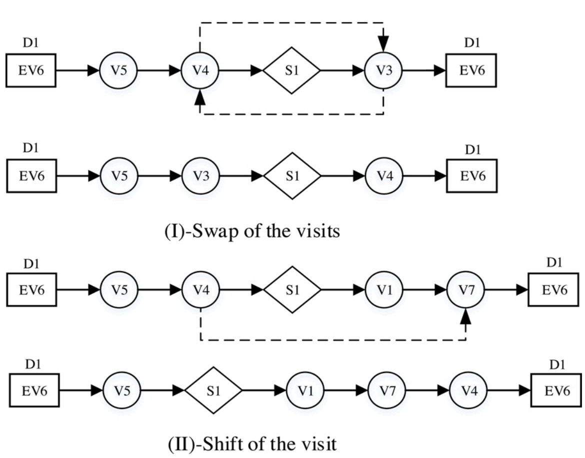

Fig. 4. Horizontal operators.

station that the EVs could visit along the route (Fig. 3-IV). The *insertion and removal of the recharge station* operators allow the EVs to keep the charge level between 1 and 100 and determine the number of recharging stations required/visited.

4.3.3. Horizontal operators

Horizontal operators are the last group that are represented in Fig. 4. *The swap of the visits* and *shift of the visit* operators provides improvements by changing the order of the assigned visits based on randomly selected EVs (Fig. 4-I-II).

4.4. Infeasibility

As mentioned before, in the field of EVRPTW, basic and simple operators such as insertion of recharging stations and swapping of visits and vehicles are used for the local search process. Therefore, in this field, several new operators, which are swap of the vehicle routes, re-assignment of the free EV, destruction of the one-visit route, and insertion of the unscheduled visit, are developed. They are used for the improvement of the objectives and for carrying out a local search in infeasible (i.e., ignoring negative charge and overcharge situations) and feasible regions. As the proposed VNS and VND algorithms seek better solutions within the infeasible region without introducing penalty costs, it is guaranteed that the improved solution is always within the feasible region.

4.5. Shaking

The local search and shaking procedures are performed iteratively in the VNS. For the perturbation move, the swap of the vehicle routes operator is employed to avoid being trapped in a local minimum. This operator changes the routes of vehicles if there is no better solution to be provided by the local search.

5. Computational Results

In this section, computational experiments of the proposed heuristic approaches for solving the EVRPTW-PR are explained. Firstly, the characteristics of benchmark instances used are described in Section 5.1. Then, comparisons of the results with the small-size benchmarks are given in Section 5.2. Finally, the solution and results of large-size EVRPTW-PR problems are given in Section 5.3.

Proposed VNS and VND algorithms were run on a PC with i7-5500 u CPU with 8GB RAM. Each benchmark instance has been run five times with a limit of 50000-maximum number of iterations. Results of heuristic solutions are presented as the average of these five runs for each instance. One of the advantages of the proposed VNS and VND algorithms in the proposed framework is being free from parameter settings and tuning processes.

5.1. Data sets

As mentioned before, some of the studies in the literature use the small-size benchmark instances, which were generated by Schneider et al. (2014). The authors created their instances based on the Solomon's (Solomon, 1987) VRPTW benchmark instances. Instances by Solomon consist of relatively small-sized samples. To test the effectiveness and efficiency of our proposed heuristics and to carry out more accurate comparisons with the exact solution approach, we generated new datasets accessible on Mendeley Data (Baç & Erdem, 2020). In addition to these small instances, which are used for comparison of proposed heuristics with exact solution approach, to test our heuristics' efficiency even further, our generated datasets also include medium and large-size problems. Moreover, our dataset covers additional realistic constraint sets to the extent of the applicability of proposed methods.

In contrast, our generated instances also involve a larger number of customers, visits, and EVs than the instances of Schneider et al., 2014Schneider et al. (2014). The traveling time, time windows, demands, service times are generated randomly. The issues such as traffic conditions, unknown demands, and delivery within unknown time windows are considered in our large-size instances. In other words, these features are generated for each instance in our datasets. After consulting local logistics companies, the most popular EV brands and models were determined and two types of EVs were selected for this study. Catalogue data of these vehicles are used to calculate their load capacities, battery capacities, charging times, and average consumptions (Electric Van & Truck, 2020; HVIP, C., 2021; Sokolsky, Silver, & Pitkanen, 2014; Today's Motor Vehicles, 2015). The estimated traveling times based on the type of EVs between locations were generated randomly considering the coordinates of specific zones in Ankara, Turkey. That is to say, the estimated traveling times depend on traffic conditions and type of EVs.

While generating the instances, it was considered that every 5 minutes is taken as 1 unit of time. For instance, four unit-times equals 20 minutes. Each type of EV has a different speed and capacity. Thus, the traveling times are uniformly distributed in (1,10) for Type 1 EVs and in (2,12) for Type 2 EVs. For instance, while traveling between two different locations/visits, it can take five unit-times for a Type 1 vehicle, the traveling time of the same distance can be eight unit-times for a Type 2 vehicle. This means that a Type 2 vehicle traveling at a slower speed and navigating in stop-and-go type urban traffic may arrive later and may consume more energy. In other words, many factors such as the speed, capacity difference, traffic conditions, and consumptions of each type of EV have been considered in the calculation of travelling times and charge levels, and our datasets are generated according to these variables by using the uniform distribution. Also, these EVs' consumption rates are different from each other according to their technical specifications (see constraints 9-13). Furthermore, the starting time of the time windows is uniformly distributed with a probability of 15% in (72,120), 15% in (120,144), 55% in (144,204), and %15 in.(204,240) (Wen, Linde, Ropke, Mirchandani, & Larsen, 2016). The time windows' ending time is computed by adding a uniformly distributed number in (5,50). Load capacities and battery capacities are generated according to these EVs' catalog data (Kaya, Alemdar, & Çodur, 2020; Oda, Aziz, Mitani, Watanabe, & Kashiwagi, 2018; Today's Motor Vehicles, 2015; Wen et al., 2016). Hence, they represent realistic values. While Type 1 EVs have 1300 kgs of load capacity and their recharging time is 72 unit-times (6 hrs.), Type 2 EVs have 2500 kgs of load capacity, and their recharging time is 66 unit-times (5.5 hrs.) (HVIP, C., 2021). In other words, consumption rates for one unit-time are 4% and 2% for Type 1 and Type 2 vehicles, respectively. As mentioned earlier, the EV with the larger load capacity has a faster recharge time because it has a different battery technology.

Table 3
The features of small-size instances.

I	Features				
	Number of				
	EV	C	V	D	S
S1	4	6	16	2	2
S2	4	6	16	2	4
S3	4	6	16	3	2
S4	4	6	16	3	4
S5	7	8	25	2	2
S6	7	8	25	2	4
S7	7	8	25	3	2
S8	7	8	25	3	4
S9	10	11	33	2	2
S10	10	11	33	2	4
S11	10	11	33	3	2
S12	10	11	33	3	4
S13	15	13	40	2	2
S14	15	13	40	2	4
S15	15	13	40	3	2
S16	15	13	40	3	4

I: instance, EV: number of EVs used, C: number of customers V: number of visits, D: number of depots, S: number of recharging stations.

Consideration of this difference enriches the dataset and increases the compatibility of our model with real-life situations. The time it takes to charge will also be limited by the maximum charging rate of the battery. In other words, an EV's battery can be charged at the maximum charge rate possible. Moreover, the customers' demands are uniformly distributed in (1,30) kgs. Then the service duration is calculated according to the demands. If the demand is between 1 and 5, it is considered as two unit-times. The rest of the service durations are considered as follows 2 (1-5), 3 (6-10), 4 (11-15), 5 (16-20), 6 (21-25), and 7 (26-30). A set of a small, medium, and large-size instances will be used to evaluate the proposed algorithms.

5.2. Results on the small-size instances

The performance of the proposed framework is first analyzed in the small-size instances. The results of the proposed solution approach, the VNS and VND algorithms, and the exact method results obtained by using CPLEX solver are then compared. The features of these instances are summarized in Table 3. The number of EVs, customers, visits, depots, and recharging stations are given for each instance. For instance, S1 involves four EVs, six customers, sixteen visits, two depots and two recharging stations. The difference between S1 and S2 is the number of recharging stations. These benchmark instances are generated

Table 4
Comparison results* with CPLEX, VNS, and VND.

