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Electric vehicle tour planning with multiple types of recharging stations

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Abstract

The study addresses the problematic nature of the effect of multiple types of recharging stations on electric vehicle tourist trip design with time windows (EVTTDPTW) in the real environment. The present model with dual objectives can maximize scores (i.e. tourists visiting at most attractions in a given time span) and minimize multiple-recharging costs. That is, it can balance providing tourists with the best possible EV touring experience with the minimum necessary recharge. Structural constraints with branch and bound algorithms were used to efficiently solve the model and obtain exact solutions. For example, the mean solution time of 258.85 minutes under previous models can be reduced greatly to 18.52 seconds by the present models in all instances of test cases. The effects of multiple types of recharging station locations on touring scores were further explored. Insights into competitive recharging service strategies as well as centralized and decentralized station deployment in terms of electric-scooter users/owners and managers such as the government are discussed.

Keywords: Electric Vehicle; recharging stations; tourist trip design; recharging costs

1. Introduction

Electric vehicles (EVs) have experienced increasing popularity in recently years due to lower energy consumption, energy costs, and less pollution. However, the market penetration of EV has remained limited for many years, due to their short driving range, high purchasing or battery price, and lack of recharging stations. However, such issues are now being more actively addressed. The main policies that governments might implement to help overcome these obstacles include establishing a charging network, increasing demand for these vehicles, industrialization and research/development programs, and the introduction of electric vehicles in programs of sustainable mobility (Perdiguero and Jimenez, 2012). The policy of establishing recharging stations or infrastructure is the most important one to solve the chicken/egg dilemma and ameliorate the "range anxiety" problem.

Nowadays, some of the charging infrastructure needed for EVs is being established in many countries. In general, there are three power levels associated with EV charging: 3kw (slow charging for small vehicles such as two-wheelers); 7kw (fast charging for common EVs); and 22-50kw (rapid charging for taxis, commercial vehicles or company cars) (Perdiguero and Jimenez, 2012). Basically, different EVs require different chargers and connectors with the exception of the slowest form of charger, the basic equipment in EVs. In practice, when an EV user arrives at a recharging station, he or she can select one of the chargers or use the basic charger to recharge their vehicle. A recharging station situated in a location may have different types of chargers. For example, in the Penghu Islands, a famous destination in Taiwan, the local government has promoted the use of electric scooters (ESs) via subsidies to replace the use of the conventional two-stroke engine motorcycles. There are currently 4104 ESs, and 330 slow-recharging stations for use by residents and tourists, and 23 battery swapping stations at 7-11 convenience stores (slow charger) for use by tourists (ESs rental from I-SUN Green-Energy scooter rental firm) and residents. Recently, other car-rental firms (EZ SWAP) have further established six automatic battery-swapping stations to serve tourists and residents.

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EV tourism is a new type of travel with benefits ranging from economic (increased tourism spending due to lower fuel cost), social (decreasing dependency on fossil fuel), and environmental (zero tailpipe emissions and decreased noise pollution). However, sufficient charging infrastructure and a general understanding of EVs must be possessed to make EV tourism a reality (Miller, 2014). Currently, recharging stations are clustered in urban areas. It is not easy for EV users to partake in long-distance travel outside these urban areas. To promote the use of EV tourism, industries such as car-rental firms or EV fleet owners can play an important role in expanding the scope of charging services, such as increasing the number of recharging stations and/or recharging rates for completing long-distance journeys. Furthermore, they can provide tourists/users a reliable trip or tour planning regarding station deployment for easily undertaking EVs travel.

In general, recharging stations sited in populated spots such as schools, parks, convenience stores, hospitals, supermarkets, gyms, etc. have either a single type or multiple types of chargers. EV trip/tour planning must consider real-world station deployment to benefit tourists and other users in planning the best possible tour and recharging schedules. To the best of our knowledge, there is little literature focusing on multiple-type recharging stations, especially in the field of EV trips or tour planning. Based upon previous research on EV orienteering or EV tourist trip design problems with time windows (Wang et al., 2018), this study further extends the formulations to consider the multiple-type of recharging stations in the real environment, and then analyzes the effects of different station-deployment strategies on the scores obtained from touring.

2. Literature review

The study extends the EV tourist trip design problem with time windows (EVTTDPTW) by considering multiple-type recharging stations. The problem was derived from the orienteering problem (OP), tourist trip design problem (TTDP) or traveling salesman problem (TSP) with profit. It intends to formulate an EV trip or tour from an origin to a destination in a given time span in which tourists can visit the greatest possible number of points of interests (POI)(i.e. maximum scores obtained) using multiple recharging and without completely running out of charge. There are entire surveys on OP, TTDP, and TSP with profit. For example, Vansteenwegen et al. (2011) surveyed OP itself, its extensions and variants and many solution strategies and applications. Gavalas et al. (2014) summarized the use of OP and its extensions to model single-tour and multiple-tour variants of TTDP. Gunawan et al. (2016) extended the summary of the survey paper by Vansteenwegen et al. (2011) regarding the OP and its variants, while also covering a number of new variants of the OP published in the last five years. Feillet et al. (2005) and Laporte and Rodriguez Martin (2007) clearly situate the OP between other routing problems (with and without profits) and indicate the difference (Vansteenwegan et al. (2011)).

Efficient EV routing or touring is an important management issue. According to the surveys undertaken by Touati-Moungla and Jost (2010) and Schiffer and Walther (2017), there are four main research streams: namely, energy shortest path problems (ESPP), electric vehicle routing problem (EVRP), facility location problem (FLP) and electric vehicle location and routing problems (EVLRP). The aim of ESPP and EVRP is to make an energy-efficient EV routing plan assuming that locations of recharging stations are given as parameters. In contrast, the problems of FLP concern station siting while the EVLRP is dedicated to simultaneously determine station siting and EV routing. It is evident that EV trip/tour planning is directly correlated to problems of the ESPP and EVRP. In addition, the literature review of recent works and developments with regard to ESPP and EVRP was given by Wang et al. (2018). However, our literature review further focuses on EV routing or touring using multi-recharging schedules, plus recharging strategies.

For recharging strategies, Wang et al. (2016) considered a special EV network composed of fixed routes for an EV fleet where each EV moves along its own cyclic tour of depots. A mixed-integer program formulation was proposed to derive four new valid inequalities for shortening the solution time using a Gurobi 6.0.3 solver. The optimal deployment of recharging stations (minimum set-up cost) and an optimal recharging schedule (minimum recharging cost) can be obtained and the best recharging time within a pre-specified duration can be determined. However, they only consider the single-type recharging station.

