International Journal of Production Economics 203 (2018) 404–413

Contents lists available at ScienceDirect

International Journal of Production Economics

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

Electric vehicle routing problem with recharging stations for minimizing energy consumption

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ARTICLE INFO

Keywords:
Vehicle routing
Electric vehicle operations
Capacitated vehicle
Energy consumption

ABSTRACT

Due to growing environmental concerns about greenhouse gas (GHG) emissions, people are more incline to use electric vehicles in various distribution services. Because of the limited battery capacity, electric vehicles are required to visit recharging stations en-route. Therefore, the routing schemes of conventional vehicles may not be suitable as the routing schemes of electric vehicles. In this paper, the Electric Vehicle Routing Problem (EVRP) is introduced, and the corresponding mathematical model is formulated. The EVRP seeks to minimize the energy consumption of electric vehicles. The comprehensive calculation of energy consumption used by electric vehicles is provided in the EVRP model. An ant colony (AC) algorithm based meta-heuristics is proposed as the solution method of the EVRP. The effectiveness of the proposed algorithms is evaluated through extensive numerical experiments on the newly generated instances. We also illustrate the benefits of using an energy consumption-minimizing objective function rather than a distance-minimizing objective function for routing electric vehicles.

1. Introduction

Global warming is becoming a serious concern and a threat to future generations, because of its negative impacts on nature, economics, and society (Revesz et al., 2014). To address the global efforts for rapid reductions of global carbon dioxide emissions, the Paris Agreement was signed by different countries at the climate change conference sponsored by the United Nations in December 2015.

Fossil energy represents the largest source of carbon dioxide emissions (EIA, 2016). As a result, non-fossil energy is gradually grabbing the attention of people. The introduction of green vehicles, such as hydrogen vehicles and electric vehicles, is a good example of people's attempts to utilize non-fossil energy. However, the scheduling and routing of green vehicles in distribution systems is complicated. Due to a technology bottleneck, the vehicles usually have a short driving range of 100–150 miles (Feng and Figliozzi, 2013) and need to visit refueling or recharging stations during the service. Furthermore, the number of refueling or recharging stations is usually limited. For example, there are only 1626 recharging points across Canada (ChargeMap, 2016). Thus, the routing schemes for traditional vehicles are not always suitable for routing green vehicles.

To properly design the routing plans for green vehicles, the Green Vehicle Routing Problem (GVRP) was introduced in operations research literature. Like the classical Vehicle Routing Problem (VRP), the GVRP seeks to minimize travelling distance, travelling time and so on, but underestimates the negative environmental effects of the vehicles' pollution. Even though the green vehicles use cleaner energy resources, they are not completely pollution-free. Electricity is the power resource of electric vehicles, and 73% of the electricity generated in 2012 came from the burning of fossil fuels, such as coal, natural gas and petroleum (EIA, 2014). In 2015, the carbon dioxide emissions from electricity generation were 1925 million metric tons (EIA, 2017). In this context, how to design a low carbon dioxide emissions routing plan is important from economic and environmental points-of-view.

Bektaş and Laporte (2011) are the first to propose the Pollution-Routing Problem (PRP) to offer insights into environmental-friendly vehicle routing. Unlike most variants of Vehicle Routing Problem (VRP), the PRP seeks to minimize the carbon dioxide emissions as well as the economic costs. The carbon dioxide emissions depend on the energy consumption of the vehicle. The energy consumption has a relationship not only with the route length but with other factors such as speeds, loads, and travelling times. Meanwhile, the carbon dioxide emissions of operating vehicles can be estimated through energy consumption. By incorporating energy consumption and the carbon dioxide emissions into the economic costs, the solutions of PRP can assist companies in achieving their sustainable goals.

In this paper, an Electric Vehicle Routing Problem (EVRP) for minimizing the energy consumption is considered, and the

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https://doi.org/10.1016/j.ijpe.2018.07.016
Received 21 September 2017; Received in revised form 10 July 2018; Accepted 15 July 2018
Available online 19 July 2018

corresponding model is formulated. In the EVRP, the electric vehicles are used on a given network for delivery. In the network, there is only one depot, and all tours start and end at it. A limited number of recharging stations are scattered across the network, and EVs can visit the recharging stations (including the depot) if battery energy depletes. Upon visiting the recharging station, the battery of the EV will be fully recharged. In the literature, partial recharge is deemed as a best policy for the electric vehicle routing problems with time widow constrains because partial recharge takes less time than full recharge (Montoya et al., 2017; Keskin and Çatay, 2016; Desaulniers et al., 2016). In this paper, the time window constraints are not considered, therefore, we assume that the electric vehicles are fully recharged at recharging stations. The objective of EVRP is to obtain a route plan which minimizes the battery energy consumption of the EVs. The main constraints in this problem include the limited vehicle capacity, the low battery capacity, and the limited number of available recharging stations in the service region. The main differences between the EVRP and the classical VRPs are two-folds. First, the EVRP in this paper considers the recharging operation during service, because the driving range of the EV is short. Second, the EVRP in this paper aims to minimize the battery energy consumption. Compared against the route distance, the battery energy consumption is more relevant to carbon dioxide emissions. The battery energy consumption is affected by numerous factors such as vehicle load, speed, travelling distance, and so on. These mentioned factors increase the complexity of the EVRP such that most of the commercial solvers cannot solve the medium size problem in a reasonable time. This paper provides an ant colony (AC) algorithm for solving the EVRP. To show the competency of the AC meta-heuristic, the ALNS used by Goeke and Schneider (2015) for EVRPTWMF is adapted for solving the same EVRP problem instances in the paper.

The main contributions of this paper are twofold. First, we introduce a new model in the literature for minimizing energy consumption of electric vehicles which requires recharging operations from time-to-time. Unlike most of the other existing models where the energy consumption is dependent only on distance, the model in this paper considers the actual energy consumption of the electric vehicle. Normally, electric vehicles are deemed as one type of pollution-free vehicle by most people. In fact, such vehicles consume electricity, and the generation type of electricity, in many places, is coal-fired generation which releases a huge quantity of carbon dioxide emissions. Therefore, the carbon dioxide emissions for operating electric vehicles can be mapped through the energy consumption. To the authors' best knowledge, this model is not available in literature yet, and the motivation for this research is to fill this gap. Second, although the model is proposed for routing electric vehicles, it is also applicable for alternative fuel vehicles (AFVs) which requires refueling due to the low tank capacity.

The rest of paper is structured as follows. Section 2 presents a review of relevant literature. Section 3 formulates the EVRP model. The AC based meta-heuristic and the adapted ALNS algorithm are designed in Section 4. Section 5 shows the numerical experiments and the analysis on the results. The conclusion of this paper is shown in Section 6.

2. Literature review

To alleviate the adverse impacts of conventional vehicles in road transportation, two main efforts are made by scholars in the VRP field. One effort is to modify the classical objective in the VRP model, so that the routing schemes fully consider the pollution of conventional vehicles. The other effort is to design the route plans for AFVs. In this context, the first effort introduces the Pollution-Routing Problem (PRP), and the second effort introduces the Green Vehicle Routing Problem (GVRP). The related literature review in these two research fields are shown in the following two subsections. For more detailed review, the interested readers may refer to Demir et al. (2014b) and Lin et al. (2014).