	Exact		VND				VNS			
			CA1		CA2		CA1		CA2	
	Partial recharging level: 0.3									
I	OF	VU	OF	VU	OF	VU	OF	VU	OF	VU
S1	**128**	4	134.95	3.4	135.54	3.7	133.3	3.6	134.13	2.6
S2	**115**	3	119.93	3	118.45	3	121.11	2.8	119.5	2.4
S3	**115**	3	118.5	3	126.2	3	117.52	2	118.1	2.5
S4	**109**	4	114.4	3	109	3	115.1	2	109	2
S5	**169**	6	177.5	4.4	176.6	4	179.2	4	181.6	4.4
S6	**162**	5	167.6	4.3	162	5	169.1	3.9	187.5	4
S7	**173**	6	182.3	4	173	6	199.5	3.4	173	6
S8	**161**	4	175.6	4	170.4	4	214.5	3	185.5	4
S9	262.64	10	287.5	9.8	313.2	5.7	301.5	7	309.2	7.4
S10	338.6	6	348.8	6.2	344.1	7.4	362.1	6	352.4	6.2
S11	333.92	5	284.2	6	265.41	6	294.5	7	304.45	7.3
S12	301	7	254.5	7	251.17	5.5	264.3	5.8	248.8	6.5
S13	454.2	10	366.4	7.6	359.7	10.2	369	8.7	371.7	10.5
S14	330	10	335.5	8	342.2	9.6	336.4	8	348.91	8
S15	497	9	303.7	8.4	302.14	7	310.11	7.4	309.69	6.7
S16	374.04	10	297.94	9.6	289.84	8	304.53	7.6	311.9	8
Avg	251.46	6.38	229.33	5.73	227.43	5.69	236.99	5.14	235.34	5.53
	Partial recharging level: 0.4									
I	OF	VU	OF	VU	OF	VU	OF	VU	OF	VU
S1	**128**	4	132.11	3.4	129.14	3.9	132.2	2.7	144.1	2.4
S2	**115**	3	116.4	2.8	115	3	115	3	127.52	2
S3	**115**	3	116.23	2.7	115.2	3	121.5	2	121.34	2
S4	**109**	4	109.6	3.8	109	4	109	4	112.8	3.5
S5	**169**	6	170	6	169	6	188.4	4.6	170.5	5.6
S6	**162**	5	164.5	4.6	162	5	177.5	4.6	188.8	3
S7	**173**	6	192.36	4.4	190.2	4.1	193.2	4.3	198.89	3.8
S8	**161**	4	181.5	4	200.2	4	219.2	4	228.75	3
S9	315	10	288.8	9.6	282.8	9	310.5	7.5	302.4	7
S10	338.6	6	342.4	7.4	333.2	7	408.2	5.4	387.3	5
S11	225.88	7	249.5	5.8	225.5	7	224.8	7	261.2	6.8
S12	301	7	265.1	7	259.5	6	278.7	5.8	276.5	5.9
S13	454.2	10	360.4	8.4	347.43	8.9	352.22	9.5	364.4	8.4
S14	332	10	325.44	8	314.4	6.4	346.1	8.4	346.5	8
S15	321.28	7	311.92	8.2	314.76	8	344.47	7.3	338.94	6.7
S16	523.4	7	314.24	8.8	294.33	9.4	319.56	9.4	308.28	8.2
Avg	246.46	6.19	227.53	6.03	222.60	5.92	240.03	5.59	242.39	5.08
	Partial recharging level: 0.5									
I	OF	VU	OF	VU	OF	VU	OF	VU	OF	VU
S1	**128**	4	132.33	3.4	130.36	3.7	130.34	3.8	134.44	3.6
S2	**115**	3	115.4	3	116.2	3	115	3	121.4	2.2
S3	**115**	3	115.54	3	115	3	122.5	2	125.36	2
S4	**109**	4	111.1	2	109	4	109	4	109	4
S5	**169**	6	169	6	169	6	184.5	4	177.8	4
S6	177	5	162	5	162	4	183.3	3	234.4	4
S7	**173**	6	183.05	5	173	6	220.2	3	173	6
S8	**161**	4	194.2	4	180.4	4	208.51	3	180.4	4
S9	267	10	279.7	10	275.7	10	333.2	7	308.1	7
S10	338.6	5	346.6	6.1	338.4	7	375.5	5	398.5	5.2
S11	225.88	7	273.45	6.4	247.21	5	258.4	7	261.2	6.6
S12	301	7	248.5	7	257.1	5	250.2	6	239.4	7
S13	454.2	12	351.46	7.5	339.4	11.4	348.2	8.8	353.4	6.9
S14	289	8	335.5	8	340.4	8.4	342.69	8	343.8	7.6
S15	492.72	9	308.42	8	304.18	7	314.57	7.6	297.98	8
S16	361.40	9.00	221.75	8.30	217.16	9.40	233.07	9.50	230.55	10.20
Avg	242.3	6.375	221.75	5.79	217.16	6.06	233.07	5.29	230.55	5.52

I: instance, OF: objective function (in unit-times: 1unit = 5mins.), VU: number of EVs used, CA: construction algorithm

* Refers to the average computational results of five runs for heuristics.

considering the aforementioned real-life constraints and shared on Mendeley Data (Baç & Erdem, 2020).

Table 4 indicates the solution results obtained by CPLEX, VNS, and VND. For each small-size instance, the objective function value and the number of EVs used are reported considering three different partial recharging levels, such as 0.3, 0.4, and 0.5. In the comparison results section, the recharging levels are considered as parameters.

The first column represents the names of the instance. The second and third columns refer to the results of the CPLEX solver. The other ones between the fourth and eleventh columns correspond to the results of the VNS and VND heuristics with different construction algorithms. Optimal solutions, which were found by using the CPLEX solver, were shown in bold in Table 4. A time limit of one hour was used as a parameter. Thus, the optimal solutions were found for the instances S1-S8 with a 0.3 partial recharging level with the current upper time limit. For some of the instances (i.e., S15), the solution was terminated due to a memory error before the upper limit was reached. As the number of jobs involved in the small-size instances increased, it was observed that the

Table 5
Deviations and runtime* of CPLEX, VNS, and VND.

I	CPLEX	VND		VNS		CPLEX	VND		VNS	
		CA1	CA2	CA1	CA2		CA1	CA2	CA1	CA2
I	LB%	Deviation (%)				Runtime (seconds)				
	Partial recharging level: 0.3									
S1	0	0.05	0.06	0.04	0.05	38.81	55.67	64.1	99.64	98.08
S2	0	0.04	0.03	0.05	0.04	14.67	49.34	52.55	83.19	97.60
S3	0	0.03	0.09	0.02	0.03	14.67	54.11	37.21	120.91	117.5
S4	0	0.05	0.00	0.05	0.00	24.56	49.49	47.35	106.70	90.29
S5	0	0.05	0.04	0.06	0.07	510.05	50.47	47.15	104.49	107.64
S6	0	0.03	0.00	0.04	0.14	1082.50	48.66	46.64	97.52	102.81
S7	0	0.05	0.00	0.13	0.00	503.59	45.72	41.84	97.05	99.46
S8	0	0.08	0.06	0.25	0.13	1635.70	41.72	44.24	107.55	121.10
S9	17.27	0.09	0.16	0.13	0.15	3600.4	47.21	39.31	100.62	126.58
S10	38.02	0.03	0.02	0.06	0.04	2455.00	40.49	41.25	132.02	115.10
S11	37.22	−0.17	−0.26	−0.13	−0.10	920.10	42.74	44.27	93.88	112.38
S12	31.1	−0.18	−0.20	−0.14	−0.21	3600.00	56.07	44.64	125.72	126.27
S13	45.32	−0.24	−0.26	−0.23	−0.22	2129.00	45.64	43.73	103.78	115.26
S14	24.17	0.02	0.04	0.02	0.05	2721.00	42.2	43.90	105.25	100.36
S15	50.21	−0.64	−0.64	−0.60	−0.60	1325.60	43.46	43.80	110.44	110.33
S16	35.22	−0.26	−0.29	−0.23	−0.20	3601.11	40.38	41.38	107.51	97.06
Avg	17.41	−0.10	−0.11	−0.06	−0.07	1511.05	47.09	45.21	106.02	108.61
I	Partial recharging level: 0.4									
S1	0	0.03	0.01	0.03	0.11	36.72	50.26	55.91	97.81	93.79
S2	0	0.01	0.00	0.00	0.10	14.98	37.58	44.08	94.53	106.60
S3	0	0.01	0.00	0.05	0.05	14.98	35.76	46.54	122.98	105.20
S4	0	0.01	0.00	0.00	0.03	24.16	43.54	46.55	99.70	90.46
S5	0	0.01	0.00	0.10	0.01	699.00	41.57	51.10	96.66	103.07
S6	0	0.02	0.00	0.09	0.14	1181.23	43.19	45.81	96.91	103.75
S7	0	0.10	0.09	0.10	0.13	1543.00	41.53	45.95	101.25	106.41
S8	0	0.11	0.20	0.27	0.30	699.20	40.18	42.44	105.55	142.10
S9	33	−0.09	−0.11	−0.01	−0.04	3155.00	43.57	40.10	104.95	125.90
S10	38.1	0.01	−0.02	0.17	0.13	2455.00	42.19	42.75	131.10	125.10
S11	5.69	0.09	0.00	0.00	0.14	3600.08	42.31	45.18	80.85	105.53
S12	29.96	−0.14	−0.16	−0.08	−0.09	3600.00	47.75	39.39	113.58	112.86
S13	46	−0.26	−0.31	−0.29	−0.25	1965.00	42.73	38.90	106.71	106.96
S14	24.59	−0.02	−0.06	0.04	0.04	3600.14	39.58	38.86	103.62	101.38
S15	21.74	−0.03	−0.02	0.07	0.05	2397.00	38.37	39.83	104.23	101.02
S16	53.4	−0.67	−0.78	−0.64	−0.70	3600.17	39.32	37.70	97.85	91.16
Avg	15.78	−0.05	−0.07	−0.01	−0.01	1786.60	41.84	43.82	103.64	107.58
I	Partial recharging level: 0.5									
S1	0	0.03	0.02	0.02	0.05	35.48	51.32	55.93	98.48	96.27
S2	0	0.00	0.01	0.00	0.05	14.89	48.74	44.76	91.69	119.08
S3	0	0.00	0.00	0.06	0.08	14.89	47.02	51.52	105.49	111.03
S4	0	0.02	0.00	0.00	0.00	24.56	51.77	55.34	90.67	96.56
S5	0	0.00	0.00	0.08	0.05	680.20	52.28	60.62	106.10	105.07
S6	14.7	−0.09	−0.09	0.03	0.24	2405.20	41.85	45.93	106.36	98.88
S7	0	0.05	0.00	0.21	0.00	753.34	43.82	46.20	104.89	98.59
S8	0	0.17	0.11	0.23	0.11	680.20	40.04	47.77	104.45	137.80
S9	18.62	0.05	0.03	0.20	0.13	2347.65	46.16	39.30	102.82	119.30
S10	38.02	0.02	0.00	0.10	0.15	2471.66	44.18	53.32	123.44	114.04
S11	5.69	0.17	0.09	0.13	0.14	3600.08	40.07	47.01	34.44	106.90
S12	29.96	−0.21	−0.17	−0.20	−0.26	3601.00	52.17	40.10	120.99	109.67
S13	45.32	−0.29	−0.34	−0.30	−0.29	1955.00	41.20	42.40	132.62	102.12
S14	12.72	0.14	0.15	0.16	0.16	3600.12	39.92	39.73	104.66	100.41
S15	49.08	−0.60	−0.62	−0.57	−0.65	1928.00	41.84	38.61	100.63	100.49
S16	32.95	−0.63	−0.66	−0.55	−0.57	3600.40	36.28	39.60	95.65	97.38
Avg	15.44	−0.07	−0.09	−0.03	−0.04	1732.04	44.92	46.76	101.46	107.10

I: instance, LB: lower bound
* Refers to the average computational results of five runs.