Daina et al. (2017) proposed a random utility model for joint EV drivers' activity-travel scheduling and charging choices for the appraisal of smart charging strategies. Such strategies deviate from previous ones which relied on simplistic or theoretical representations of the charging and travel behavior of drivers. The duration of a recharging operation depends on the vehicle and charger characteristics and on the recharging strategy adopted by supplier. The model empirically captures the behavioral nuances of tactical charging choices (i.e. target energy, effective charging time and charging cost) using the estimated charging preference.

Wang et al. (2017) proposed a mixed-integer linear programming model to optimize an electric bus recharging schedule (using fast chargers) which can at once determine both planning and operational decisions while minimizing total annual cost. The model was tested using a real-world transit network in Davis, California. Sensitivity analysis (including driving range, charging duration, battery deterioration rate, electricity pricing scheme etc.) provided the guidance on the utilization of electric buses and development of a fast-charging system.Armstrong et al. (2013) studied strategies for the battery switch stations to buy and sell the electricity through the day-ahead market. They determine what the optimal strategies would have been for a large fleet of EVs for the Vehicle-to-Grid and Grid-to-Vehicle cases.

Bessler and Grønbæk (2012) investigated the problem of electric vehicle recharge scheduling with time windows (EVRSTW), requiring that the charging takes place within the time window of the activity, has different speeds (slow and fast charging), and is limited by the total power available in each of the time periods. In short, the problem is a resource allocation problem which is NP-hard. The problem was formulated using an integer linear program and solved by using a local ratio heuristic. The preliminary results show that greedy is too slow and the accuracy need to be improved.

These works explored the best charging strategy with the consideration of the power supply in a grid. These models choose an optimal charging period and charging rate to minimize their charging cost or maximize profit. Although these works are not directly related to our study, the factors considered in the formulation of the model such as recharging cost, recharging duration, time window, load constraints, and different types of chargers are nonetheless instructive.

Regarding EV routing or station siting, Felipe et al. (2014) extended the green vehicle routing problem (GVRP) proposed by Erdogan and Hooks (2012) by considering the multiple technologies and partial recharges (GVRP-MTPR). The routing plans based on the amount of energy recharged and the technology used are determined using constructive and local search heuristics, and extensive computational results on varying instances are reported. The results show that several technologies (Medium, Fast, Ultra-Fast) available to choose for each recharge are better (lower recharging cost) than the individual one, and the partial recharge also can provide significant cost and energy saving.

Sathaye and Kelley (2013) proposed continuous facility location models to optimally locate the publicly-founded recharging stations while dealing with demand uncertainty. A case study is presented for highway corridors in the Texas Triangle megaregion. Two types of recharging stations (AC level 2 and DC level 2) were used to site at different site types. The approach is computationally less burdensome than previous methods, which is an important concern for large-scale facility deployment in general.

Catay and Keskin (2017) presented a variant of EVRP by considering the multiple technologies and partial recharging with time windows. Where the customers are associated with service time windows and the stations may be equipped with normal and quick rechargers, 0-1 integer programming models were proposed for the single and multiple charger cases, and were solved using a commercial solver (CPLEX). The results showed that fast charging might reduce fleet size and decrease energy cost.

Cuchý et al. (2018) formulated the problem of whole-day mobility planning using electric vehicles (WDMEV), rather than planning for single trips only. It is a variant of EVTSP with considerations of the temporal and state of charge (SOC) constraints. In the model, the battery is recharged using a charging rate and only a set of SOC levels can be achieved to reduce the search space. The proposed models were solved by using a label-setting heuristics search algorithm including several speed-ups. The experiment results show that the whole-day approach reduces the time for one's day EV travel and also renders it cheaper. However, effects of the different charging rates on the saving of the recharging time is not significant, since the driver can employ the dwell or activity time to recharge.

Mehar and Rémg (2013) proposed an advanced electric vehicle fleet management framework that can enable economic itinerary planning for EV. The best routes, in term of electric power consumption, are determined based on input parameters including road topology, weather conditions, vehicle characteristics, driver profile, traffic conditions and recharging-station locations. Regarding of battery drop, new routes passing by the nearest charging stations are recalculated for the EV driver. The architecture is the first solution that considers both EV range limitation and all factors influencing power consumption.

Lin and Wang (2017) explored the wireless charging facility problem. Its objective is to assist the government planner on optimally locating multiple types of battery electric vehicle (BEV) recharging facilities to satisfy the need for different BEV types within a given budget to minimize the public social cost. The model considers wireless static and dynamic charging, and is formulated by a tri-level programming method. The model is first treated as a black box optimization, and then solved by an efficient surface response approximation model-based solution algorithm. Numeric tests show that the location plan can be obtained efficiently.

Cui et al. (2018) formulated the models addressing the EV charging station location problem with the consideration of multiple types of charging stations with various numbers of chargers as a 0-1 mixed integer program in order to minimize the total trip travel time of all agents. The models are solved by a commercial solver (CPLEX). The test results show that when the budget increases, the more chargers with higher rates are built and then the travel time for all agents can be reduced.

Usman et al. (2017) presented a planning simulation model which can evaluate the feasibility of electric vehicle driving range when recharging is considered at home, at work or at quick charging-stations in Flanders, Belgium. The quick-charging station has a fixed number of chargers of identical power. The proposed procedure using a realistic travel demand serves to plan a charging strategy, in terms of minimum time loss, for each electric vehicle so that entire scheduled tours of the individual can be executed successfully. The results indicate the use of all charging stations over the day and also the waiting time as a function of charging points at each charging station.

These works indicate the needs of setting multiple-types of recharging stations in real-world EV routing or travel. There are two classes of multi-recharging stations depending on the equipped charger types in each location. That is, there could be single-type or multiple types of chargers in each station location, but there are multiple types of chargers in the locations of a planning area. From the viewpoints of model formulation, multiple recharging choices at each site will be complicated and need more time to solve. In general, multiple types of recharging stations can provide and support the multi-recharging choices for the different EV types for their travel considerations of saving recharging numbers and time or cost.

Regarding EV trip or tour planning, Lee et al. (2012) designed a tour and charging scheduler and developed its search engine based on simulated annealing techniques. The scheduler considers charging-station locations so as to save charging time. That is, the selected recharging points are as near as possible to tourist attractions. If not, the amount of charge tends to be small to reduce the waiting time for recharges. They recommend tours/trips with less wasted recharging time. However, a major shortcoming in the study is that the scheduler only considers the single-type of charging stations.

Lee et al. (2013) has since designed a tour recommendation scheme for EV to save waiting time induced from battery charging by recommending sites or spots with chargers in addition to tour activities. Genetic operations are tailored to create a tour plan consisting of essential selected and optional recommended spots by means of combining the legacy traveling salesman problem and orienteering problem solvers. The recommendation service can reduce time waste by up to 67% for given parameter settings. However, the study did not show the formulations for the problem.