2.1. Pollution-Routing Problem

In the Pollution-Routing Problem (PRP), the aim is to extend the classical Vehicle Routing Problem with a more comprehensive and broader objective which considers the environmental costs, such as the costs of fuel consumption and GHG emissions as well as the operational costs.

There are various studies on measuring conventional vehicles' fuel consumption and carbon dioxide emissions. Based on simulation, the Comprehensive Modal Emission Model and the Parametric Analytical Model of Vehicle Energy Consumption are proposed to predict the consumption of fuel and the rate of carbon dioxide emissions (Barth and Boriboonsomsin, 2009; Simpson, 2005). However, in terms of transportation planning, there are few studies addressing the pollution issues as an objective. In his PhD thesis, Palmer (2007) illustrates an integrated routing and emissions model which calculates the travelling time as well as the carbon dioxide emissions and manifests the effects of the vehicle speed on the carbon dioxide emissions under different time windows constraints and congestion scenarios. Maden et al. (2010) formulate a vehicle routing and scheduling problem with time window. The interesting characteristic in their model is the consideration of time-depended vehicle speed which affects the power consumptions of vehicles.

Bektaş and Laporte (2011) are the first to introduce the PRP model and develop a comprehensive objective function which considers carbon dioxide emissions, fuel consumption and travel times. The proposed PRP model reveals the tradeoffs between several performance measures of vehicle routing, such as costs, emissions, distance, and load. Demir et al. (2012) propose an Adaptive Large Neighborhood Search (ALNS) for the PRP. The effectiveness of the proposed algorithm is confirmed through extensive numerical experiments. Franceschetti et al. (2013) introduce the Time-Dependent Pollution-Routing Problem (TDPRP) which extends the PRP by taking traffic congestions into considerations. Demir et al. (2014a) extend the PRP to the bi-objective PRP. The two objectives used pertain to minimize the driving time and the fuel consumption separately. An enhanced ALNS is used for solving the proposed problem. Assuming a heterogeneous vehicle fleet, the study of Koç et al. (2014) examines the impact of different fleet sizes on the results of the mix Pollution-Routing Problem. Kramer et al. (2015a) propose a new algorithm to optimize the speed and departure time of vehicles in the PRP to reduce the operational costs. Kramer et al. (2015b) design an Iterated Local Search (ILS) with a Set Partitioning (SP) procedure and a Speed Optimization Algorithm (SOA) to solve the PRP. Soysal et al. (2015) propose a time-dependent two-echelon capacitated vehicle routing problem which considers the vehicles' emissions. By studying a case of Dutch supermarket chain, they find that the two-echelon distribution was more environmental-friendly than the single-echelon distribution. Zhang et al. (2015) study a Vehicle Routing Problem with fuel consumption and carbon emissions and design a tabu search algorithm named RS-TS for solving the problem. Suzuki (2016) considers a practical pollution routing problem and uses a dual-objective meta-heuristic approach to solve the problem. Many studies have focused on the PRP model with conventional vehicles, but there is no study in the literature that focuses on designing the PRP model for routing green vehicles.

2.2. Green Vehicle Routing Problem

GVRP is mainly focused on alleviating the negative influences on the environment associated with conventional vehicles. One way of alleviating such impacts is to employ the AFVs. Compared with conventional vehicles, the AFVs use clean energy like electricity and hydrogen as power sources. However, the AFVs have some shortcomings such as limited energy storage (e.g. low battery capacity of electric vehicles) and access to AFSs. Consequently, the refueling issue becomes more important in solving the routing problem of the AFVs, which makes the route selection for the AFVs complicated.

Erdoğan and Miller-Hooks (2012) propose a GVRP model to overcome the difficulties brought by the limited number of refueling infrastructures and the short driving range of the AFVs. A savings heuristic and a Density-Based Clustering algorithm are proposed as solution methods. Based on the previous studies, Felipe et al. (2014) consider a routing problem in which the electric vehicles are used for delivery. In their model, the recharging station and the recharging time are decided simultaneously. Schneider et al. (2014) consider the time windows of customers as well as the limited vehicle capacity in their Electric Vehicle Routing Problem. A hybrid heuristic combining the tabu search and the adaptive large neighborhood search is proposed as a solution method. Goeke and Schneider (2015) study the Electric Vehicle Routing Problem with time window and mixed fleet (EVRPTWMF) to optimize the routing of a fleet consisting of both conventional vehicles and electric vehicles. An Adaptive Large Neighborhood Search (ALNS) algorithm with local search is designed for addressing this problem. Tiwari and Chang (2015) consider a GVRP model with the emissions-minimizing objective and estimate the carbon dioxide emissions based on travelling distance and truck load. A block recombination approach is used to solve the proposed problem Montoya et al. (2016) develop a simple but effective two-phase heuristic to solve the GVRP. They also perform extensive experiments on 52 instances from the literature to test their heuristic.

The models in the GVRP commonly assume a linear relationship between the energy consumption and the travelling distance of vehicles. However, some models in the PRP literature indicate that the energy consumption of a vehicle is also affected by other factors such as speed, load, and travelling distance, and these factors need to be considered in research.

This paper studies an EVRP model for minimizing energy consumption. The proposed model is derived from a combination of the GVRP and the PRP. The highlights of this model can be summarized as two aspects. (1) Recharging needs are fully considered so that the visits to the recharging stations are arranged in the routing plan. The Recharging needs are caused by the low battery capacity of EVs and requires EVs to visit recharging stations during service. The scarce availability of recharging stations makes the recharging issue of EVs more serious. (2) A comprehensive calculation of the energy consumption is performed. In our model, the calculation of a vehicle's energy consumption considers factors such as curb weight, cargo load, speed, and road friction. All the considered factors are incorporated in the model, though many current studies consider only the linear relationship of energy consumption with distance. The comprehensive calculation of the energy consumption provides sufficient information for the recharging decision-making. In addition, the energy consumption can be used to roughly estimate the amount of the carbon dioxide released in electricity generation.

3. Problem formulation

To formulate the EVRP model, the calculation of an EV's battery energy consumption is required. The battery energy consumption in our model is calculated as follows. First, the mechanical energy requirement of an EV on each arc is calculated based on the models in the literature. The mechanical energy requirement is affected by different factors such as travel distance, vehicle weight, speed, engine efficiency, etc. Barth and Boriboonsomsin (2009) show how to measure the mechanical energy requirements of conventional vehicles. In developing their work, Bektaş and Laporte, (2011) proposed the calculation of the mechanical energy for the conventional vehicles in the PRP model. Second, in considering motor efficiency, we convert the required amount of mechanical energy to the electric power used by electric motor. Third, the electric energy needed by the motor is converted to the amount of battery energy based on the battery discharging efficiency.

Furthermore, the model in this paper intends to estimate the carbon dioxide emissions which are indirectly induced by the operations of EV. To estimate the emissions, the battery energy required on each arc is translated to the amount of electric power which would be transmitted from the power plant. This amount is determined by the recharging efficiency of the battery. Finally, the carbon dioxide emissions are estimated using the factor of average emissions from the coal-fired electricity generation process.