CPLEX solver left some jobs unscheduled in some of the instances. Hence, this means an increase in the objective function value. Although the VNS and VND algorithms yielded solutions with higher deviations, all of the jobs were regarded as a part of the solutions.

When Table 4 is investigated further, solutions with the minimum number of EVs lead to a worse objective function value. There are two reasons for this: Employing the minimum number of EVs increases the deviation from time windows and increases the time they spend on the recharging stations.

Table 5 illustrates the lower bound (LB) of CPLEX solutions and the deviations of VND and VNS. The rest of the columns represent the runtime of solutions. As shown in the results, proposed heuristics achieved finding very close solutions to the optimal values in much shorter and reasonable times, even for small instances.

It was reported that CPLEX could not solve a 10-customer-size instance within 12 hours (Goeke & Schneider, 2015), and the optimal solutions of the same size instances could not be found for EVRPTW (Schneider et al., 2014). Therefore, this study deals with heuristics in order to yield good solutions for medium and large-size instances within a reasonable time.

Table 6
Computational results*.

Features						Objective function value (in unit-times)				Number of EVs used			
						VND		VNS		VND		VNS	
I	EV	C	V	D	S	CA1	CA2	CA1	CA2	CA1	CA2	CA1	CA2
1	20	70	150	2	2	6181.45	**4777.92**	7484.40	8269.32	20.0	20.0	19.8	20.0
2	20	70	150	2	4	4573.06	**4351.40**	7564.20	6644.24	20.0	20.0	20.0	20.0
3	30	70	150	2	2	5140.28	**4810.69**	6455.58	5683.38	26.0	26.8	23.4	23.6
4	30	70	150	2	4	5155.28	4844.41	**4781.09**	7255.20	26.2	26.2	23.2	23.4
5	50	90	300	2	2	10877.69	**10857.94**	12615.22	20376.08	49.6	49.8	48.4	49.2
6	50	90	300	2	4	**9788.04**	10154.99	15831.30	15491.54	49.0	49.6	48.6	49.0
7	75	90	300	2	2	**10167.01**	10048.91	13932.05	15933.64	56.8	56.2	53.0	52.0
8	75	90	300	2	4	**10013.32**	10072.03	14095.50	12958.75	57.4	58.0	50.6	52.4
9	100	200	600	2	2	**20277.19**	22351.56	34749.94	45466.20	98.8	99.2	98.6	99.6
10	100	200	600	2	4	21707.90	**20606.49**	30440.92	31465.39	99.6	99.75	99.0	99.6
11	100	200	600	4	2	**21100.25**	22011.00	36573.78	31478.72	99.4	99.2	98.0	98.8
12	100	200	600	4	4	20522.31	**19415.10**	33344.34	34866.02	99.4	99.0	98.4	98.8
13	150	200	600	2	2	**19563.96**	20982.70	26681.70	26062.54	112.6	113.6	104.4	106.2
14	150	200	600	2	4	**16854.54**	21787.74	28458.69	34228.32	114.0	113.8	107.8	105.6
15	150	200	600	4	2	21237.99	**20265.67**	35325.15	29329.31	117.2	116.0	108.0	105.2
16	150	200	600	4	4	19751.12	**19565.31**	42147.41	36103.64	112.8	113.6	104.0	105.8
17	250	400	1500	4	2	67398.58	**62505.61**	191222.61	204452.84	248.0	248.8	249.6	249.0
18	250	400	1500	4	4	74058.07	**63796.13**	230435.21	211281.95	248.2	249.2	249.4	249.4
19	250	400	1500	6	2	**61913.02**	69130.84	209308.41	198909.63	249.2	248.4	249.4	249.6
20	250	400	1500	6	4	67625.24	**62825.32**	195833.74	184094.03	247.2	248.2	249.2	249.8
21	300	400	1500	4	2	**56030.18**	56475.57	145439.49	145966.86	272.8	269.8	268.2	267.6
22	300	400	1500	4	4	**50731.14**	66016.03	113342.94	121640.95	272.0	271.6	267.2	265.8
23	300	400	1500	6	2	**58675.95**	60855.35	140380.98	147505.14	270.6	269.6	267.6	267.0
24	300	400	1500	6	4	59340.65	**49631.87**	123791.15	122629.78	271.8	270.2	268.4	269.0
25	300	600	1750	4	2	90818.42	98596.76	79800.41	**64709.44**	295.4	297.2	299.4	299.0
26	300	600	1750	4	4	96292.57	93819.75	71562.12	**60818.70**	297.4	296.6	299.8	299.2
27	300	600	1750	6	2	103990.60	107071.72	78287.20	**70972.24**	295.0	296.2	298.2	299.6
28	300	600	1750	6	4	146003.00	135233.04	76579.60	**70981.19**	295.0	296.8	299.8	299.2
29	400	600	1750	4	2	90760.60	85666.81	**58520.18**	71315.18	326.4	324.8	319.4	314.6
30	400	600	1750	4	4	97027.28	93059.74	**55294.90**	74057.84	321.6	322.0	315.6	315.6
31	400	600	1750	6	2	88688.62	88530.99	**57848.44**	62148.46	322.8	321.6	316.0	317.4
32	400	600	1750	6	4	98979.15	89927.77	73194.76	**66494.14**	323.4	325.6	318.8	313.6
33	400	800	2000	4	4	78609.23	**74215.45**	175483.31	213254.04	363.4	364.8	358.6	358.0
34	400	800	2000	4	6	**83145.26**	86540.73	212328.62	194164.96	361.6	361.0	356.4	354.4
35	400	800	2000	6	4	91785.16	**83096.01**	222844.54	218852.39	349.4	345.6	340.8	339.8
36	400	800	2000	6	6	80803.78	98153.04	219848.33	205363.57	363.8	363.8	360.2	352.8
37	500	800	2000	4	4	131694.47	103757.00	74526.17	**65130.17**	380.6	380.2	369.2	362.4
38	500	800	2000	4	6	124538.97	109481.30	89633.99	**85530.11**	382.6	381.2	366.4	364.0
39	500	800	2000	6	4	95824.08	97257.54	77559.73	**76915.50**	377.2	376.6	365.4	365.4
40	500	800	2000	6	6	117710.99	113625.69	**72413.39**	75860.05	377.2	374.0	365.8	364.6
41	600	1000	3000	4	4	388097.85	353536.82	255151.45	**232731.76**	550.0	542.2	546.0	546.0
42	600	1000	3000	4	6	376362.22	330548.52	249477.10	**220060.31**	544.6	545.0	543.2	544.4
43	600	1000	3000	6	4	290768.76	329013.63	241026.84	**186507.10**	531.2	532.8	525.2	530.0
44	600	1000	3000	6	6	390604.60	380337.09	**240625.19**	242683.82	542.0	548.2	541.8	545.0
45	750	1000	3000	4	4	186012.62	223840.50	125196.30	**112447.76**	569.4	567.8	548.8	550.6
46	750	1000	3000	4	6	233574.17	195004.34	136932.93	**107352.44**	573.8	569.2	555.2	550.8
47	750	1000	3000	6	4	236559.60	236069.01	**145465.20**	176788.27	482.4	482.4	484.4	485.6
48	750	1000	3000	6	6	283125.26	268477.07	183444.92	**167855.98**	480.6	478.6	482.8	483.4
49	750	1200	4000	6	8	384080.54	372250.39	279061.31	**226081.52**	701.4	703.8	706.2	701.8
50	750	1200	4000	6	10	400034.74	351524.93	213521.66	**197850.28**	705.6	709.8	706.4	707.0
51	750	1200	4000	8	8	369266.93	326869.26	236161.14	**203638.62**	700.4	707.4	708.8	704.0
52	750	1200	4000	8	10	368406.38	338038.67	211614.96	**210224.50**	706.0	706.0	704.4	706.6

I: instance, EV: number of EVs used, C: number of customers V: number of visits, D: number of depots, S: number of recharging stations, CA: construction algorithm.
* Refers to the average computational results of five runs.