Lee and Park (2014) proposed a distance-based heuristic in selecting a DC charger to create an EV tour schedule with better responsiveness. As a variant of the well-known traveling salesman problem, the tour scheduler finds a visiting order for a given set of destinations and an additional charging spot out of multiple candidates. The results obtained from a prototype implementation reveals that the proposed scheme just increases the tour length by 2.9% and finds a feasible schedule over 70%.

Lee and Kim (2014) designed a spatial data-centric tour and changing scheduler. The hybrid orienteering problem solver determines a feasible tour schedule for user-selected tour spots and optimal system-recommended charging spots to reduce waiting time.

Wang et al. (2018) extended the orienteering problem with time windows by considering electric vehicles with limited range. The EV tour planning problem was formulated by using the mixed integer linear program and was solved by a heuristic. The model was tested in real-world instances and the results show that the network-scale of 58 nodes with 142 links is quite near the limitation of the branch-and-bound method. In contrast, the heuristic method can still find the optimal solution within one hour. The solution time for the exact solution of this kind of NP-hard problem can only be applied to the non-real time tourist tour design service. The formulation should be improved and/or a fast heuristic should be developed to obtain feasible solutions in just a few seconds for real-time application.

Lee et al. (2012~2014) performed a series of studies to solve the EV touring problem. Essentially, they treat the problem as variants of TSP and OP, and use the heuristic to attain feasible solutions. In their studies, they did not propose the formulations or models and undertake the analysis of feasible solutions accuracy in comparison with the exact solutions. In contrast, Wang et al. (2018) proposed a formulation using real-world instances to test the model. The test results using heuristics were compared with exact ones using brand-and-bound. However, they all involve single-type recharging stations.

To the best of our knowledge, there is little literature exploring the effects of multiple types of recharging stations on EV tourist trip design. However, the related research fields including EVRP, ESPP, FLP are indeed considering the factors of multiple types of recharging stations and their effects. In practice, with multiple-type recharging stations situated in a district or destination, an EV tourist can have multiple choices for tour recharges to reduce recharging time and cost.

In the next section, this paper extends the previous models proposed by Wang et al. (2018) for EV trip planning by considering the multiple types of recharging stations, and some refined formulas are also described. Section 4 presents a case study to assess the applicability of the proposed models, and the comparisons of solution time between the present model and the previous one are also discussed. Section 5 highlights the management implications for EV trip planning with multiple types of recharging stations, while section 6 presents the conclusions of this work.

3. Model formulation

The new formulation, mainly based on the previous one proposed by Wang et al. (2018) for the EV tour planning problem, further considers the multiple recharging option. To greatly reduce the solution time in the previous model, this study introduces some structural or integral constraints.

The previous formulations generally have two classes of constraints. One is for simulating the changes of a battery charge or electrical energy between points. The other is for imitating time movement between nodes. They focus on the individual points, but not on the total or integral part. This formulation will generate a lot of constraints, thus increasing solving time.
For example, the time movement constraints are demonstrated as follows

$$t_j \geq (t_i + t_{ij}x_{ij}) + y_i s_i - (1 - x_{ij})T \quad \forall_{ij} \in A \tag{1}$$

$$t_j \leq (t_i + t_{ij}x_{ij}) + y_i s_i + (1 - x_{ij})T \quad \forall_{ij} \in A \tag{2}$$

$$t_j \leq (\textstyle\sum_i x_{ij})T \quad \forall_j \in N \tag{3}$$

where t_{ij} is the travel time from node i to node j; ti is the time arrival at node i ; s_i means the length of stay at node i; y_i represents an EV stop at a node i or not; and T is a given time span.

Constraints (1), (2), and (3) specify the time on arrival at each node. If there is no active link toward node j, $\sum_i x_{ij} = 0$, the time on arrival at that node will remain zero using constraint (3); otherwise constraints (1) and (2) will mean that $t_j = (t_i + t_{ij}x_{ij}) + y_i s_i$, and $t_j \leq T$ using constraint (3), so the time on arrival at node j equals the time on arrival at prior node i of the touring path plus the length of stay at node i and the travel time between them. Moreover, constraints (1) and (2) can also prevent the generation of subtours.

These constraints are reasonable and complete. However, the formulas in the model generate a lot of constraints, and subsequently produce more restrictive choices or combinations that will increase the solution time. In fact, the constraints (2) can be removed and replaced by a new constraint as

$$\sum x_{ij} \times t_{ij} + \textstyle\sum_{i \in N} s_i \leq T \qquad \forall ij \in A \tag{4}$$

It represents the total travel time during a trip plus the total length of stay at spots which must be less than or equal to a given time span. The new formulas can greatly reduce the number of constraints, therefore decreasing the solution time. That is, the constraint can remove a lot of the violated touring and greatly reduce the solution time. Meanwhile, only using the constraint (1) alone can prevent the subtours.

For example, suppose that there is a feasible trip or tour from the origin node 0 to the destination D, and going through node A, node B, and node C in an orderly manner. From the microscopic view, we focus on the EV individual movements between nodes, which should satisfy the time constraints, such as if an EV departs from the origin node A(t_A), the arrival time to node B will be t_B. Three constraints, $t_B \le T$, $t_B \ge t_O + t_{OA} + S_A$, $t_B \le t_O + t_{OA} + S_A$ are needed. Thus, that necessitates twelve constraints (3*4) to guarantee the trip is feasible. In contrast, from the macroscopic view, since a trip is composed of arcs and nodes, only one constraint can ensure the trip is feasible: $t_o + t_{0A} + t_{AB} + t_{BC} + t_{CD} + s_A + s_B + s_c \le T$. However, the constraint must be coordinated with the continuity constraint to guarantee the connections between nodes and arcs.

In addition, a network with 58 nodes and 142 links—instance 5 in Wang et al. (2018)— using formula (2) can additionally generate 186 constraints and 639 non-zero values in comparison to using formula (4). The solution time using formula (2) and (4) is 165.15 minutes and 16 seconds, respectively. That is, the solution time using formula (2) is around 600 times that of formula (4).

Similarly, for energy constraints (5), (6) and (7),

$$e_j \ge \left(e_i - d_{ij}x_{ij}\right) + r_i - (1 - x_{ij})\beta \quad \forall_{ij} \in A \tag{5}$$

$$e_j \le \left(e_i - d_{ij}x_{ij}\right) + r_i + (1 - x_{ij})\beta \quad \forall_{ij} \in A \tag{6}$$

$$e_j \le (\textstyle\sum_i x_{ij})\beta \quad \forall_j \in N \tag{7}$$

where d_{ij} is the energy consumption by traveling from node i to node j; β means the vehicle energy capacity; e_j represents the energy level on arrival at node j; and r_i is the amount of energy replenished at node i.