The detailed calculation of the required battery power and indirectly-released emissions are shown in next subsection.

3.1. Calculation of energy consumption

To calculate the consumption required by the EV, the mechanical power requirement P_t is needed. The mechanical power requirement of the EV is needed to overcome rolling, drag and wind resistance, and gravitational force as well as to enable the acceleration. P_t can be calculated as:

$$P_t = Mas + Msgsin\theta + 0.5C_d A\rho s^3 + MgC_r cos\theta s$$

where M is the vehicle mass (kg), a is the acceleration (m/s^2), g is the gravitational constant (9.81 m/s^2), θ is the angle of road, C_d is the rolling resistance coefficients, and C_r is the drag resistance coefficients, ρ is the air density (1.225 kg/m^3) which is dependent on altitude and temperature, s is the vehicle's speed (m/s), and A is the vehicle's frontal surface area (m^2).

To calculate the mechanical power requirement the EV on each arc (i, j), we assume that the parameters remain constant on each arc, but they may differ from one arc to another. The EV travels on an arc (i, j) at an average speed s_{ij}, carrying a total load of $M = L_{ij} + w$, where L_{ij} is the load carried by vehicle on this arc and w is the curb weight of vehicle. The length of the arc (i, j) is denoted as d_{ij}. Finally, M_{ij} the amount of mechanical energy required by EV on the arc, can be calculated using the mechanical power P_t as follows.

$$ME_{ij} \approx P_t(d_{ij}/s_{ij}) = \frac{P_t d_{ij}}{s_{ij}} = \alpha_{ij}(w + L_{ij})d_{ij} + \beta s_{ij}^2 d_{ij}$$

where, $\alpha_{ij} = a + gsin\theta + gC_r cos\theta$ is an arc specific coefficient and $\beta = 0.5C_d A\rho$ is a vehicle specific coefficient. The result is in joules ($J = kgm^2/s^2$) which can be translated into kilowatt hour (kWh).

With the consideration of the motor efficiency (eff_m) of an EV, the mechanical energy required by an EV on each arc is converted to the electric energy needed by the electric motor of the vehicle. We have to estimate how much battery energy is needed to provide the corresponding electric energy with the discharging efficiency of battery (eff_d). The total amount of battery energy for travelling on arc (i, j) is calculated as follows.

$$E_{ij} = eff_d \bullet eff_m \bullet ME_{ij} = eff_d \bullet eff_m \bullet [\alpha_{ij}(w + L_{ij})d_{ij} + \beta s_{ij}^2 d_{ij}]$$

where, $eff_m = 1.25$ and $eff_d = 1.11$ is provided by Feng and Figliozzi (2013) and Murakami (2017) respectively.

In the model of this paper, the indirect carbon dioxide emissions from the use of an EV can be estimated based on the amount of battery energy used. Considering the recharging efficiency of a battery as $eff_p = 1.25$ (Feng and Figliozzi, 2013), the battery energy required by the EV is translated to the amount of electric power which is transmitted from the power plant. If the type of electric generation is coal-fired generation, then the rate at which electric energy is converted to the emissions is $r = 0.69kg/kW \bullet h$ (Feng and Figliozzi, 2013). Thus, we can estimate the carbon dioxide emissions of an EV on each arc as follows.

$$GE_{ij} \approx eff_d \bullet eff_m \bullet ME_{ij} \bullet eff_p \bullet r = eff_d \bullet eff_m \bullet [\alpha_{ij}(w + L_{ij})d_{ij} + \beta s_{ij}^2 d_{ij}] \bullet eff_m \bullet r = eff_{tot} \bullet r$$

where, $eff_{tot} = eff_d \bullet eff_m \bullet eff_m$.

3.2. Formulation of the EVRP

The EVRP can be defined by the following. Let $G = (V, E)$ be a complete and directed graph, in which V is a set of vertices and E is a set of edges between different vertices. Vertex set V contains three subsets: customer set $C = \{1,2,3,\ldots,N\}$, recharging station set $S = \{N + 2, N + 3, \ldots N + Ns + 2\}$, and depot set $D = \{0, N + 1\}$, so that $V = C \cup S \cup D$ and $|V| = N + Ns + 3$. It is assumed that the depot can recharge EVs when they are loading. When EVs reach either a recharging station or a depot, they are recharged to battery capacity T. The edge set $E = \{(c_i, c_j): c_i, c_j \in V, i \neq j\}$ stands for edges connecting different vertices of V. Every element of E is associated with distance d_{ij} (in m), energy consumption f_{ij} (in Joule) and speed s_{ij} (in m/s) for travelling this arc. The EVRP model assumes that vehicles travel each arc at different speeds and that energy consumption is relevant to the speed, load (in kg) and travelling distance of vehicles.

In the EVRP, EVs start from a depot, visit a set of customers and, finally, return to depot. If it is a necessary to get recharged during service, EVs visit a recharging station. The number of recharging stations visited by a vehicle in one tour can be greater than one. Also, any recharging station can be visited more than once by any vehicle. When carried products are delivered completely, the vehicle returns to depot. To ensure the efficiency of delivery, every customer is visited only once, and the demand of each customer needs to be satisfied after this visit. On the contrary, EVs can visit any recharging station more than once. To permit multiple visits to some recharging stations, we can augment graph G by creating graph $G' = (V', E')$, with dummy vertices set $S' = S \cup \gamma$, where $\gamma = \{N + Ns + 2 + 1, N + Ns + 2 + 2, \ldots, N + Ns + 2 + n_{N+2}, \ldots\ldots, N + Ns + 2 + \sum_{i=N+2}^{N+Ns+1} n_f, \ldots, N + Ns + 2.$
$+ \sum_{i=N+2}^{N+Ns+2} n_f$
Each element in γ represents a possible visit to a recharging station. Here, n_i is a non-negative integer which is the number of dummy vertices for every recharging station $i \in S$. In this way, the number of visits for every recharging station is recorded by n_f. Other notations used in the EVRP formulation are presented in Table 1.

The mathematical model of the EVRP with energy-minimizing objective can be formulated as follows:

$$\min\left(\sum_{\substack{i,j\in V'\\ i\neq j}} \alpha_{ij} d_{ij} w x_{ij} + \sum_{\substack{i,j\in V'\\ i\neq j}} \alpha_{ij} m_{ij} d_{ij} + \sum_{\substack{i,j\in V'\\ i\neq j}} d_{ij}\beta s_{ij}^2 x_{ij}\right)\cdot eff_d \cdot eff_m \tag{1}$$

Subject to

$$\sum_{\substack{j\in V'\\ i\neq j}} x_{ij} = 1, \quad 5\ \forall\ i \in C \tag{2}$$

$$\sum_{\substack{j\in V'\\ i\neq j}} x_{ij} \leq 1, \quad \forall\ i \in S' \tag{3}$$

$$\sum_{\substack{j\in V'_{N+1}\\ i\neq j}} x_{ji} - \sum_{\substack{i\in V'_0\\ i\neq j}} x_{ij} = 0, \quad \forall\ i \in V'_0 \tag{4}$$

$$\sum_{i\in V'_0\setminus\{0\}} x_{0i} \leq l \tag{5}$$

$$\sum_{i\in V'_{N+1}\setminus\{N+1\}} x_{i(N+1)} \leq l \tag{6}$$

$$f_j \leq f_i - [\alpha_{ij}(w + m_{ij})d_{ij} + \beta s_{ij}^2 d_{ij}]\bullet x_{ij} + T(1 - x_{ij}), \quad \forall\ j \in V'_{N+1}, i \in C_0, i \neq j \tag{7}$$

Table 1
The parameter and variable definitions of the EVRP model.