5.3. Results on the large-size instances

After dealing with the computational comparison with the exact solution and heuristics, we focus on medium and large-size instances. To test the efficiency and effectiveness of proposed heuristics, we need to generate larger datasets in this study which also considers realistic constraints. The properties of data generated is summarized in Table 6, and the full dataset is shared on Mendeley Data (Baç & Erdem, 2020). Furthermore, another difference between the previous subsection (5.2) and this subsection (5.3) is the recharging levels. Here, the partial

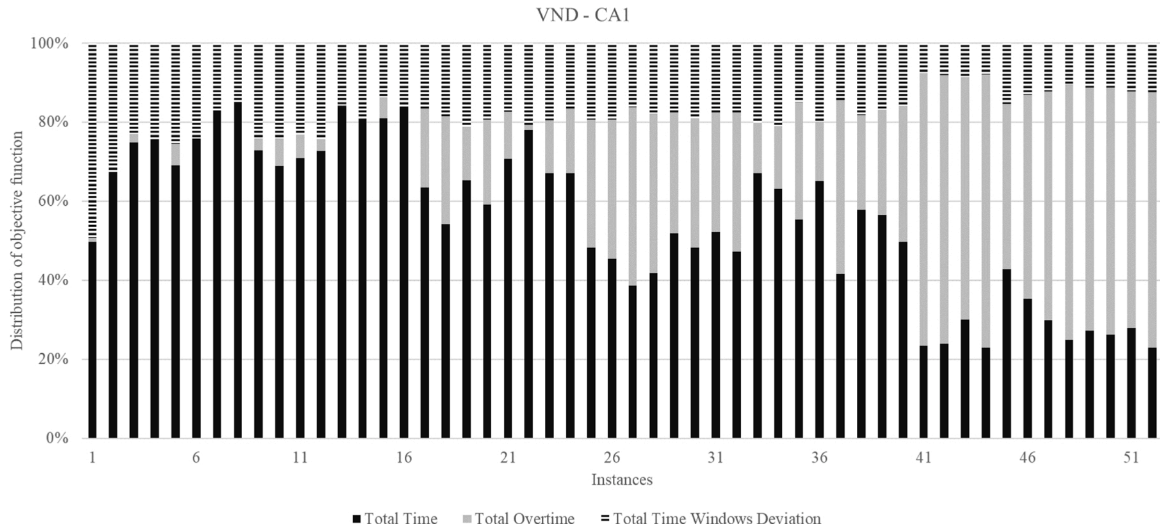

Fig. 5. Distribution of the objective function components of VND-CA1.

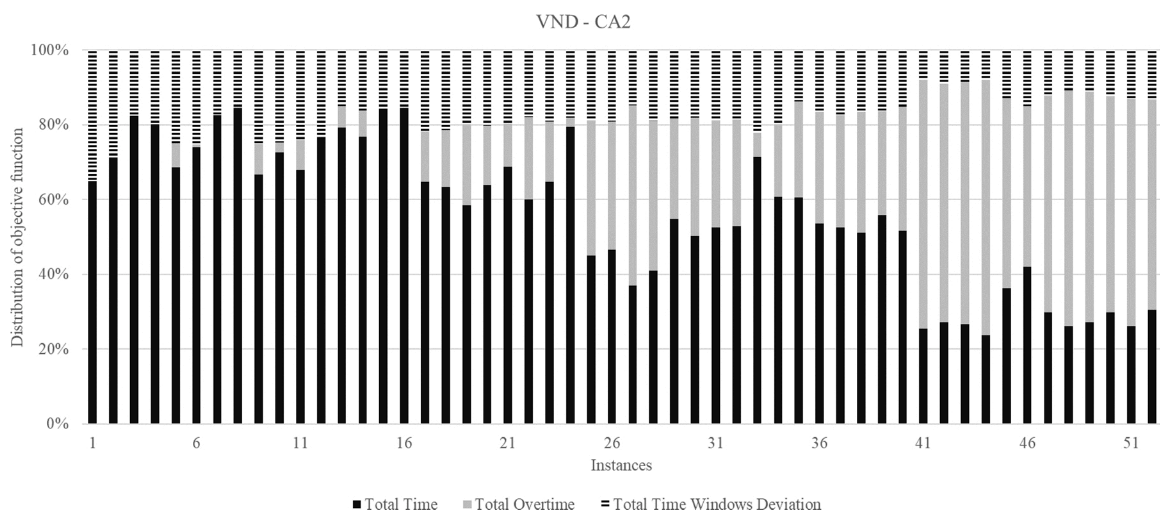

Fig. 6. Distribution of the objective function components of VND-CA2.

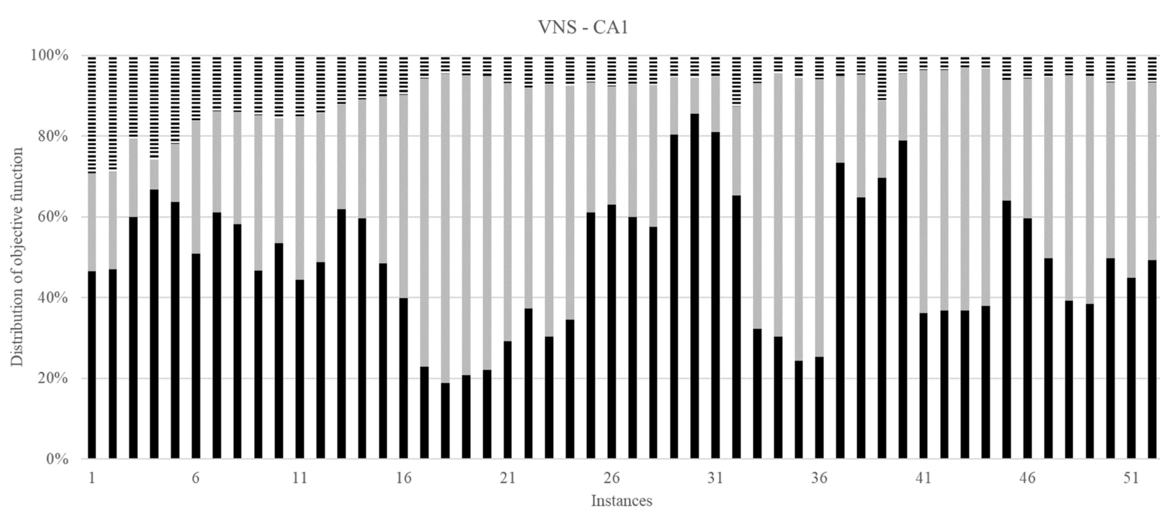

Fig. 7. Distribution of the objective function components of VNS-CA1.

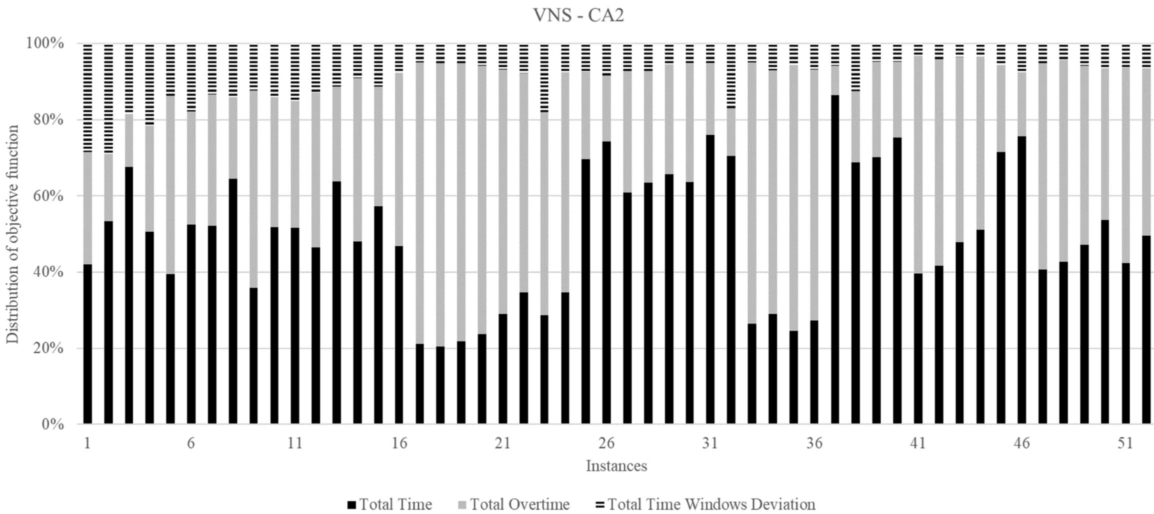

Fig. 8. Distribution of the objective function components of VNS-CA2.

Table 7
Efficiency* of proposed neighbourhood operators (part-1).

	All strategies				Without all strategies			
	VND		VNS		VND		VNS	
	CA1	CA2	CA1	CA2	CA1	CA2	CA1	CA2
Instance	25	25	25	25	25	25	25	25
Total time	43800.71	44368.80	48793.20	45022.88	45093.92	45298.02	45115.60	44860.80
Total overtime	98.09	119.00	85.40	49.80	260.88	236.20	131.00	107.40
Total time windows deviation	17591.32	18527.96	5387.21	4746.57	20080.52	19853.27	8084.21	7508.09
Total objective function value	90818.42	98596.76	79800.41	**64709.44**	143438.43	136011.29	92499.81	84588.89
Number of EVs used	295.40	297.20	299.40	299.00	299.80	300.00	299.80	300.00
Runtime (seconds)	168.56	190.74	600.69	617.84	140.68	139.09	558.87	519.05
Instance	26	26	26	26	26	26	26	26
Total time	43734.12	43673.13	45119.81	45181.89	45035.72	45141.79	44989.21	45008.59
Total overtime	113.20	107.00	69.67	34.92	196.40	182.00	87.07	101.42
Total time windows deviation	18598.46	18046.62	5541.91	5160.81	20863.46	20934.24	7262.71	7256.14
Total objective function value	96292.57	93819.75	71562.12	**60818.70**	124819.17	120676.03	78372.32	82691.93
Number of EVs used	297.40	296.60	299.80	299.20	300.00	300.00	300.00	300.00
Runtime (seconds)	183.84	192.18	600.01	613.08	191.08	179.33	545.81	527.27
Instance	27	27	27	27	27	27	27	27
Total time	43601.60	43519.36	44861.00	45214.65	45098.60	45085.57	44658.00	44713.83
Total overtime	170.00	189.60	81.80	78.80	228.00	304.00	112.00	110.40
Total time windows deviation	18323.29	17435.36	5429.98	5333.96	19725.09	20360.97	7529.38	5679.62
Total objective function value	112924.89	117834.72	74830.98	**74188.61**	133223.69	156646.54	85787.38	83513.44
Number of EVs used	295.00	296.20	298.20	299.60	299.80	300.00	299.20	299.60
Runtime (seconds)	170.79	181.51	644.99	486.18	162.25	161.24	519.85	523.54
Instance	28	28	28	28	28	28	28	28
Total time	43513.40	43895.85	45072.40	44999.22	44933.20	45024.00	44813.60	44601.58
Total overtime	139.60	142.80	91.60	69.40	264.80	232.20	80.40	65.60
Total time windows deviation	18597.20	20335.87	5734.80	5153.02	21629.80	20549.04	7646.00	6699.61
Total objective function value	103990.60	107071.72	78287.20	**70972.24**	146003.00	135233.04	76579.60	70981.19
Number of EVs used	295.00	296.80	299.80	299.20	300.00	300.00	300.00	300.00
Runtime (seconds)	170.18	276.20	485.26	506.55	145.67	197.25	514.45	511.34

CA: construction algorithm; all-time values and objective function values are represented in unit-times (1unit = 5mins.).
* Refers to the average computational results of five runs.