Constraints (5), (6), and (7) track the level of energy on arrival at each node. If there is no active link toward node j, $\sum_i x_{ij} = 0$, the energy level at node j will remain zero using constraint (7); otherwise, constraints (5) and (6) will mean that $e_j = \left(e_i - d_{ij}x_{ij}\right) + r_i$, and thus the energy level when arriving at node j equals the energy level at a prior node i plus the energy recharged at node i minus the energy consumed when travelling between them.

Constraint (6) can be replaced by a new constraint;

$$\beta + \textstyle\sum_{i \in N} r_i \ge \sum d_{ij}\, x_{ij} \qquad \forall ij \in A \tag{8}$$

The constraint means that vehicle range plus recharging at stations are equal to or greater than energy consumption during the trip. It also can remove the violated touring recharges and greatly reduce the solution time.

The new model can simulate the spatial-temporal touring and multiple-recharging behaviors of EV tourists, and can be used to find the best routes with minimum recharging cost to visit the most POIs within the time windows of a given time span. To simplify the new formulation and clearly present the differences in formulations between the new and previous ones proposed by Wang et al. (2018), we follow Wang et al.'s notations and reuse some formulas in formulating the new model.

A directed transportation network is denoted as $G = (N, A)$, where N is the set of nodes with element $n \in N$ consisting of attractions (N_D), recharging stations (N_S), and intersections (N_J); and N_D is a set of attractions (i.e. POIs), N_S is a set of recharging stations (i.e. convenience stores), N_J is a set of road intersections, and A is the set of directed links with element $ij \in A$. K is the set of types of recharging stations with element $k \in K$. Many assumptions are made to formulate the model, including a single-type of EV with a constant range, a linear relationship between energy consumption and driving distance, a fixed travel time between nodes, and single visit to each of the recharging stations with a fixed recharging time. Additional notations are defined as follows and will be used throughout this research.

Parameters

w_i: The weight score of visiting node i.

T_{max}: The limit of a tour/trip duration, or the total allowed duration.

t_{ij}: The travel time from node i to node j.

s_i: The length of stay s_i at node i.

d_{ij}: The energy consumption by traveling from node i to node j.

t_o: The departure time from the origin node.

U_i: The upper bound of the opening hours or service time for RS at node i.

L_i: The lower bound of the opening hours or service time for RS at node i.

e_o: The initial energy level at the origin node o.

β: The vehicle energy capacity.

h_i: =1 if node i is a designated recharging station, and 0 if otherwise.

R_k: The recharging rate using a k-type station.

C_k: The unit cost using a k-type station.

Decision variables

e_j: The energy level on arrival at node j.

t_j: The time on arrival at node j.

y_i: =1 if node i has been visited, and 0 if otherwise.

t_{ij}: The travel time from node i to node j.

r_i: = The amount of energy replenished at node i.

Z_{ik}: =1 if the vehicle is recharging the battery at node i using a k-type station, and 0 if otherwise.

e_d: The energy level on arrival at destination node d.

With these notations, the problem of EV touring planning with multiple recharging stations can be formulated as follows:

Maximize $(\sum_{i\in N} y_i \times w_i - \sum_{k\in K}\sum_{i\in N} Z_{ik} \times C_k)$ (9)

Subject to

$$\sum_i x_{ij} \geq y_j \qquad \forall_j \in N \tag{10}$$

$$\sum_j x_{ij} - \sum_i x_{ij} = \begin{cases} 1, & i = 0 \\ -1, & i = d \\ 0, & o/w \end{cases} \qquad \forall_{ij} \in A, \forall_i \in N \tag{11}$$

$$e_j \geq \left(e_i - d_{ij}x_{ij}\right) + r_i - \left(1 - x_{ij}\right)\beta \qquad \forall_{ij} \in A \tag{12}$$

$$\beta + \sum_{i\in N} r_i \geq \sum \ d_{ij}\, x_{ij} \qquad \forall_{ij} \in A \tag{13}$$

$$e_j \leq (\textstyle\sum_i x_{ij})\beta \qquad \forall_j \in N \tag{14}$$

$$t_j \geq \left(t_i + t_{ij}x_{ij}\right) + y_i s_i - \left(1 - x_{ij}\right)T \qquad \forall_{ij} \in A \tag{15}$$

$$\sum \ x_{ij} \times t_{ij} + \sum_{i\in N} s_i \leq T \qquad \forall_{ij} \in A \tag{16}$$

$$t_j \leq (\textstyle\sum_i x_{ij})T \qquad \forall_j \in N \tag{17}$$

$$\sum_{k\in K} z_{ik} \leq h_i \qquad \forall_i \in N \tag{18}$$

$$\sum_{k\in K} z_{ik} \leq y_i \qquad \forall_i \in N \tag{19}$$

$$r_i \leq \sum_{k\in K} z_{ik} \times R_k \times s_i \qquad \forall_i \in N \tag{20}$$

$$r_i \geq \sum_{k\in K} z_{ik} \times R_k \times s_i - e_i \qquad \forall_i \in N \tag{21}$$

$$r_i \leq \beta - e_i \qquad \forall_i \in N \tag{22}$$

$$e_i \geq 0 \qquad \forall_i \in N \tag{23}$$

$$e_o = \beta \tag{24}$$

$$t_o = 0 \tag{25}$$

$$U_j \geq t_j \geq L_j \qquad \forall_j \in N_D \tag{26}$$

$$y_i, x_{ij}, z_{ki} = \{0,1\} \qquad \forall i \in N, \forall k \in K, \forall ij \in A \tag{27}$$

Objective function (9) serves to maximize the sum of the weighted score of visited attractions along the touring path, and minimize the multiple recharging cost. A weight can be used to evaluate the importance between the two objective functions. Constraint (10) states that node i cannot be visited unless a link toward the node is active. Constraint (11) is a flow reservation constraint, which ensures that the arrival EV at node i must equal the departure from that node, and guarantees the tour or trip starts in node o and ends in node d. Constraints (12) and (14) track the level of energy on arrival at each node. If there is no active link toward node j, $\sum_i x_{ij} = 0$, the energy level at node j will remain zero using constraint (14); otherwise, constraint (12) will mean that $e_j \geq (e_i - d_{ij} \times x_{ij}) + r_i$, and thus the energy level when arriving at node j is greater than or equal to the energy level at a prior node i plus the energy recharged at node i, minus the energy consumed when travelling between them. Constraint (13) denotes vehicle range plus recharging at stations which are greater than and equal to the energy consumption during the trip. Constraints (15) and (17) specify the time on arrival at each node. If there is no active link toward node j, $\sum_i x_{ij} = 0$, the time on arrival at that node will remain zero using constraint (17); otherwise constraint (15) will mean that $t_j \geq (t_i + t_{ij} \times x_{ij}) + y_i \times s_i$, and $t_j \leq T$ using constraint (17). Thus, the time on arrival at node j is greater than or equal to the time on arrival at a prior node i of the touring path plus the length of stay at node i and the travel time between them. Constraint (16) ensures the limited time budget. That is, the total travel time during a trip plus the total length of stay at spots must be less than or equal to a given time span. Moreover, constraint (15) can also prevent the generation of subtours. Constraint (18) ensures that a vehicle cannot be recharged at node i unless this node is designated as a recharging station. Constraint (19) states that if a vehicle is recharging its battery at node i, then the vehicle must stay at this node. We use the length of stay at a recharging station to express the time needed for battery recharging. Constraint (20) states that the amount of energy recharged depends on the recharging rate and length of stay at a station. Constraints (21) and (22) ensure that the energy level of the battery will be reset whenever it is recharged. Note that if $z_{ik} = 1$, constraints (21) and (22) can be transferred to $r_i + e_i \leq \beta$, and thus the energy level can be set to partial or full charge. Constraint (23) ensures the vehicle travelling along the touring path will not run out of energy. Constraint (24) states that the energy level at the origin node is fully charged. Constraint (25) sets the zero value of the departure time from the origin node. Constraint (26) enforces the time windows of the attractions. Constraint (27) is a binary constraint.