0, $N + 1$	Depot Instances
S'	Set of visits to recharging, including the dummy vertices of recharging stations set S
$S_0{}'$	Set of visits to depot instance 0 and recharging stations vertices
C_0	Set of depot instance 0 and customer vertices
V'	Set of visits to customers and recharging stations: $V' = C \cup S'$
V'_0	Set of visits to customers, recharging stations and depot instance 0: $V_0^{'} = V' \cup \{0\}$
$V_{N+1}^{'}$	Set of visits to customers, recharging stations and depot instance $N + 1$: $V_{N+1}^{'} = V' \cup \{N + 1\}$
$V_{0,N+1}^{'}$	Set of visits to customers, recharging stations, depot instance 0 and $N + 1$: $V_{0,N+1}^{'} = V' \cup \{0\} \cup \{N + 1\}$
d_{ij}	Distance between vertices i and j
e_i	The demand of vertex$i$. If $i \in S'_0$, $e_i = 0$
Q	Vehicle capacity
T	Battery capacity
w	Vehicle curb weight
l	The maximum number of vehicles used
α_{ij}	An arc specific constant, $\alpha_{ij} = a + g sin\theta_{ij} + gC_r cos\theta_{ij}$
$\beta\beta = 0.5C_dA\rho$	, a vehicle specific constant
s_{ij}	The speed of vehicle when travelling on arc (i, j)
f_j	Decision variable specifying the remaining energy level after visiting vertex j
m_{ij}	Decision variable specifying the remaining cargo when vehicle travels from i to j
x_{ij}	Binary decision variable indicating whether vehicle travel on arc (i, j)
r	The conversion rate of transfer required energy to carbon dioxide emissions

$$f_j \leq T - [\alpha_{ij}(w + m_{ij})d_{ij} + \beta s_{ij}^2 d_{ij}]\bullet x_{ij}, \quad \forall\ j \in V'_{N+1}, i \in S'_0 \tag{8}$$

$$\sum_{\substack{j\in V'_0\\ i\neq j}} m_{ji} - \sum_{\substack{j\in V'_{N+1}\\ i\neq j}} m_{ij} = e_i \quad \forall\ i \in V' \tag{9}$$

$$e_j x_{ij} \leq\ m_{ij} \leq (Q - e_i)x_{ij}, \quad \forall\ i \in V'_0, j \in V'_{N+1}, i \neq j \tag{10}$$

$$x_{ij} \in \{0,1\}, \quad \forall\ i, j \in C_0 \tag{11}$$

Equation (1) is the objective function which seeks to minimize a vehicle's energy consumption in kWh. Constraints (2) guarantee that every customer is visited only once. Constraints (3) indicate that, every recharging station (and corresponding dummy vertex) has, at most, one successor. The flow conservation is established in constraints (4) which make the number of incoming vehicles equal to the number of outgoing vehicles at each vertex. Constraints (5) and (6) enforce the rule?? that the number of vehicles used is, at most, l. Based on the type and sequence of the vertex, the remaining energy level of the vehicle is tracked by constraints (7). Constraints (8) ensure that the energy level of the vehicle is non-negative. The balance of cargo flows in constraints (9) is to ensure the fulfilment of customer demands during vehicles' visits. Constraints (10) restrict the total cargo on the vehicle by vehicle capacity Q. Constraints (7)–(10) eliminate the possibility of generating sub-tours. Constraints (11) show the binary decision variable x_{ij}. If arc (i, j) is traveled by vehicle in the solution, $x_{ij} = 1$; otherwise, $x_{ij} = 0$.

The EVRP model with an emission-minimizing objective function can be formulated as follows:

$$\min Z = \left(\sum_{\substack{i,j \in V' \\ i \neq j}} \alpha_{ij} d_{ij} w x_{ij} + \sum_{\substack{i,j \in V' \\ i \neq j}} \alpha_{ij} m_{ij} d_{ij} + \sum_{\substack{i,j \in V' \\ i \neq j}} d_{ij} \beta s_{ij}^2 x_{ij} \right) \bullet r \bullet eff_{tot} \tag{12}$$

subject to constraints (2)–(11).

4. Solution method

As the solution method to the EVRP, an ant colony (AC) algorithm is proposed. Afterwards, we use the Adaptive Large Neighborhood Search (ALNS) algorithm for addressing the EVRP. To the best of our knowledge, this is the first time that the AC algorithm is proposed to solve the EVRP problem. Considering the similarities between the EVRP problem in this paper and the EVRPTWMF problem in the study of Goeke and Schneider (2015), the ALNS algorithm is adapted to be compared with the AC algorithm.

4.1. Ant colony algorithm based meta-heuristic

Ant colony (AC) algorithm is inspired by the food-searching behavior of ants (Dorigo et al., 1996). The AC algorithm was first designed to solve the VRP by Bullnheimer et al. (1999). After this work, the developed AC algorithms have been widely used to effectively solve different variants of the VRP problem (e.g., Gajpal and Abad, 2009; Yu et al., 2009; Yu and Yang, 2011; Abdulkader et al., 2015; Schyns, 2015; Gajpal et al., 2017; Zhang et al., 2017). In this paper, the AC algorithm is hybridized with iterated local search (ILS) to seek high quality solutions (Lourenço et al., 2003). The basic procedures of the proposed AC algorithm are listed below.

Step 1: Initialize the trail intensity matrix and create one artificial ant.

Step 2: Do the following steps, while the termination condition is not fulfilled.

- By using the trail intensity, generate an ant solution.
- Carry out the ILS to improve the ant solution.
- Update the best ant solution.
- Carry out the ILS to further improve the best solution.
- Update the elitist ants.
- Based on the elitist ant solutions, update the trail intensity matrix.

Step 3: Report the best solution.

In the following subsections, the detailed procedures of the proposed AC algorithm for solving the EVRP are described.

4.1.1. Generation of ant solutions

In the AC algorithm, trail intensity τ_{ij} captures the information on the suitability of visiting customer i to customer j. At the beginning of the algorithm, the trail intensities of all possible visits are initialized with the same value 0.01.

To generate the initial EVRP solution, we first construct an ant solution for the VRP, i.e. battery capacity constraint is not considered. Afterwards, the VRP solutions are used for generating the EVRP solution. The detailed steps are shown as follows.