Table 8
Efficiency* of proposed neighbourhood operators (part-2).

	All strategies				Without all strategies			
	VND		VNS		VND		VNS	
	CA1	CA2	CA1	CA2	CA1	CA2	CA1	CA2
Instance	37	37	37	37	37	37	37	37
Total time	54713.79	54583.20	54738.64	56306.81	63138.19	63045.78	59907.04	59590.35
Total overtime	116.20	62.20	32.00	10.00	98.00	129.20	53.40	36.40
Total time windows deviation	18880.68	18073.80	3787.53	3823.36	11272.08	11059.60	4801.33	4143.63
Total objective function value	131694.47	103757.00	74526.17	**65130.17**	123410.27	138705.38	91408.37	81933.98
Number of EVs used	380.60	380.20	369.20	362.40	452.20	450.40	423.40	421.80
Runtime (seconds)	359.15	329.05	1002.99	1032.55	223.25	270.18	675.97	758.12
Instance	38	38	38	38	38	38	38	38
Total time	54950.99	54731.37	54200.62	53952.54	63336.79	63035.90	59234.02	58967.91
Total overtime	45.80	69.20	51.00	29.40	98.60	70.00	50.40	44.00
Total time windows deviation	17301.18	17711.94	3987.58	9797.27	11902.18	11445.40	5199.98	4562.20
Total objective function value	95152.17	107043.31	83688.19	**78449.81**	124538.97	109481.30	89633.99	85530.11
Number of EVs used	382.60	381.20	366.40	364.00	451.20	452.40	418.00	414.80
Runtime (seconds)	310.60	304.89	773.85	713.61	187.78	203.64	550.44	567.23
Instance	39	39	39	39	39	39	39	39
Total time	54128.20	54296.83	53966.86	53947.18	62762.60	62994.56	58125.66	58176.86
Total overtime	51.20	54.00	29.80	38.40	121.20	125.00	149.20	26.80
Total time windows deviation	16095.88	15960.71	8692.88	3768.32	11385.28	12868.12	5520.51	4484.70
Total objective function value	95824.08	97257.54	77559.73	76915.50	134747.88	138362.68	138246.17	**76061.57**
Number of EVs used	377.20	376.60	365.40	365.40	451.00	452.40	412.00	416.00
Runtime (seconds)	380.33	399.93	685.26	728.96	183.92	199.18	542.84	564.77
Instance	40	40	40	40	40	40	40	40
Total time	54579.93	54053.80	53934.78	53880.70	63569.13	60433.96	59343.18	58103.78
Total overtime	75.20	69.60	22.60	28.60	106.60	95.80	46.40	32.80
Total time windows deviation	17469.59	15956.13	3136.93	3409.99	12647.99	11365.16	4324.93	9258.48
Total objective function value	109649.52	104809.92	**68371.71**	71590.69	129517.12	119699.12	86868.11	83762.26
Number of EVs used	377.20	374.00	365.80	364.60	455.40	449.40	420.40	410.60
Runtime (seconds)	375.92	430.32	905.52	1093.26	194.54	259.96	544.16	559.90

CA: construction algorithm; all time values and objective function values are represented in unit-times (1unit = 5mins.).
* Refers to the average computational results of five runs.

recharge level is regarded as a decision variable. The objective function values obtained from all instances and the number of vehicles used are shown in Table 6. Instance 1 consists of 20 EVs, 70 customers, 150 visits, two depots, and two recharging stations. This instance's best objective function was found 4777.92 unit-times by using the VND algorithm, which was initialized by CA2. In addition to this solution, the average number of EVs used is 20.

Roughly, if the dataset is divided into two groups according to the scale, which is medium (instances 1-24) and large (instances 25-52), two situations arise concerning the results of objective functions. When the dataset from instances 1-24 are considered, the VND produces better solutions than the VNS. Similarly, for the same instances, the VND algorithm appears to perform slightly better when using the initial solutions generated by CA2 (random) instead of using initial solutions produced by CA1 (deterministic). On the other hand, when instances 25-52 are considered, the VNS has mostly been found to be better than the VND. It is obviously seen that the random solution construction algorithm yields better solutions than the deterministic algorithm.

Figs. 5–8 illustrate the distribution of the objective function components' results for each heuristic. Total time, overtime and deviation from the time windows were represented as black, gray and horizontal line patterned bars, respectively. While the vertical axis of the chart indicates the objective function's distribution, the horizontal axis corresponds to the instances.

When we consider the experiment results as to the instances, the total time measurement that covers travelling time, waiting time, and the duration of visits and recharging is often reduced in the VND algorithm. If the goal was only to minimize the vehicles' total time, VND-CA1 could be offered as the first option and VND-CA2 as the second option. It has been observed that the VND algorithm (for instances 1-24) always provides minimum overtime work, while the overtime work increases as the sample size increases (instances 25-52). Given the large size (instances 25-52) samples, VNS-CA2 yields less overtime work.

The VND and VNS algorithms lead to almost equal deviations from visiting time windows for the medium-size (instances 1-24) dataset. On the other hand, the VNS algorithm leads to a more minor deviation from time windows in solutions produced using the large-size dataset. Therefore, the VNS provides better delivery to customers on time when compared with the VND. In addition, although there is not much difference in the number of vehicles used, the VNS often offers better solutions by using fewer vehicles. When run times are taken into consideration, the VNS needs more time to generate a solution. The most crucial reason for the increased run times is the shaking procedure used by the VNS heuristic. Furthermore, the results of some selected instances with a different number of depots, recharging stations, and EVs are examined in Appendix B in Tables B1 and B2 and Figs. B1 and B2.

In order to evaluate the efficiency of the proposed neighbourhood operators within the local search process, additional runs are achieved, and the results of these instances are represented in Tables 7 and 8. Here, the columns 2-5 represent the performance of all strategies, while columns 6-9 refer to all strategies except the one-visit route, removal and re-assignment of the recharge station and re-assignment of the free EV. The proposed neighbourhood operators within the local search yield less deviation from the time windows and employ a minimum number of EVs.

As seen in Tables 7 and 8, solutions with all strategies produce less overtime work and better total time values. Except for instance 39, in which there is a slight improvement in the objective function value. Even though usage of all strategies in local search causes increases in run times, they provide a higher diversification.

6. Discussion

In terms of small-size problems, we compared the performance of proposed heuristics and the mathematical model's exact solution. When the number of entities in these problems increases, the run time also increases because of the problem's complexity. Without considering different partial recharging strategies, VNS and VND heuristics with newly developed neighbourhood structures generate high-quality solutions in general. In terms of construction algorithms, average computational results of five runs indicate that the number of EVs used and the objective function's value are slightly better than starting phase with randomly generated initial solutions. It is evident that the problem class is NP-hard; hence, there may be numerous local minima in the search space. One of the main reasons for the random route construction algorithm (CA2) to show better results is due to its feature, which commences with a different search area at each run. Furthermore, comparison results also indicate a direct relationship between the objective value and the number of EVs used. Solutions with the minimum number of EVs resulted in higher time window deviations. At the beginning of the improvement phase, heuristics may yield solutions with the highest number of EVs, but later neighbourhood structure tries to reduce them. Proposed heuristics are capable of generating high-quality solutions within a reasonable time. Moreover, the computational results also show that the recharging rate affects the solution quality directly.

Regarding the medium and large-size problems, we noticed that the average results of VNS are better than the average results of VND in terms of objective function values. One of the main objectives is to minimize the total time that consists of traveling time, waiting time, the duration of visit, and recharging time spent at stations. However, we noticed that the VND outperforms the VNS significantly according to the total time, meaning the improvement in routing and charging decisions and minimum idleness of EVs. Furthermore, the random route construction algorithm (CA2) outperforms the deterministic algorithm (CA1). Based on these comparison results, if the total time decreases, the total overtime also decreases, but the total time windows deviation increases. In other words, while there is a positive correlation between the total time and the total overtime, there is a negative correlation between the total time and the total time windows deviation. If the deviation from time is ignored, if customer satisfaction is not considered, the solution will improve, just like the current studies in the literature. However, this also indicates that the trade-off between the available resources and the customer expectations should be considered as a whole in the planning phase. In terms of the medium and large-size problems, there is no general conclusion that the number of depots and charging stations directly impacts the solution.