4. Case study

We use the road networks of Penghu Island and the Magong urban area derived from Wang et al. (2018) to demonstrate the new model and compare its performance, such as solution time, with the previous one. The model is further used to evaluate the recharging station location strategies to serve tourists or residents.

4.1 Data acquisition

Penghu Archipelago has an area of only 126.8 square kilometers, and is located off the coast of Taiwan, attracting more than 1,000,000 tourists per year. It has six administrative areas; Magong City, and the five townships of Husis, Baisha, Siyu, Wangan, and Chimei. Most of the districts, including Magong City and the three townships of Husis, Baisha, and Siyu, are on the main island of Magong. Most tourist activities are also on this island, and there are three popular tours, including northern, eastern and southern tours. This main island covers an area of 97.4 square kilometers, and around 40 slow-recharging stations with 337 charging poles (each one with a socket) have been established there; with most of them located in the urban area (i.e. Magong City), rental ES have gradually become a common transportation mode for tourists and residents. At present, there are about 4,104 ES on the island, around 1000 of which are used for vehicle rental. The rental firms have alliances with local convenience stores (7-Eleven) to provide a manpower battery swap service (MBSS) for undertaking long-distance journeys. Recently, the car-rental firm EZSWAP further established automatic battery swap station systems (ABSS). There are six stations located at the main-road intersections and nearby attractions in the main island, and two stations situated in the outlying islands. Figure 1 shows a network representation of the popular scenic touring routes on Penghu Island. This network is an extension of the original one described in Wang et al. (2018), with the aim of reaching a greater number of attractions. In the network, there are three types of nodes, including attractions (nodes d1, d2….d30) marked with triangles, intersections (nodes J1, J2….J30) marked with circles, multiple-types of recharging stations (i.e. nodes S1, S2….S8 (convenience stores) S9, S10…S14 (ABSS), and some slow-recharging stations sited in suburban attractions) marked with diamonds. In the case study, the driving range of the electric scooter is assumed to be a constant value of 30 km when fully charged. The tourists' average length of stay and weighted scores for each attraction, as listed in Table 1, are based on our previous survey, with the weighted scores ranked based on the number of tourist visits (Wang et al. (2018)). The time spent at the intersection points and battery exchange stations is assumed to be 0 and 10 minutes, respectively. The 10 minutes at a station is seen as the average time needed for manpower battery swapping, but this time can be adjusted when considering other types of recharging stations. For example, an automatic battery swapping normally takes 5 minutes to fully recharge an ES. In addition, we also use an urban network (i.e. Magong area) (as shown in Figure 2 (Wang et al., 2018)) to evaluate the performance of the new model.

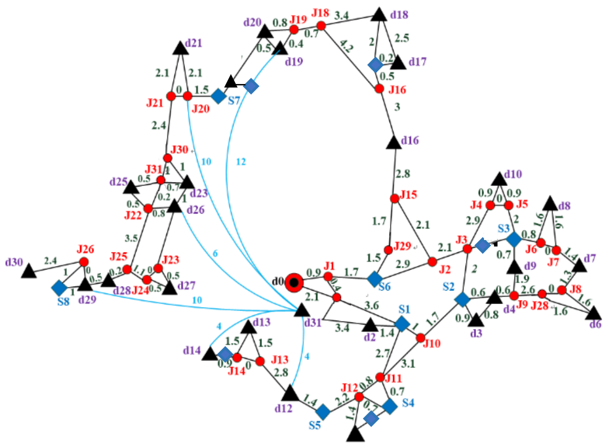

Figure 1 (a) A network representation of Penghu Island

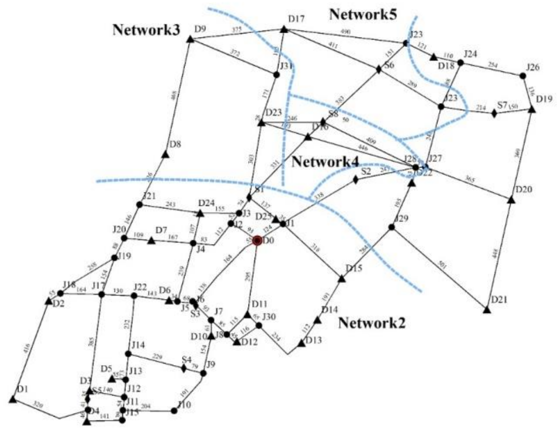

Figure 2 A network representation of Magong urban area

Table 1. The parameters of length of stay and weighted score for all attractions used in the cases studies

Index	Weighted score	Length of stay (min)	Index	Weighted score	Length of stay (min)	Index	Weighted score	Length of stay (min)
				Penghu network				
d2	1	20	d12	3	30	d23	5	50
d3	3	20	d13	2	10	d25	3	10
d4	3	20	d14	4	20	d26	5	10
d6	2	20	d16	4	10	d27	4	30
d7	4	20	d17	5	60	d28	4	20
d8	5	40	d18	2	20	d29	4	30
d9	2	40	d19	5	30	d30	5	30
d10	1	20	d20	5	10	d31	0	0
d11	3	30	d21	5	50			
				Magong network				
D0	0	0	D9	10	20	D18	10	30
D1	5	40	D10	2	10	D19	10	30
D2	10	60	D11	5	30	D20	8	25
D3	5	30	D12	2	10	D21	10	50
D4	3	20	D13	1	30	D22	2	20
D5	5	40	D14	1	10	D23	2	15
D6	2	20	D15	1	10	D24	2	20
D7	3	20	D16	5	30	D25	5	20
D8	2	40	D17	10	30			

4.2 Solutions for the model

The solutions shown in Table 2 were obtained using the parameters shown in Table 1 and following additional parameters: the range of the ES (30 km), the battery's state of charge at the origin point (fully charged: 30 km), the ES speed of 30 km/h, and the given locations of the single-type battery swapping stations. We estimate the travelling time for each link by dividing its distance by the travel speed. For example, the ES spends 2 minutes to travel a distance of 1 km ((1km/30km/h)*60min). In this case study, we use the network of the Penghu main island (i.e. instance 1) and the Magong City network (i.e. instance 4 and 5) to test and compare the solution time for the new model and previous one proposed by Wang et al. (2018).