1. Construct the TSP solutions using the trail intensity

Saving value and trail intensity are two factors which affect the probability of unvisited customer as the next customer through attractiveness value, which is calculated as follows: $\xi_{ij} = [Sav_{ij}]^{\alpha}[\tau_{ij}]^{\beta}$, where Sav_{ij} is the saving value, α is the saving value bias, and β is the trial intensity bias. The saving value is calculated as $Sav_{ij} = d_{i0} + d_{0j} - d_{ij}$. Parameters α and β are given at the beginning of algorithm execution.

Based on the attractiveness value, the next customer in the TSP solution is selected from Ω_q which represents the set of q unvisited customers. The probability of selecting customer y_j in Ω_q is calculated by: $P_{xy_i} = \frac{\xi_{xy_i}}{\sum_{j=1}^{q} \xi_{xy_j}}$, in which $1 \leq i \leq q$ and x is the current customer. In this way a complete TSP route is built.

2. Construct the VRP solution from the TSP solution

In this step, the depot is inserted in the TSP solution to construct the VRP solution. If the remaining carried products of the vehicle are less than the demand of the next customer in the TSP solution, a depot needs to be inserted (visited) in the TSP solution. When all customers are visited, a depot needs to be inserted as a destination so that the complete VRP solution is constructed.

3. Construct the EVRP solution from the VRP solution

The VRP solution is used to construct the initial EVRP solution. The recharging stations are inserted in the VRP route when the remaining energy of the vehicle is not enough to allow the vehicle to reach the next customer. We assume that the vehicle starts from the depot with full battery capacity. The remaining energy level is calculated after a visit of a customer (say customer j) from the VRP route. If the remaining energy level is not sufficient to visit next customer (say customer k) of the VRP route then the possible insertion of recharging stations is evaluated. A recharging station (say recharging station F) is inserted in the VRP route if it satisfies two conditions, 1) the remaining energy level allows the visit of recharging station and 2) full battery capacity allow the visit from recharging station F to next customer k. The violation of one of these two conditions makes the insertion of recharging station F after customer j infeasible. All recharging stations are considered for possible insertion after customer j. There might be a situation when none of the recharging stations can be feasibly inserted. In this case, the insertion of recharging stations is checked in all other places before customer j starting from the immediate predecessor of customer j.

The generated EVRP solution is used as the initial solution to be modified through the improvement scheme.

4.1.2. ILS improvement scheme of the EVRP solutions

The initial EVRP solution is improved through an iterative local search (ILS). The pseudo-codes of the improvement scheme are shown in Fig. 1.

First, the initial EVRP solution is perturbed by randomly removing μ number of customers and recharging stations, where μ is a uniform random number generated from $\left[\frac{N}{10}, \frac{N}{2}\right]$. Then, the removed customers are re-inserted into the solution by the cheapest insertion to generate the perturbed solution S_i'. The improvement scheme allows the solution to search in infeasible regions as well. Therefore, the generalized objective function provided by Goeke and Schneider (2015) is used for

Input:
The initial EVRP solution S

Output:
The best EVRP solution B

Pseudo-codes:
1: Initialize the best EVRP solution B as the initial EVRP solution.
2: **Do** the following steps for ε times
- Perturb solution S to generate the perturbed solution S'.
- Apply the local search on S' to generate S''.
- If S'' is better than the best EVRP solution B, then update B and the trail intensity τ_{ij}.

end while
3: Output the best EVRP solution B.

Fig. 1. Basic steps of the improvement scheme.

evaluating the solutions. The generalized objective function is given below.

$$f_{gen}(S) = f_e(S) + \gamma_{cap}\cdot L_{cap}(S) + \gamma_{batt}\cdot L_{batt}(S),$$

where $f_e(S)$ is the total energy consumption of the vehicle, $L_{cap}(S)$ is the vehicle capacity violations, and $L_{batt}(S)$ is the vehicle battery violations. The violations are penalized in the generalized objective function by the corresponding factors γ_{cap} and γ_{batt}. For the sake of lowering the computation complexity, we use a surrogate violation function $L'_{batt}(S)$ to replace the exact violation function $L_{batt}(S)$ and another one $f'_e(S)$ to replace the exact energy consumption function $f_e(S)$. The reason is that when one vertex is removed from the solution, the energy consumption at each vertex before the removed vertex changes. The surrogate functions assume that the energy consumption of the preceding vertices remains unchanged so that the previous battery constraint is not violated.

The ant solution S_i' is improved using the local search which contains the following four moves: 2-opt* move (Potvin and Rousseau, 1995), relocate move (Savelsbergh, 1992), exchange move (Savelsbergh, 1992), and stationInRe move (Schneider et al., 2014). The 2-opt* move is a modified version of the 2-opt heuristic and is applied to the arc between two different routes. The relocate move considers the relocation of vertices to other position in the same route (i.e. intra-route move) and in other routes (i.e., inter-route move). The relocate move considers customer vertices as well as recharging station vertices for possible relocations. The exchange move considers the swap of two customer vertices within the routes (intra-route move) and between the routes (i.e., inter-route move). The exchange move does not consider the swap between recharging stations or the swap between a recharging station and a customer. The stationInRe move considers the removal of an existing recharging stations as well as the insertion of an extra recharging station. The stationInRe move is the only move that can increase or decrease the number of recharging stations in current solution. All moves are utilized in each iteration of the local search, until there are no improvements in the generalized objective function.

The improvement schemes are repeated for ε times. The value of parameter ε is set to 25 when it is used to improve the ant solution, while it is set to 10 when it is applied to improve the best solution.

4.1.3. Elitist ants and trail intensity update

The set of elitist ants contains the best λ EVRP routes found until the current iteration. The main purpose of using the elitist ants is to change the trail intensity. The elitist ants are updated by comparing them to the current ant solutions. The equation to update the trail intensity τ_{ij} of the arc connecting customers i and j is as follow:

$$\tau_{ij}^{iter+1} = \tau_{ij}^{iter} \times \phi + \sum_{m=1}^{\lambda} \Delta\tau_{ij}^{m},\ \ i \neq j \text{ and } i, j = 1,2,\ \ldots,n$$

where the first term of the right-hand side stands for the old trail intensity from the information of last iteration. The term ϕ is trial persistence which is between 0 and 1. The second term shows that the increase in trail intensity is brought by the m^{th} elitist ants. The value of $\Delta\tau_{ij}^{m}$ is calculated by the following equation:

$$\Delta\tau_{ij}^{m} = \begin{cases} \frac{1}{l_m}, \text{ if the arc between customer } i \text{ and } j \text{ is in the elitist ant route} \\ 0, \text{ otherwise,} \end{cases};$$

where l_m is the route length of the m^{th} elitist ant solution. In this paper, ϕ is set to 0.9, indicating that pheromone density decreases slowly in every iteration.

4.1.4. Parameter settings

The number of iterations and the quantity of ants are two main factors which affect the solution performance and computation time of the AC algorithm. Considering the complexity of the EVRP, we fix the number of iterations at 150, i.e., $T = 150$. In every iteration, one ant is generated to find the solution. The initial ant solution is improved through using the perturbation scheme and the local search for ε times. The value of ε is set to 25 when it is used to improve ant solution, while it is set to 10 when it is used to improve the best solution. In this paper, the parameters are set as: $\alpha = 5$, $\beta = 5$ and $\lambda = 10$. The value of ϕ is set to 0.9, which is recommended by Reed et al. (2014).