7. Conclusions

Along with their advantages, such as lower GHG emissions, EVs have a long recharging time, which poses an important drawback for these vehicles (Oda et al., 2018), and makes them less favorable vehicles in the logistics sector. Reliable, accurate, efficient and fast working optimization techniques are needed for the route planning and recharge scheduling specifically developed for EVs to make these vehicles more desirable in industrial and commercial sectors. This issue is more critical for developing countries like Turkey, considering the investment cost of EVs and the necessary infrastructure for these vehicles (Kaya et al., 2020). In this paper, we proposed a solution based upon the VNS and VND heuristics for the EVRPTW. In the local search procedure, a series of neighbourhood operators were developed in this field. These neighbourhood operators increase the diversification capacity and decrease the number of used EVs to supply the customers' demands; hence, it decreases the investment cost of EVs and increases their usage rates in the sector. The proposed solution approach was tested on the small, medium, and large-size datasets with randomly generated realistic instances. We also examined the effects of various depots and recharging stations on the objective function value, and the results indicated no significant effect.

The originality of the proposed approach is the consideration of partial recharging for the EVRPTW with the multiple depots and heterogeneous fleet structure under real-life constraints such as multiple customer visits. The idle time and recharging time of EVs are integrated into the objective function of the mathematical model. Furthermore, different customer requests, a variety of time windows of customers, and drivers' overtimes are also considered. It is proved that consideration of these real-life constraints and application of VNS and VND heuristics on the solution of EVRPTW-PR provides efficient and accurate results in a timely manner. The proposed framework can easily be applied to a wide range of EV recharge scheduling and routing problems concerning a range of EVs from private use to heavy-duty freights.

Our framework can be extended to cover some other issues such as: nonlinear charging and recharging processes and the capacity of recharging stations. Furthermore, after satisfying all assigned tasks, EVs can return to the closest depot if preferred.

Declaration of Competing Interest

The authors report no declarations of interest.

Acknowledgment

The authors are deeply grateful to the anonymous reviewers for their suggestions, which have helped make the quality and clarity of this article better.

Appendix A

```
Initialization. Select the neighbourhood structures N_k, k=1,2,...,k_max , generate an initial
solution (x) by means of a construction algorithm, and choose a stopping condition
(number of iterations)
while (until the stopping condition met) do
    k←1
    while k ≤ k_max do
        x' = Shaking(x, N_k)
        x'' = VND(x'', x', N_k) //Local Search
        If f(x'') < f(x)
            x'' (x ← x'') and k←1
        else
            k ← k+1
        end if
    end while
end while
```

Pseudocode A.1. The procedure of the VNS (Hansen et al., 2010; Mladenović & Hansen, 1997)

```
Initialization. Select the neighbourhood structures N_k, k=1,2,...,k_max , generate an initial
solution (x) by means of a construction algorithm, and choose a stopping condition
(number of iterations)
while (until the stopping condition met) do
    k←1
    while k ≤ k_max do
        x' = arg min_{y∈N_k} f(y) //Find the best neighbour
        If f(x') < f(x)
            (x ← x') and k←1 //Move
        else
            k ← k+1
        end if
    end while
end while
```

Pseudocode A.2. The procedure of the VND (Hansen et al., 2010; Mladenović & Hansen, 1997).

Appendix B

The results of some selected instances with a different number of depots, recharging stations, and EVs are examined in Tables B1 and B2 and Figs. B1 and B2. Instances 9, 10, 12, and 13 involve the same number of EVs, customers, and visits. On the other hand, they consist of a different number of depots and recharging stations. The objective function, for instance number 9, was found 20276.99 unit-times by using the VND algorithm, which CA1 was initialized. In addition, total overtime and total time window deviations were computed as 5.88 and 4896.95, respectively. However, the inspection of trends seen in Figs. B1 and B2, it can be said that for medium-size instances weight of total time is smaller in VNS when compared to VND. On the other hand, the weight of total time in VNS solutions is higher than the VND solutions for large-size instances. Nevertheless, total objective function values show opposite results where VND performs better for medium-size instances and VNS performs better for large-size instances, as seen in Tables B1 and B2. Although there is an increase in the number of depots, recharging stations, and EVs, it is hard to reach a general conclusion on the objective function value since the instances are randomly generated.

Table B1
Results* of instances with different number of vehicles, depots, and stations (part-1).

	VND		VNS	
	CA1	CA2	CA1	CA2
Instance	9	9	9	9
Total time	14791.64	14920.57	16195.34	16294.59
Total overtime	5.88	18.13	134.38	235.64
Total time windows deviation	4896.95	5617.14	5116.20	5607.60
Total objective function value	**20276.99**	22350.51	34749.94	45466.20
Instance	10	10	10	10
Total time	14962.10	14974.78	16292.88	16282.78
Total overtime	14.97	5.30	93.85	107.45
Total time windows deviation	5249.00	5101.71	4763.24	4437.40
Total objective function value	21707.90	**20606.49**	30440.92	31465.39
Instance	11	11	11	11
Total time	14961.12	14925.67	16237.08	16239.34
Total overtime	12.40	18.00	147.41	105.05
Total time windows deviation	4899.53	5285.73	5595.51	4734.19
Total objective function value	**21100.25**	22011.00	36573.78	31478.72
Instance	12	12	12	12
Total time	14937.16	14842.40	16259.99	16229.84
Total overtime	5.81	0.13	123.00	141.62
Total time windows deviation	5003.94	4559.91	4784.35	4474.59
Total objective function value	20522.31	**19415.10**	33344.34	34866.02
Instance	13	13	13	13
Total time	16460.32	16624.68	16513.08	16624.49
Total overtime	0.70	8.13	46.10	43.33
Total time windows deviation	2998.03	3138.22	3253.02	2938.25
Total objective function value	**19563.96**	20982.70	26681.70	26062.54
Instance	14	14	14	14
Total time	13632.14	16730.98	16956.82	16465.80
Total overtime	0.00	10.08	55.85	97.64
Total time windows deviation	3222.40	3544.16	3124.08	3117.12
Total objective function value	**16854.54**	21787.74	28458.69	34228.32
Instance	15	15	15	15
Total time	17209.64	17045.07	17130.26	16800.35
Total overtime	7.40	0.00	97.58	61.44
Total time windows deviation	2918.35	3220.60	3558.50	3312.36
Total objective function value	21237.99	**20265.67**	35325.15	29329.31
Instance	16	16	16	16
Total time	16553.34	16527.02	16790.76	16939.40
Total overtime	0.00	0.20	141.47	109.23
Total time windows deviation	3197.78	3008.09	4136.45	2780.03
Total objective function value	19751.12	**19565.11**	42147.41	36103.64

All values are represented in unit-times (1unit = 5min).
* Refers to the average computational results of five runs.

Table B2
Results* of instances with different number of vehicles, depots, and stations (part-2).

	VND		VNS	
	CA1	CA2	CA1	CA2
Instance	41	41	41	41
Total time	91128.40	89910.40	92345.80	92138.49
Total overtime	446.00	392.00	256.20	221.60
Total time windows deviation	29369.45	28426.42	9085.65	7633.27
Total objective function value	388097.85	353536.82	255151.45	**232731.76**
Instance	42	42	42	42
Total time	90195.50	89905.34	91798.88	91825.59
Total overtime	425.80	351.60	247.60	198.40
Total time windows deviation	30686.72	29683.18	9118.21	9194.73
Total objective function value	376362.22	330548.52	249477.10	**220060.31**
Instance	43	43	43	43
Total time	87127.69	87517.66	88712.03	89221.60
Total overtime	297.40	355.80	241.40	151.00
Total time windows deviation	25201.07	28015.97	7474.81	6685.50
Total objective function value	290768.76	329013.63	241026.84	**186507.10**
Instance	44	44	44	44
Total time	89599.00	90429.51	91323.82	124210.79
Total overtime	450.40	432.40	235.81	183.40
Total time windows deviation	30765.60	30467.58	7816.57	8433.04
Total objective function value	390604.60	380337.09	**240625.19**	242683.82
Instance	45	45	45	45
Total time	79440.06	81103.90	80089.60	80363.36
Total overtime	104.00	151.68	50.00	34.20
Total time windows deviation	28572.56	28979.60	7606.70	6434.40
Total objective function value	186012.62	223840.50	125196.30	**112447.76**
Instance	46	46	46	46
Total time	82585.66	82084.31	81591.66	81127.96
Total overtime	160.40	111.60	63.20	24.20
Total time windows deviation	30688.51	29220.02	7941.27	8074.48
Total objective function value	233574.17	195004.34	136932.93	**107352.44**
Instance	47	47	47	47
Total time	70671.60	70522.05	72411.60	72018.50
Total overtime	182.40	182.40	87.00	127.60
Total time windows deviation	29088.00	28746.96	7803.60	9069.76
Total objective function value	236559.60	236069.01	**145465.20**	176788.27
Instance	48	48	48	48
Total time	70586.26	70059.70	71986.08	71664.18
Total overtime	244.08	225.80	136.60	118.60
Total time windows deviation	29482.00	29067.37	9008.83	7241.80
Total objective function value	283125.26	268477.07	183444.92	**167855.98**

All values are represented in unit-times (1unit = 5min).
* Refers to the average computational results of five runs.