Table 2 compares the solution times when using different models for the cases in the various instances. In each case, some critical parameters, including trip duration (T), O-D, time-windows (TW), and residual state of charge at a node (E), were selected to test the model solutions using the branch-and-bound method. For example, in instance 5, the O-D ranged from D0 to D15. Trip durations of 180, 240, and 300 minutes were set for Cases 1, 2, and 3, respectively.

From Table 2, we can obtain the following major properties and differences of solution times using the models.

(1) All of the solution times with the new model are significantly shorter than those of the previous iteration. In all of cases, the solution times can be reduced greatly using the new formulation. For example, in instance 5, with regard to cases 10-1, 10-2 and 10-3, solution times of 578.2, 213.2 and 165.15 minutes using the previous model can be reduced to 3, 13 and 15 seconds using the new one. In addition, the recharging station locations determined by the new model can be different from the ones using the previous model.
(2) When the network-scale is small (such as in instance 1) or a trip length is short, the solution times are short regardless of using the previous or new model. For example, with regard to case 3 in instance 1, the solution times for the previous and new model are 2 minutes and 33 seconds, respectively. That is, the differences in solution times are not very significant when using the two models, and the effects of the constraints of time windows and residual state of charge on the solution time are also not significant with a small network.
(3) When the networks are scaled up (i.e. from network 4 to network 5), the solution times are much larger in the previous model. In effect, the network-scale of 58 nodes with 142 links is quite near the limitation of the branch-and-bound method in the previous model. For example, with regards to case 10-1, the solution time is up to 578.2 minutes. Nevertheless, the new model can still find the optimal solution within 15 seconds.

Table 2 Comparison of the solution times for the different models using the branch-and-bound method.

case	Parameters	The previous case			The new case		
		Scores	Solution time (min.)	Charging stations	Scores	Solution time (sec.)	Charging stations
Instance 1							
1	D0→D30 ,180≦TW≦300 T=400, E(D30)≧11.22	46	19.26	S7	46	32	S7
2	D0→D31, 180≦TW≦300 T=480, E(D31)≧0	44	40.33	S7	44	10	S7
3	D0→D14, 180≦TW≦300 T=390, E(D14)≧13.53	28	2	(S3, S4)	28	33	(S3, S4)
4	D0→D31, 180≦TW≦300 T=360, E(D30)≧0	24	7.53	S3	24	56	S4
5	D29→D0, T=300	35	47.65	S7	35	9	S7
5-1	D29→D0, T=240	30	741.06	S7	30	3	S6
5-2	D29→D0, T=210	26	1553.48	S6	26	4	S7
5-3	D29→D0, T=360	40	43.03	S7	40	13	S3
6	D0→D31, T=380	35	1793.81	S6	35	5	S6
6-1	D0→D31, T=480	44	45.46	S7	44	9	S7
6-2	D0→D31, T=540	48	36.54	(S3,S7)	48	9	S7
6-3	D0→D31, T=500	44	29.88	S7	44	7	S7
Instance 4							
9-1	D0→D25, T=180	27	92.73	no	27	2	no
9-2	D0→D24, T=240	34	40.9	S1	34	51	S1
9-3	D0→D24, T=300	39	32.83	(S1,S5)	39	48	S1
9-4	D0→D24, T=360	47	18.65	(S5,S8)	47	15	S8
9-5	D0→D15,T=180	27	232.72	no	27	3	no
9-6	D0→D15, T=240	33	104.96	S8	33	19	S8
9-7	D0→D15, T=300	41	67.85	S8	41	19	S8
9-8	D0→D15, T=360	47	46.43	S3	47	48	S1
Instance 5							
10-1	D0→D15, T=180	30	578.2	S8	30	3	S1
10-2	D0→D15, T=240	40	213.2	S1	40	13	S1
10-3	D0→D15, T=300	47	165.15	S1	47	15	S1

4.3 Evaluation of recharging station locations

The case of rental firms deploying battery swap stations to serve their tourists for completing long-distance travel are used to test the new model with multiple types of recharging stations (i.e. slow-recharging and battery swapping). The first firm has cooperated with convenience stores (7-11) to support the manpower battery exchange service. There are 23 stations, with six stations located in the suburban area (i.e. nodes S1, S2,…S8). The total time for manpower battery swapping is set to 10 minutes. The second firm supports an automatic battery swapping station. On the main island, there are 5 stations situated in the suburban area (i.e. nodes S9, S10, ….S13). The total time for the automatic battery swapping is around 5 minutes.

Popular northern tours (from d0 to d30) with and without time windows at the node of d25 (for lunch) are used to test the performance of different settings of the stations.

The parameters shown in Table 1 and following additional parameters are used for the northern trip: the ES trip starts from Magong C.B.D. (origin) and ends at Siyu lighthouse (destination). The trip must be completed within T minutes; d24 (Chingshin Seafood) must be reached within the time window from 180 to 300 minutes, and the energy level when arriving at the destination (the minimum required energy level) must be greater than 11.22% for the return trip. The minimum required energy level for the return trip is estimated by the distance from the destination to its nearest BSS. In addition, a weight of 5 is given for the second objective function, and a unit cost of 0.1 for slow-recharging and 1 for battery swapping.

Table 3 shows a comparison of the score, recharging cost and locations for the different deployments. From Table 3, we can obtain the following major properties and differences between the station deployments.

(1) The BSS location deployment of firm A is obviously better than the one of firm B based on the score obtained, with or without time windows. That is, the scores obtained using the station deployment of firm A are higher than the ones using the station deployment of firm B. For example, with regard to cases having durations 540, 510, 480, 240 min, with a time window, the scores obtained by the firm A deployment are higher by around 1-3 times than the ones obtained by firm B. In these cases of firm A deployment with higher scores in comparison with firm B, some recharging cost must be paid. For example, for the case having a duration of 480 min, the tour with firm A deployment can be recharged via an BSS sited in s_8 to increase the travel distance, and in turn their obtained scores. However, some recharging cost (around NT$20) and waiting time for manpower battery swapping must be paid.

(2) The scores without time window and residual energy constraints are better than with time window and residual energy constraints; since solution space is restricted, the algorithm must spend more time to look for the exact solutions. For example, in the cases of firm A the average solution time with and without a time window is 35.88 and 11.66 seconds, respectively.