4.2. Adaptive large neighborhood search

In this section, an adapted ALNS is proposed for solving the EVRP. The ALNS is widely used for the different variants of VRP, like the PRP (Demir et al., 2012), the VRP with Backhauls (Ropke and Pisinger, 2006), and the EVRPTWMF (Goeke and Schneider, 2015). The ALNS is also the best performing state of the art meta-heuristic for GVRP as shown by Goeke and Schneider (2015). To show the competency of our proposed AC meta-heuristic, the ALNS used by Goeke and Schneider (2015) for EVRPTWMF is adapted for solving the EVRP problem instances in the paper. The numerical experiment performed in their study shows the superiority of ALNS for an EVRPTWMF problem, a VRPTW problem, and an EVRPTW problem. The main steps of the adapted ALNS algorithm are provided in Fig. 2. For more detailed information, the interested readers may refer to the study of Goeke and Schneider (2015).

From Fig. 2, we can see that the ALNS first generates an initial solution randomly. Afterwards, the subinterval in which the random number δ generated is selected from a set of subintervals in $[\Omega_{min}, \Omega_{max}]$ based on the probability π_i. Then, the ALNS randomly chooses a destroy operator and a repair operator with the δ removed customers based on the probabilities π^- and π^+. The local search is performed on the generated solution *R'*. The solution *R'* is accepted for the next iteration based on the simulated annealing criteria. All steps are followed in each iteration until the termination condition is met.

In the adapted ALNS for the EVRP, the generalized objective function is the same as the one used in our AC algorithm which is shown in Section 4.1.2. The same destroy operators used in the ALNS of Goeke and Schneider (2015) are also implemented in our ALNS except the

Input:
d_{ij}Distance between each vertex $i,j \in S'$
e_i Demand of vertex i
w Curb weight of vehicle
Q Loading capacity of vehicle
T Battery capacity of vehicle
N Number of customers
Ns Number of charging stations
α_{ij} An arc specific constant
β A vehicle specific constant

Output:
Route solution S of EVRP

Pseudo-codes:
1: Randomly generate an initial solution S.
2: **While** the termination condition is not satisfied **do**
- Generate a random number δ from one of ω subintervals in $[\Omega_{min}, \Omega_{max}]$. The probability of selecting each of the subintervals is π_i, $i = 1,2,\ldots,\omega$.
- Remove δ customers from S and randomly select and apply a destroy operator to the solution. The new generated solution is denoted as S'. The probabilities of selecting destroy operators are π^-.
- Randomly select a repair operator and apply it to S'. The probabilities of selecting repair operators are π^+.
- Apply local search to S'.
- **if** S' satisfies accept criterion **then**
  replace S with S'
  end if
- Update the scores of intervals, destroy operators and repair operators.
- Based on the new scores, update the selection probabilities of the intervals, destroy operators and repair operators, i.e. π, π^- and π^+.

end while

Fig. 2. Basic steps of the ALNS algorithm.

Table 2
The AC and ALNS results for the small size problem instances.

Inst.	N	CPLEX		ALNS			AC		
		Energy used (kWh)	Time (s)	Energy used (kWh)	Time (s)	Absolute gap	Energy used kWh	Time (s)	Absolute gap
C12R2	12	95.48	4.02	101.00	0	5.78	98.33	0	2.99
C13R2	13	103.26	6.32	134.89	0	30.63	104.83	0	1.52
C14R2	14	108.96	4.31	122.20	0	12.15	110.53	0	1.44
C15R2	15	111.64	2.15	114.92	0	2.94	112.47	0	0.74
C16R2	16	120.62	3.91	140.48	1	16.47	123.44	1	2.34
C17R2	17	121.73	13.71	141.59	1	16.31	121.73	1	0.00
C18R2	18	125.66	11.94	126.43	1	0.61	129.00	1	2.66
C19R2	19	133.76	36.22	141.68	1	5.92	145.69	1	8.92
C20R2	20	132.25	26.24	146.13	1	10.49	132.52	1	0.20
C21R2	21	137.69	64.09	153.08	2	11.17	148.95	1	8.18
C22R2	22	144.64	1923.73	157.26	2	8.73	154.16	2	6.59
C23R2	23	145.51	4890.62	153.20	2	5.29	149.61	2	2.82
C24R2	24	147.30	8014.90	157.37	2	6.84	151.95	2	3.16
Avg.		**121.78**	**1000.28**	**137.71**	**10.33**	**10.26**	**129.48**	**0.92**	**3.20**

cluster removal operator. The destroy operators used in our ALNS are the random removal, the worst removal (Ropke and Pisinger, 2006), the Shaw removal (Shaw, 1997), and the station vicinity removal (Goeke and Schneider, 2015). As for the repair operators, we used greedy insertion, regret insertion (Ropke and Pisinger, 2006), and GRASP insertion (Feo and Resende, 1989).

The local search used in the adapted ALNS contains the same moves used in our proposed AC algorithm. The four moves are 2-opt, Relocate, Exchange, and stationInRe.

5. Numerical results

In this section, an extensive numerical experiment is performed to evaluate the performance of the proposed AC algorithm. Because the benchmark problem instances of the EVRP are not available in current literature, new benchmark problem instances are generated. In the first experiment, to assess the quality of the solutions achieved by the AC algorithm, the small size instances are solved using the CPLEX solver, the AC algorithm and the ALNS algorithm respectively. The corresponding solutions are compared. In the second experiment, we use the AC algorithm and the ALNS algorithm to give the solution to the large size EVRP problem instances. The comparison between the solutions of the AC and those of the ALNS is performed to validate the solution quality and the computation efficiency of the AC algorithm. The analysis on changing the number of recharging stations and the lowest energy level allowed are also carried out. Finally, we compare the different solutions achieved by setting different objective functions to illustrate the importance of using the new objective functions in routing electric vehicles to lower the environmental costs of distribution.

The proposed AC and ALNS algorithms are coded in C programming language and are implemented on AMD Opteron 2.3 GHz with 16 GB of RAM. The optimal solution for the small size problem instances are obtained using the CPLEX solver which is carried by the AMPL running on a desktop with Core i5-4590, 3.3 GHz with 8 GB of RAM.

5.1. Generation of EVRP benchmark instances

Fifteen small size, benchmark problem instances with 2 recharging stations are generated. The number of customers in these instances varies from 10 to 24. Forty instances which consider 25, 50, 75, 100 and 150 customers (C) and 2, 4, 6 and 8 recharging stations (R) are generated for the large size instances. The locations of customers in the two instances are same, but the locations of the recharging stations are different. All instances have only one depot which is located at the center of a 200 by 200 miles grid. The customers are randomly scattered within the grid. and the recharging stations are randomly situated. The demand of each customer is generated randomly between 0.05 and 0.15 tons of products. It is assumed that the electric vehicle has a battery capacity of 110 kWh (3.69×10^8 J), which is a reasonable amount as indicated by Pelletier et al. (2017). On each arc between two vertices, the vehicle is assumed to run at a constant speed, which is randomly selected from the speed set [30, 40, 60, 80]km/h. The vehicle capacity is set to be 3 tons. The arc specific constant α_{ij} is 0.0981, and the vehicle specific constant β is 2.11.