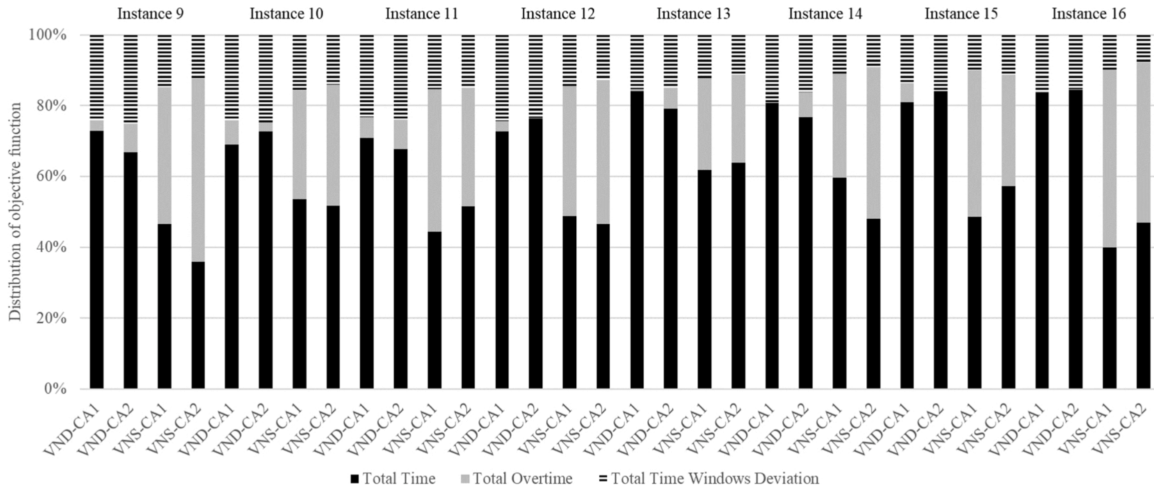

Fig. B1. Distribution of the objective function components for Instances 9-16.

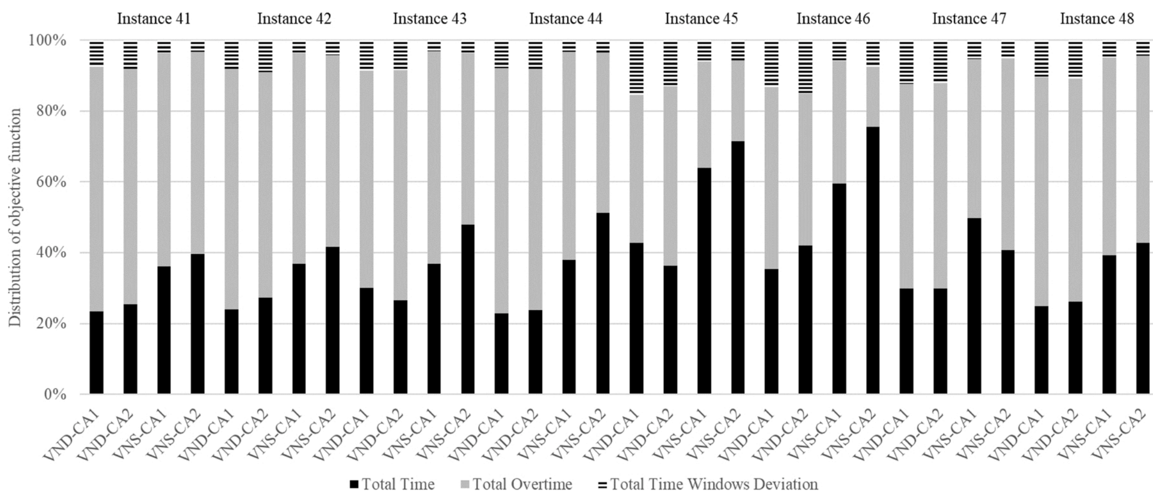

Fig. B2. Distribution of the objective function components for Instances 41-48.

References

Afroditi, A., Boile, M., Theofanis, S., Sdoukopoulos, E., & Margaritis, D. (2014). Electric vehicle Routing problem with industry constraints: Trends and insights for future research. *Transportation Research Procedia, 3*, 452–459. https://doi.org/10.1016/j.trpro.2014.10.026

Aloise, D. J., Aloise, D., Rocha, C. T. M., Ribeiro, C. C., Ribeiro Filho, J. C., & Moura, L. S. S. (2006). Scheduling workover rigs for onshore oil production. *Discrete Applied Mathematics, 154*, 695–702. https://doi.org/10.1016/j.dam.2004.09.021

Alves, J., Baptista, P. C., Gonçalves, G. A., & Duarte, G. O. (2016). Indirect methodologies to estimate energy use in vehicles: Application to battery electric vehicles. *Energy Conversion and Management, 124*, 116–129. https://doi.org/10.1016/j.enconman.2016.07.014

Baç, U., & Erdem, M. (2020). Data set for optimization of electric vehicle recharge schedule and routing problem with time windows and partial recharge: A comparative study for an urban logistics fleet. *Mendeley Data, 1*. https://doi.org/10.17632/zr5x7h25r3.1 [dataset].

Belhaiza, S., de Abreu, N. M. M., Hansen, P., & Oliveira, C. S. (2005). Variable neighborhood search for extremal graphs. Chapter XI. Bounds on Algebraic Connectivity. In D. Avis, A. Hertz, & O. Marcotte (Eds.), *Graph theory and combinatorial optimization* (pp. 1–16). Boston, MA: Springer US.

Bräysy, O., & Gendreau, M. (2005). Vehicle routing problem with time windows, part II: Metaheuristics. *Transportation Science, 39*, 119–139. https://doi.org/10.1287/trsc.1030.0057

Brandão, J. C. S., & Mercer, A. (1998). The multi-trip vehicle routing problem. *Journal of the Operational Research Society, 49*, 799–805. https://doi.org/10.1057/palgrave.jors.2600595

Brinkel, N. B. G., Schram, W. L., AlSkaif, T. A., Lampropoulos, I., & van Sark, W. G. J. H. M. (2020). Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits. *Applied Energy, 276*, Article 115285. https://doi.org/10.1016/j.apenergy.2020.115285

Cattaruzza, D., Absi, N., & Feillet, D. (2016). Vehicle routing problems with multiple trips. *4OR, 14*, 223–259. https://doi.org/10.1007/s10288-016-0306-2

Conrad, R. G., & Figliozzi, M. A. (2011). The Recharging Vehicle Routing Problem. In *Industrial Engineering Research Conference*.

Cordeau, J.-F., Laporte, G., Savelsbergh, M. W. P., & Vigo, D. (2007). Chapter 6 Vehicle routing. In B. Cynthia, & L. Gilbert (Eds.), *Handbooks in operations research and management science* (pp. 367–428). Elsevier, 14.

Desaulniers, G., Lavigne, J., & Soumis, F. (1998). Multi-depot vehicle scheduling problems with time windows and waiting costs. *European Journal of Operational Research, 111*, 479–494. https://doi.org/10.1016/S0377-2217(97)00363-9

Desaulniers, G., Errico, F., Irnich, S., & Schneider, M. (2016). Exact algorithms for electric vehicle-routing problems with time windows. *Operations Research, 64*, 1388–1405. https://doi.org/10.1287/opre.2016.1535

Duman, A. C., Erden, H. S., Gönül, Ö., & Güler, Ö. (2021). A home energy management system with an integrated smart thermostat for demand response in smart grids. *Sustainable Cities and Society, 65*, Article 102639. https://doi.org/10.1016/j.scs.2020.102639

Electric Van & Truck. (2020). *Electric Fiat Ducato by Zenith Review*. Retrieved from http://electricvanandtruck.com/electric-fiat-ducato-by-zenith/. (Accessed 20 March 2021).

Erdoğan, S., & Miller-Hooks, E. (2012). A green vehicle routing problem. *Transportation Research Part E: Logistics and Transportation Review, 48*, 100–114. https://doi.org/10.1016/j.tre.2011.08.001

European-Commission. (2011). *White Paper Roadmap to a Single European Transport Area–Towards a competitive and resource efficient transport system*.

Faria, R., Moura, P., Delgado, J., & de Almeida, A. T. (2012). A sustainability assessment of electric vehicles as a personal mobility system. *Energy Conversion and Management, 61*, 19–30. https://doi.org/10.1016/j.enconman.2012.02.023

Feng, W., & Figliozzi, M. (2013). An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market. *Transportation Research Part C: Emerging Technologies, 26*, 135–145. https://doi.org/10.1016/j.trc.2012.06.007

Felipe, Á., Ortuño, M. T., Righini, G., & Tirado, G. (2014). A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges. *Transportation Research Part E: Logistics and Transportation Review, 71*, 111–128. https://doi.org/10.1016/j.tre.2014.09.003

Feng, J., Xu, S. X., & Li, M. (2021). A novel multi-criteria decision-making method for selecting the site of an electric-vehicle charging station from a sustainable perspective. *Sustainable Cities and Society, 65*, Article 102623. https://doi.org/10.1016/j.scs.2020.102623

Forrest, K., Kinnon, M. M., Tarroja, B., & Samuelsen, S. (2020). Estimating the Technical Feasibility of Fuel Cell and Battery Electric Vehicles for the Medium and Heavy Duty Sectors in California. *Applied Energy, 276*, Article 115439. https://doi.org/10.1016/j.apenergy.2020.115439

Gao, X., Zhou, Y., Amir, M. I. H., Rosyidah, F. A., & Lee, G. M. (2018). A hybrid genetic algorithm for multi-emergency medical service center location-allocation problem in disaster response. *International Journal of Industrial Engineering: Theory, Applications and Practice, 24*, Article 4299.

Goeke, D., & Schneider, M. (2015). Routing a mixed fleet of electric and conventional vehicles. *European Journal of Operational Research, 245*, 81–99. https://doi.org/10.1016/j.ejor.2015.01.049

Gong, L., Cao, W., Liu, K., & Zhao, J. (2020). Optimal charging strategy for electric vehicles in residential charging station under dynamic spike pricing policy. *Sustainable Cities and Society, 63*, Article 102474. https://doi.org/10.1016/j.scs.2020.102474

Guo, H., Wang, X., & Li, L. (2019). State-of-charge-constraint-based energy management strategy of plug-in hybrid electric vehicle with bus route. *Energy Conversion and Management, 199*, Article 111972. https://doi.org/10.1016/j.enconman.2019.111972

Hansen, P., & Mladenović, N. (2001). Variable neighborhood search: Principles and applications. *European Journal of Operational Research, 130*, 449–467. https://doi.org/10.1016/S0377-2217(00)00100-4

Hansen, P., Mladenović, N., Brimberg, J., & Pérez, J. A. M. (2010). Variable neighborhood search. In M. Gendreau, & J.-Y. Potvin (Eds.), *Handbook of metaheuristics* (pp. 61–86). Boston, MA: Springer US.