(3) When the given time span over 480 min, the BBS will be used to recharge for completion of long-distance travel, with or without a time window. In contrast, for the time span below 480 min, the tours can recharge at slow public recharging stations. In addition, when the given time span increases, the solution time is increased. For example, in the case of firm A with a time window, the solution time increases from 27 seconds to 118 seconds when the given time span increases from 480 to 540 min. However, for a one-day tour, a tour of over 540 min (i.e. 9 hours) travel time is not common.

(4) There is a trade-off between the two objective functions (i.e. maximum scores obtained and minimum recharging cost). That is, if a tour intends to reduce the recharging cost, the obtained scores might also be reduced. For example, with regards to the cases of time spanning 390 and 420 min with a time window in firm A, the optimal value of the single objective function (i.e. maximum scores) can have 46 and 49 in contrast to 45 and 47 for the dual objective functions (i.e. maximum scores and minimum recharging cost).

Table 3 Comparison of the scores, recharging cost and locations for the different stations setting.

T	firmA				firmB			
	Optimal value	Scores	Cost	Charging stations	Optimal value	Scores	Cost	Charging stations
With time windows								
540	50	55	1*1	S7	49	54	1*1	S10
510	50	55	1*1	S7	49	54	1*1	S10
480	49	54	1*1	S8	48.5	50	3*0.1	D17,D19,D21
420	45.5	47	3*0.1	D17,D19,D26	46	47	2*0.1	D17,D19,D26
390	43.5	45	3*0.1	D17,D19,D26	43	44	2*0.1	D17,D19
360	41	42	2*0.1	D17,D19	41	42	2*0.1	D17,D19
330	39	40	2*0.1	D17,D19	38	40	2*0.1	D17,D19
300	36	37	2*0.1	D17,D19	35	37	2*0.1	D17,D19
240	29	30	2*0.1	D17,D19	29	30	2*0.1	D17,D19
Without time windows								
540	56	61	1*1	S7	54	59	1*1	S10
510	52	57	1*1	S7	52	57	1*1	S10
480	51	53	4*0.1	D17,D19,D21,D26	50	52	4*0.1	D17,D19 D21,D26
420	46.5	48	3*0.1	D17,D19 ,D26	46	47	2*0.1	D17,D19
390	43.5	45	3*0.1	D17,D19 ,D26	43	44	2*0.1	D17,D19
360	41.5	43	3*0.1	D17,D19 ,D26	41	42	2*0.1	D17,D19
330	39	40	2*0.1	D17,D19	38	39	2*0.1	D17,D19
300	36	37	2*0.1	D17,D19	35	36	2*0.1	D17,D19
240	30	31	2*0.1	D17,D19	28	29	2*0.1	D17,D19

5. Management implications

The deployment of recharging stations to serve EV tourists for long-distance travel is a strategic problem related to construction cost and practical demand. Car fleet owners and car-rental firms should consider the effects of station locations on user utility, such as the number of visited attractions and the recharging cost. That is, the station locations can indeed extend travel-distance using the minimum recharging cost or times; as such, the tourist can visit more points of interest. From this point of view, the recharging stations should be located at the sites of attractions or POIs, with public recharging stations sited (free or low-cost, without waiting time), rather than in private locations (high cost with waiting and recharging time). Unfortunately, there are not enough stations deployed, especially in suburban areas. Furthermore, public deployments tends to be the slow-recharging type with low construction costs, although the government has launched an electric vehicle action plan (MOEA, 2015) to promote the establishment and use of fast recharging stations in Taiwan. Therefore, in practice, firms should establish their own stations to serve their tourists and residents using fast-type rechargers, such as battery swapping stations or fast recharging stations, to alleviate "range anxiety". In fact, the development of recharging stations has tended to favor automatic battery swapping stations (as with the leading firm, Gogoro) and fast recharging stations (the leading firm of Chinese Petroleum) in Taiwan.

For electric scooter touring, there are multiple types of recharging stations (slow-recharging and battery swapping stations). Automatic battery swapping stations/systems have been in development and production for many years, and are indeed the most popular ones. As of late, there are a lot of companies engaging in the development of the battery swapping system. However, there is no standard for communication among the different systems, although the government intends to promote the standard of the Gogoro BSS. Clearly, battery ownership is still the key barrier to promote the use of battery exchange. Therefore, we can see that the ES car-rental firm or producers have cooperated with convenience stores (such as 7-11) to promote the use of automatic BSS. For example, Gogoro has forged a strategic alliance with 7-11 convenience stores to establish a network of automatic BSS. The Chinese Petroleum Company intends to establish a network of fast recharging stations. The company has strategically allied with conventional motorcycle and ES producers such as CMC, SYM, KYMCO etc. to establish and promote the use of the fast recharging stations.

The nature or properties of multiple-type recharging stations in the real-world environment will be enforced. Despite the deployment of BSS or FRS, the construction cost is the first factor to consider. Thus, how to reduce the number of recharging stations being sited is an important issue. Firms should have an appropriate analysis tool to identify the practical performance of the different station deployments. The analysis is based on the recharging demand of users. For example, in Penghu Island, the firm of I-sun Green Energy has cooperated with convenience stores to establish manpower battery swapping stations. Thus, there are 23 BSSs to serve around 750 ESS for tourists and residents. Thus, long-distance travel using an EV is readily available.

In addition, when the recharging stations are sited, car-rental or feasible tours/trips may support recharging schedules via mobile equipment such as mobile phones. That is, firms should inform EV users of suitable trips or tours from origin to destination under a time budget, and their recharging times and locations. Therefore, the model solution time is the key point for the use of mobile equipment. As such, the suitable solution time falls within 3 seconds. Due to the complexity of the EV touring design problem, an exact solution is not easy to obtain when the size of problem increases. Therefore, the development of a heuristics algorithm is more appropriate for quickly obtaining feasible solutions.

6. Conclusions

EV currently needs one or more recharging stops to complete longer trips due to range limitations. To serve the requirements of EV recharging for long-distance travel, car-rental firms and car fleet owners need to deploy additional fast recharging stations in the given locations of public recharging stations (i.e. slow-recharging ones). This study extends the EV tour planning problem with consideration of the multiple-type of recharging stations. The new formulation introduces some structural or integral constraints to effectively reduce the solution time in contrast to the previous one. The case study on the evaluations of different recharging station locations demonstrates that the new model can be used to identify their performances of EV tour and recharging schedules with or without time windows, via the scores obtained and recharging cost and locations, etc.