5.2. Numerical experiments on the small size problem instances

The AC solutions for small size instances are compared with the ALNS solution and the optimal solutions found by CPLEX solver as shown in Table 2. The AC and the ALNS algorithms are carried out for each instance for one run. The average results are calculated by taking the average of all instance results. To measure the solution gap between the two solution methods, the percentage gap from the optimal solution is used. The absolute gap is calculated as follows:

$$\text{Absolute Gap} = \frac{(Sol - OPT)}{OPT} \times 100\%$$

Where Sol can be the solution achieved by our AC algorithm or that achieved by the ALNS algorithm. OPT is the optimal solution achieved using the CPLEX solver.

The results reported in Table 2 shows that the average absolute gap between the AC solution and optimal solution is 3.2% and that between the ALNS and optimal solution the gap is 10.26. This indicated the AC algorithm can achieve the close-to-optimal solution for small size instances. Meanwhile, the AC algorithm works better on solving the instances than the ALNS does. It is notable that the computation time of CPLEX solver increases sharply as the size of the instance grows. In contrast, the computation time of our AC algorithm increases slowly. This experiment can illustrate the advantages of our AC algorithm: acceptable solutions within reasonable computation time.

5.3. Numerical experiments on the large size problem instances

Even though the commercial solvers such as CPLEX can solve small size problem instances optimally, they are not able to solve large size problem instances in a reasonable time. However, the proposed AC algorithm can provide good quality solutions.

5.3.1. Comparisons between the solutions of the AC and the ALNS

The numerical results of medium size problem instances with an energy-minimizing objective and the CPU time are reported in Table 3. The reported energy consumption can be converted to carbon dioxide

Table 3
Numerical results of the AC and ALNS algorithms.

Instance	ALNS			AC		
	Energy consumption (kWh)	Time (s)	RPD_{j1}	Energy consumption (kWh)	Time (s)	RPD_{j2}
C25R2-1	159.30	2.00	2.32	155.70	2.00	**0.00**
C25R2-2	216.41	12.00	**0.00**	217.78	12.00	0.63
C25R4-1	289.42	36.00	0.66	287.52	32.00	**0.00**
C25R4-2	354.92	74.00	1.44	349.88	63.00	**0.00**
C25R6-1	444.94	255.00	0.23	443.94	183.00	**0.00**
C25R6-2	173.55	3.00	4.00	166.87	2.00	**0.00**
C25R8-1	235.46	14.00	1.82	231.26	12.00	**0.00**
C25R8-2	293.17	36.00	**0.00**	293.43	32.00	0.09
C50R2-1	347.84	74.00	**0.00**	348.74	63.00	0.26
C50R2-2	449.56	242.00	0.10	449.13	178.00	**0.00**
C50R4-1	164.49	3.00	2.27	160.84	2.00	**0.00**
C50R4-2	215.44	12.00	4.36	206.44	11.00	**0.00**
C50R6-1	289.94	34.00	3.25	280.80	29.00	**0.00**
C50R6-2	347.63	71.00	1.49	342.53	62.00	**0.00**
C50R8-1	439.98	231.00	3.08	426.85	180.00	**0.00**
C50R8-2	145.37	2.00	**0.00**	148.62	2.00	2.24
C75R2-1	230.68	13.00	**0.00**	230.68	12.00	**0.00**
C75R2-2	270.00	33.00	**0.00**	270.03	29.00	0.01
C75R4-1	349.58	73.00	2.67	340.50	61.00	**0.00**
C75R4-2	435.42	233.00	0.91	431.49	172.00	**0.00**
C75R6-1	178.05	3.00	**0.00**	178.05	2.00	**0.00**
C75R6-2	212.32	13.00	1.11	209.98	12.00	**0.00**
C75R8-1	287.57	35.00	**0.00**	288.65	32.00	0.38
C75R8-2	346.98	76.00	1.46	341.98	64.00	**0.00**
C100R2-1	457.23	234.00	1.57	450.17	188.00	**0.00**
C100R2-2	171.26	2.00	6.82	160.32	2.00	**0.00**
C100R4-1	245.17	12.00	1.44	241.69	12.00	**0.00**
C100R4-2	275.57	35.00	1.62	271.17	30.00	**0.00**
C100R6-1	331.00	72.00	**0.00**	336.35	60.00	1.62
C100R6-2	445.73	241.00	0.79	442.21	178.00	**0.00**
C100R8-1	170.56	3.00	1.10	168.70	2.00	**0.00**
C100R8-2	238.32	13.00	**0.00**	242.14	12.00	1.61
C150R2-1	274.41	36.00	1.03	271.61	31.00	**0.00**
C150R2-2	339.74	81.00	0.10	339.41	61.00	**0.00**
C150R4-1	445.46	236.00	**0.00**	449.65	172.00	0.94
C150R4-2	194.38	4.00	5.87	183.60	2.00	**0.00**
C150R6-1	222.22	14.00	**0.00**	226.05	12.00	1.72
C150R6-2	305.67	36.00	**0.00**	309.90	30.00	1.38
C150R8-1	356.30	78.00	0.87	353.23	65.00	**0.00**
C150R8-2	440.92	248.00	0.61	438.26	181.00	**0.00**
Average	294.80	73.13	1.32	292.15	57.18	**0.27**

The best RPD for each instance is marked in bold.

emissions by multiplying the product of two constants r and eff_{tot} which are shown in Equation (12).

The results of the two algorithms are evaluated by using the relative percentage deviation (RPD). The formula to calculate the RPD_{ij} of the ith algorithm (1 for the AC and 2 for the ALNS) for the jth problem instance is shown as follows:

$$RPD_{ji} = \frac{(H_j^i - B_j)}{B_j} \times 100\%$$

where, H_j^i represents the ith algorithm solution in the jth problem instance and B_j represents the best algorithm solution in the jth problem instance.

It is clear from Table 3 that all instances can be solved by the AC algorithm within 10 min. This demonstrates that our algorithm can solve the large size problem instances efficiently. The RPD of the proposed AC is 0.27%, while the RPD of ALNS is 1.32%. This result implies the proposed AC is 1.05% better than the ALNS. Meanwhile, the AC solves the problem faster than the ALNS does. The computing time for AC is 57.18 s and that for ALNS is 73.13 s. It can be concluded that our AC algorithm overtakes the ALNS algorithm in terms of solution quality and computing time.

Table 4
Average results of problem instances with same number of recharging stations.

Instances	Average energy consumption (kWh)	Average number of visits to recharge stations
R2 group	292.36	0.40
R4 group	294.12	0.70
R6 group	288.90	0.60
R8 group	293.24	0.90

From the perspective of the algorithm applications, the AC is easier to implement. The reason is that there are too many repair and destroy operators in the ALNS and each operator has a couple of relevant parameters. In the proposed AC, the perturbation scheme is used to replace the destroy and repair operators.