Hannan, M. A., Begum, R. A., Al-Shetwi, A. Q., Ker, P. J., Al Mamun, M. A., Hussain, A., et al. (2020). Waste collection route optimisation model for linking cost saving and emission reduction to achieve sustainable development goals. *Sustainable Cities and Society, 62*, Article 102393. https://doi.org/10.1016/j.scs.2020.102393

Hiermann, G., Puchinger, J., Ropke, S., & Hartl, R. F. (2016). The electric fleet size and mix vehicle routing problem with time windows and recharging stations. *European Journal of Operational Research, 252*, 995–1018. https://doi.org/10.1016/j.ejor.2016.01.038

HVIP, C. (2021). *Step & Panel Van*. Retrieved from: https://californiahvip.org/vehicle-category/van/. (Accessed 20 March 2021).

Jarboui, B., Derbel, H., Hanafi, S., & Mladenović, N. (2013). Variable neighborhood search for location routing. *Computers & Operations Research, 40*, 47–57. https://doi.org/10.1016/j.cor.2012.05.009

Kaya, Ö., Alemdar, K. D., & Çodur, M. Y. (2020). A novel two stage approach for electric taxis charging station site selection. *Sustainable Cities and Society, 62*, Article 102396. https://doi.org/10.1016/j.scs.2020.102396

Keskin, M., & Çatay, B. (2016). Partial recharge strategies for the electric vehicle routing problem with time windows. *Transportation Research Part C: Emerging Technologies, 65*, 111–127. https://doi.org/10.1016/j.trc.2016.01.013

Koç, Ç., & Karaoğlan, I. (2016). The green vehicle routing problem: A heuristic based exact solution approach. *Applied Soft Computing, 39*, 154–164. https://doi.org/10.1016/j.asoc.2015.10.064

Li, S., Huang, Y., & Mason, S. J. (2016). A multi-period optimization model for the deployment of public electric vehicle charging stations on network. *Transportation Research Part C: Emerging Technologies, 65*, 128–143. https://doi.org/10.1016/j.trc.2016.01.008

Melendez, K. A., Das, T. K., & Kwon, C. (2020). Optimal operation of a system of charging hubs and a fleet of shared autonomous electric vehicles. *Applied Energy, 279*, Article 115861. https://doi.org/10.1016/j.apenergy.2020.115861

Mirhedayatian, S. F., & Yan, S. (2018). A framework to evaluate policy options for supporting electric vehicles in urban freight transport. *Transportation Research Part D: Transport and Environment, 58*, 22–38. https://doi.org/10.1016/j.trd.2017.11.007

Mladenović, N., & Hansen, P. (1997). Variable neighborhood search. *Computers & Operations Research, 24*, 1097–1100. https://doi.org/10.1016/S0305-0548(97)00031-2

Montoya-Torres, J. R., Franco, J. L., Isaza, S. N., Jiménez, H. F., & Herazo-Padilla, N. (2015). A literature review on the vehicle routing problem with multiple depots. *Computers & Industrial Engineering, 79*, 115–129. https://doi.org/10.1016/j.cie.2014.10.029

Montoya, A., Guéret, C., Mendoza, J. E., & Villegas, J. G. (2016). A multi-space sampling heuristic for the green vehicle routing problem. *Transportation Research Part C: Emerging Technologies, 70*, 113–128. https://doi.org/10.1016/j.trc.2015.09.009

Montoya, A., Guéret, C., Mendoza, J. E., & Villegas, J. G. (2017). The electric vehicle routing problem with nonlinear charging function. *Transportation Research Part B: Methodological, 103*, 87–110. https://doi.org/10.1016/j.trb.2017.02.004

Muñoz-Villamizar, A., Santos, J., Montoya-Torres, J. R., & Velázquez-Martínez, J. C. (2020). Measuring environmental performance of urban freight transport systems: A case study. *Sustainable Cities and Society, 52*, Article 101844. https://doi.org/10.1016/j.scs.2019.101844

Oda, T., Aziz, M., Mitani, T., Watanabe, Y., & Kashiwagi, T. (2018). Mitigation of congestion related to quick charging of electric vehicles based on waiting time and cost–benefit analyses: A Japanese case study. *Sustainable Cities and Society, 36*, 99–106. https://doi.org/10.1016/j.scs.2017.10.024

Pan, L., Yao, E., Yang, Y., & Zhang, R. (2020). A location model for electric vehicle (EV) public charging stations based on drivers' existing activities. *Sustainable Cities and Society, 59*, Article 102192. https://doi.org/10.1016/j.scs.2020.102192

Prandtstetter, M., Raidl, G. R., & Misar, T. (2009). A hybrid algorithm for computing tours in a spare parts warehouse. In C. Cotta, & P. Cowling (Eds.), *Evolutionary computation in combinatorial optimization: 9th European Conference, EvoCOP 2009* (pp. 25–36).

Sachan, S., Deb, S., & Singh, S. N. (2020). Different charging infrastructures along with smart charging strategies for electric vehicles. *Sustainable Cities and Society, 60*, Article 102238. https://doi.org/10.1016/j.scs.2020.102238

Sa'adati, R., Jafari-Nokandi, M., & Saebi, J. (2021). Allocation of RESs and PEV Fast-Charging Station on Coupled Transportation and Distribution Networks. *Sustainable Cities and Society, 65*, Article 102527. https://doi.org/10.1016/j.scs.2020.102527

Sayarshad, H. R., & Mahmoodian, V. (2021). An intelligent method for dynamic distribution of electric taxi batteries between charging and swapping stations. *Sustainable Cities and Society, 65*, Article 102605. https://doi.org/10.1016/j.scs.2020.102605

Sayarshad, H. R., Mahmoodian, V., & Gao, H. O. (2020). Non-myopic dynamic routing of electric taxis with battery swapping stations. *Sustainable Cities and Society, 57*, Article 102113. https://doi.org/10.1016/j.scs.2020.102113

Schiffer, M., & Walther, G. (2017). The electric location routing problem with time windows and partial recharging. *European Journal of Operational Research, 260*, 995–1013. https://doi.org/10.1016/j.ejor.2017.01.011

Schneider, M., Stenger, A., & Goeke, D. (2014). The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science, 48*, 500–520. https://doi.org/10.1287/trsc.2013.0490

Škugor, B., & Deur, J. (2016). A bi-level optimisation framework for electric vehicle fleet charging management. *Applied Energy, 184*, 1332–1342. https://doi.org/10.1016/j.apenergy.2016.03.091

Solomon, M. M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations Research, 35*, 254–265. https://doi.org/10.1287/opre.35.2.254

Sokolsky, S., Silver, F., & Pitkanen, W. (2014). *Heavy-duty truck and bus natural gas vehicle technology roadmap*. The Southern California Gas Company.

Today's Motor Vehicles. (2015). *Motiv launches electric powertrain for Ford chassis*. Retrieved from: https://www.todaysmotorvehicles.com/article/commercial-truck-design-electrification-motiv-ford-030415/. (Accessed 20 March 2021).

Tu, R., Gai, Y. J., Farooq, B., Posen, D., & Hatzopoulou, M. (2020). Electric vehicle charging optimization to minimize marginal greenhouse gas emissions from power generation. *Applied Energy, 277*, Article 115517. https://doi.org/10.1016/j.apenergy.2020.115517

Wang, R., Li, X., Xu, C., & Li, F. (2020). Study on location decision framework of electric vehicle battery swapping station: Using a hybrid MCDM method. *Sustainable Cities and Society, 61*, Article 102149. https://doi.org/10.1016/j.scs.2020.102149

Wen, M., Linde, E., Ropke, S., Mirchandani, P., & Larsen, A. (2016). An adaptive large neighborhood search heuristic for the Electric Vehicle Scheduling Problem. *Computers & Operations Research, 76*, 73–83. https://doi.org/10.1016/j.cor.2016.06.013

Yao, E., Liu, T., Lu, T., & Yang, Y. (2020). Optimization of electric vehicle scheduling with multiple vehicle types in public transport. *Sustainable Cities and Society, 52*, Article 101862. https://doi.org/10.1016/j.scs.2019.101862

Zhao, Y., Ercan, T., & Tatari, O. (2016). Life cycle based multi-criteria optimization for optimal allocation of commercial delivery truck fleet in the United States. *Sustainable Production and Consumption, 8*, 18–31. https://doi.org/10.1016/j.spc.2016.04.003

Zhang, S., Gajpal, Y., & Appadoo, S. S. (2017). A meta-heuristic for capacitated green vehicle routing problem. *Annals of Operations Research, 269*, 753–771. https://doi.org/10.1007/s10479-017-2567-3

Zhao, J., Ma, Y., Zhang, Z., Wang, S., & Wang, S. (2019). Optimization and matching for range-extenders of electric vehicles with artificial neural network and genetic algorithm. *Energy Conversion and Management, 184*, 709–725. https://doi.org/10.1016/j.enconman.2019.01.078

Zhang, Y., Liu, X., Wei, W., Peng, T., Hong, G., & Meng, C. (2020). Mobile charging: A novel charging system for electric vehicles in urban areas. *Applied Energy, 278*, Article 115648. https://doi.org/10.1016/j.apenergy.2020.115648