Since public recharging stations are clustered in urban areas, long-distance travel between urban areas is still not easy to achieve. The establishment of sufficient stations are essential. Governments can consider an extension plan to establish public recharging stations at places of public utility such as attractions along popular tours and routes to serve the urgent needs of EV recharging. Due to high construction cost, private sectors should evaluate the effects of multiple types of stations located on EV tours before the stations are actually deployed by using an appropriate analysis tool. Governments should integrate the different charging systems as soon as possible by setting common standards for use within the recharging market. In addition, the cases of Penghu Island and the Magong urban area are small-scale problems. Although the solution time in all of cases are within one minute with the branch-and-bound algorithm using Lingo solver, it can only be used for non-real time EV tour design. In future works, solution techniques used with new models need to be examined and improved in order to efficiently solve the problem of large-scale networks.

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References

Angel, F., Ortuño, M., T., Giovanni, R., Gregorio, T., 2014. A Heuristic Approach for The Green Vehicle Routing Problem with Multiple Technologies and Partial Recharges, Transportation Research Part E, 71, 111-128.

Armstrong, M., Moussa, C. E. H., Adnot, J., Galli, A., Riviere, P., 2013. Optimal Recharging Strategy for Battery-Switch Sstations for Electric Vehicles in France, Energy Policy, 60, 569-582.

Bulent, C., Merve, K., The Impact of Quick Charging Stations on The Route Planning of Electric Vehicles, 2017. IEEE Symposium on Computers and Communications, 152-157.

Bessler, S., Grønbæk, J., 2012. Routing EV Users Towards an Optimal Charging Plan, World Electric. Veh. J. 5.3, 688-695.

Cui, S., H., Zhao, H., Zhang, C., P., 2018. Multiple Type of Plug-In Charging Facilities' Location-Routing Problem with Time Windows for Mobile Charging Vehicles, sustainability, 10, 2855.

Cui, S., H., Zhao, H., Wen, H., Zhang, C., P., 2018. Locating Multiple Size and Multiple Type of Charging Station for Battery Electricity Vehicles, sustainability, 10, 3267.

Chen, Y., W., Cheng, C., Y., Li, S., F., Yu, C., H., 2018. Location Optimization for Multiple Types of Charging Stations for Electric Scooters, Applied Soft Computing 67, 519-528.

Daina, N., Sivakumar, A., Polak, J. W., 2017. Electric Vehicle Charging Choices: Modelling and Implications for Smart Charging Services, Transportation Research Part C, 81, 36-56.

Feillet, D., Dejax, P., Gendreau, M., 2005. Traveling Salesman Problems with Profits. Transportation Science 39, 188-205.

Gunawan, A., Lau, H. C., Vansteenwegen, P., 2016. Orienteering Problem: A survey of Recent Variants, Solution Approaches and Aplications, European Journal of Operational Research, 255, 315-332.

Gavalas, D., Konstantopoulos, C., Mastakas, K., & Pantziou, G., 2014. A survey on Algorithmic Approaches for Solving Tourist Trip Design Problems, Journal of Heuristic. 20(3). 291-328.

Industrial Development Burea, MOEA, 2015. Smart Electric Vehicle Industries Promotion Project, 1-66.

Laporte, G., Rodriguez Martin, I., 2007. Locating a Cycle in a Transportation or a Telecommunications Network, Networks, 92-108.

Lee, B. J., Lee, S., Im, D. Y., Kim, H. Y., Park, G. L., Lee, J., 2012. Tour and Charging Scheduler Development Based on Simulated Annealing for Electric Vehicles, Computer Applications for Bio-technology, Multimedia, and Ubiquitous City, 189-194.

Liao, C. S., Lu, S. H., Shen, Z. J. M., 2016. The Electric Vehicle Touring Problem, Transportation Research Part B, 86, 163-180.

Lee, J., Kim, S. W., Park, G. L., 2013, A Tour Recommendation Service for Electric Vehicles Based on a Hybrid Orienteering Model, Proceedings of the 28th Annual ACM Symposium on Applied Computing, 1652-1654.

Lee, J., Kim, S., 2014, Spatial Query-Combined Tour Scheduler for Electric Vehicles, Applied Mechanics and Materials, 686, 612-615.

Lee, J., Park, G. L., 2014, DC Charger Selection Scheme for Electric Vehicle-Based Tours Visiting Multiple Destinations, RACS '14 Proceedings of the 2014 Conference on Research in Adaptive and Convergent Systems, 7-11.

Luo, L., Z., Gu, W., Zhou, S., Y., Huang, H., Gao, S., Han, J., Wu, Z., Dou, X., B., 2018. Optimal Planning of Electric Vehicle Charging Stations Comprising Multitypes of Charging Facilities, Applied Energy 226, 1087-1099.

Liu, H., X., Wang, D., Z., W., 2017. Locating Multiple Types of Charging Facilities for Battery Electric Vehicles, Transportation Research Part B, 103, 30-55.

Liu, X., Y., Bie, Z., H., 2019. Optimal Allocation Planning for Public EV Charging Station Considering AC and DC Integrated Chargers, Energy Procedia 159, 382-387.

Perdiguero, J., Jiménez, J. L., 2012. Policy Options for the Promotion of Electric Vehicles: A Review, Research Institute of Applied Economics, 1-43.

Marek, C., Michal, S., Michal, J., 2018. Whole Day Mobility Planning with Electric Vehicles, In Proceedings of the 10th international Conference on Agents and Artificial Intelligence, Volume 2, 154-164.

Miller, J., 2014. Electric Vehicle Tourism: A White Paper, 1-21. file:///C:/Users/Master/AppData/Local /Packages/ Microsoft.MicrosoftEdge_8wekyb3d8bbwe/TempState/Downloads/Electric_Vehicle_Tourism_White_Paper%20(1).

Mehar, S., Senouci, S., M., 2013. EV-Planning: Electric Vehicle Itinerary Planning, International Conference on Smart Communications in Network Technologies (SaCoNeT).

Nakul, S., Scott, K., 2013. An Approach for The Optimal Planning of Electric Vehicle Infrastructure for Highway Corridors, Transportation Research Part E, 59, 15-33.

Sandford, B., Jesper G., Routing EV Users Towards an Optimal Charging Plan, 2012. EVS26 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium.

Sachan, S., Adnan, N., 2018. Stochastic Charging of Electric Vehicles in Smart Power Distribution Grids, Sustainable Cities and Society, 40, 91-100.

Vansteenwegen, P., Souffriau, W., Oudheusden, D. V., 2011. The Orienteering Problem: A Survey, European Journal of Operational Research, 209, 1-10.

Wang, I. L., Wang, Y., Lin, P. C., 2016. Optimal Recharging Strategies for Electric Vehicle Fleets with Duration Constraints, Transportation Research Part C, 69, 242-254.

Wang, Y. W., Lin, C., Lee, T. J., 2018. Electric Vehicle Tour Planning, Transportation Research Part D: Transport and Environment, 63, 121-136.

Wang, Y. S., Huang, Y. X., Wu, J. P., Barclay, N., 2017. Optimal Recharging Scheduling for Urban Electric Buses: A case study in Davis, Transportation Research Part E, 100, 115-132.