5.3.2. Analysis on the problem instances with different numbers of recharging stations

The average results of the instances with the same number of recharging stations are shown in Table 4. The instances which have same number of recharging stations are put into one group. For example, R4 group includes the instances which have 4 recharging stations (C25R4-1, C25R4-2, C50R4-1, C50R4-2, C75R4-1, C75R4-2, C100R4-1, C100R4-2, C150R4-1 and C150R4-2). From the results, it is quite interesting that the problem instances with 6 recharging stations are low in the average energy consumption. Moreover, the number of visits to recharge stations increases as the available number of recharge stations rises. More recharging stations are supposed to bring more flexibilities to the selection of the recharging timing so that the energy consumption of vehicle is lowered. However, it seems that too many recharging stations may lead to unnecessary recharging operations. This finding indicates that more recharging stations do not guarantee lowering the energy consumption of the electric vehicles. This phenomenon is worthy of studying and can bring more managerial insights. The optimal number of recharging stations needed is important for designing the recharging network of companies. In future research, more analysis can be conducted for finding the optimal number of recharging stations in the network.

5.3.3. Analysis on the problem instances with different reserved battery energy levels

In practice, the EVs are usually instructed to visit the stations when the vehicles reach the reserved energy level. Therefore, we change the reserved energy level in the problem instances to 10% and 20% respectively, i.e., 90% (99 kWh) and 80% (88 kWh) energy in the battery can be consumed by the EV. The AC algorithm is used to solve the modified problem instances. The results are presented in Table 5.

From the results, we conclude that the changes in the reserved energy level have slight effects on the energy consumption of the EVs. One speculation is that, the battery capacity in this problem is so small that the objective value may not be sensitive to the changes in the reserved energy level. However, the average number of visits to recharging stations are affected by the changes in the recharging threshold. This observation is reasonable because the more battery energy reserved, the EVs are more likely to visit recharging stations.

Table 5
Average results of problem instances with the different lowest energy levels.

The lowest battery energy level	Average energy consumption (kWh)	Average number of visits to recharge stations
0%	292.22	0.65
10%	292.61	1.00
20%	292.15	1.60

5.4. Minimizing energy consumption V.S. Minimizing distance

In this section, we illustrate the importance and value of using the energy-minimizing objective instead of the distance-minimizing objective. We change the objective to the distance-minimizing one and use the AC algorithm to solve these instances. Other parameters remain unchanged. The energy consumptions of the distance-minimizing solutions are compared with those of the energy-minimizing solutions in Table 6.

The solutions of the problem instances with the distance-minimizing objective have 16.44% more energy consumption than the results of the same instances with the energy-minimizing objective on average. This experiment demonstrates the importance of using the energy-minimizing objective rather than the distance-minimizing objective, when we try to achieve the optimum energy consumption of vehicles. It is notable that the energy consumption of a vehicle affects the energy costs which is a big portion of the economic costs of operating electric vehicles. Meanwhile, if the electricity is generated by burning fossil fuel, the indirect carbon dioxide emissions can be lowered by considering the energy-minimizing objective. Thereby, the energy-minimizing objective is more successful than the distance-minimizing objective for reducing economic and environmental costs simultaneously.

Table 6
Numerical results with different objective functions for the AC algorithm.

Instance	Energy-minimizing objective used	Distance-minimizing objective used	Percentage increase in energy consumption
	Energy consumption (kWh)	Energy consumption (kWh)	
C25R2-1	155.70	161.87	3.97
C25R2-2	217.78	235.90	8.32
C25R4-1	287.52	347.98	21.03
C25R4-1	349.88	411.91	17.73
C25R6-1	443.94	491.66	10.75
C25R6-2	166.87	189.42	13.51
C25R8-1	231.26	330.86	43.07
C25R8-2	293.43	354.84	20.93
C50R2-1	348.74	429.31	23.10
C50R2-2	449.13	495.09	10.23
C50R4-1	160.84	186.49	15.95
C50R4-2	206.44	273.80	32.63
C50R6-1	280.80	329.18	17.23
C50R6-2	342.53	388.79	13.50
C50R8-1	426.85	491.70	15.19
C50R8-2	148.62	179.48	20.77
C75R2-1	230.68	288.62	25.12
C75R2-2	270.03	315.60	16.88
C75R4-1	340.50	397.11	16.62
C75R4-2	431.49	482.70	11.87
C75R6-1	178.05	231.48	30.01
C75R6-2	209.98	246.39	17.34
C75R8-1	288.65	360.05	24.73
C75R8-2	341.98	378.08	10.56
C100R2-1	450.17	540.12	19.98
C100R2-2	160.32	194.93	21.59
C100R4-1	241.69	264.35	9.38
C100R4-2	271.17	342.60	26.34
C100R6-1	336.35	411.00	22.19
C100R6-2	442.21	513.52	16.12
C100R8-1	168.70	185.74	10.10
C100R8-2	242.14	272.42	12.50
C150R2-1	271.61	293.00	7.88
C150R2-2	339.41	401.84	18.39
C150R4-1	449.65	486.55	8.21
C150R4-2	183.60	222.24	21.05
C150R6-1	226.05	253.14	11.98
C150R6-2	309.90	330.68	6.71
C150R8-1	353.23	401.19	13.58
C150R8-2	438.26	496.29	13.24
Average	292.15	340.20	16.44

6. Conclusion

In this paper, the Electric Vehicle Routing Problem (EVRP) for minimizing energy consumption is considered. The EVRP aims to find a routing plan for the electric vehicles by minimizing energy consumption. Several real-life constraints related to vehicle capacity, battery capacity, recharging operation, and energy consumption are considered. As a variant of the VRP, this problem is hard to solve because of the NP-hardness. Meanwhile, the comprehensive objective which minimizes the energy consumption also increases the difficulty of solving this problem.

The AC algorithm is proposed for solving the EVRP problem. The ALNS algorithm is adapted as a competitive solution method for the AC algorithm. The extensive numerical experiments on different problem instances are conducted to examine the effectiveness of the proposed AC algorithm. First, the numerical experiments show that the AC can provide close-to-optimal solutions for the small size instances. Second, the AC overtakes the ALNS algorithm for large size problem instances, in terms of solution quality and computing time. Third, the importance of using the energy-minimizing objective rather than the classical distance-minimizing objective is illustrated. Solving the EVRP as an approximation to the classical VRP increases the energy consumption by 16.44% on average. This result indicates that the classical objective function which minimizes the route distance cannot guarantee that the energy consumption is minimized at the same time.

In future study, more constraints such as time window constraints, multi-depot constraints, partial recharge constraints, and so on can be considered in the model. The time window constraint requires that the delivery to the customers be fulfilled within certain specific time window. The multi-depot constraint notes that the EVs can start from any one of several depots in the given area. The partial recharge constraint indicates that the battery of EV may not be fully recharged at the stations; thus, the recharging time may be reduced to meet certain operation purposes. Meanwhile, new solution techniques for this complex problem are also worthy of investigating to achieve high quality solutions.

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