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A Framework for an Optimization Process to Locate Electric Vehicle Charging Stations

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Abstract **-** To reduce the huge amounts of harmful gases emitted from vehicles emissions and to improve the environmental conditions, countries need to start planning and encouraging the use of electric vehicles (EVs). However, before extensively using EVs, charging stations need to be planned to meet the changing needs of electric vehicles. These charging stations need to be placed at various locations so that they can serve the maximum number of EVs, without significant delays. In this paper, a procedure for optimizing the locations of EVs charging stations is presented. The proposed approach uses the simulation software DYNASMART to simulate different percentages of EVs under different traffic congestion levels. To be able simulate EVs in DYNASMART, two main components have to be coded in the software. First, a subroutine is added to simulate EVs (i.e., tracking the battery charge level). The second component considers the operations within the charging stations. Additionally, an optimization procedure is proposed to optimize the location of EVs charging stations. The problem considers predefined possible locations of the charging stations based on the electric grid system (m possible locations). The optimization procedure seeks to determine the best location for a set of (n) charging stations (n ≤ m). The objective function of this model includes two components, which are the waiting and traveling time to the charging station and it is subject to several constrain.

Keywords**:** Charging Stations, EVs, Optimization, Traffic Simulation.

1. Introduction

As reported by the U.S. international energy outlook of the 2023, almost 45% of the total energy consumption [1]. Additionally, a report by International Energy Agency in 2015 stated that 23% of the greenhouse gasses emission is produced by the transportation sector [2]. Therefore, alternatives to conventional vehicles need to be considered. EVs are one of these alternatives as they nowadays being considered and gaining a great attention in different countries around the world for their benefits [3]. It is expected that the EVs will represent between 29% to 54% of all vehicles globally in 2050 [1]. There are several advantages of EVs such as they can reduce air pollution, reduce greenhouse gases emission, have more efficient and economical operation compared to normal vehicles. According to research by TU et al. [4], the implementation of electric taxis in China resulted in a significant reduction in the carbon emission. In addition, deploying EVs will result in reducing the demand on fossil fuels and will lead to a cleaner environment. China is one of the countries that encourages residents to buy EVs through implementing preferential policies and reducing related consumption taxes [5, 6]. Nowadays in the city of Dalian in China, people favor buying an EV over normal cars. The city is applying a no-purchase-tax policy and there are more than 2000 vehicles used as means of public and private transportation such as buses and taxis [6]. To satisfy the needs of EVs recharging, there are some charging stations nowadays that are located at some parking spaces. However, this will not be enough to satisfy the rapid increase in the number of EVs as here will be a need for on street charging stations. For example, the Chinese government invested a lot of money in preparing for the EVs such as constructing charging stations' infra-structure [5]. Charging stations cannot be combined with the existing gas stations as there are major safety concerns. The process for charging an EV requires a longer time as compared to the time required for refueling a normal vehicle. Accordingly, the impact of EVs charging station on traffic congestion has to be considered. Therefore, the size and location of the charging stations need to be planned accurately.

In this paper, an optimization model is proposed to minimize the sum of waiting and travel time to the charging stations, which is subject to several constraints. Further-more, solution procedures will be developed to solve the proposed optimization model.

2. 2 Literature Review

Several researchers investigated the impact of EVs on the traffic stream. Different optimization models were developed to optimize the size and location of charging stations. In addition, other studies look at the electrification of public transport and some study the impact of EVs on traffic. In general, different approaches have been considered for this problem as they can be classified into the three categories Integer Programming (IP), Mixed Integer Programming (MIP) and other optimization models. The following subsections provide a brief discussion of these approaches, the use of EVs in public transportation, the impact of charging stations on traffic performance, and the charging facilities installation.

2.1. Integer Programming Optimization Models

Firstly, several integer programming problem optimization models [4, 6, 7] were developed. In one of these studies [7], the authors developed an optimization model, and the objective of that model was to minimize two different costs including the waiting time cost of the EVs and the cost of operating the charging stations. This model is a binary programming which is a special case of integer programming [7]. The solution procedure is based on the exhaustion method or the implicit enumeration method [8]. It was concluded that the ratio of utilization of the charging stations in this paper found out to be better than that planned by the government. Another optimization model, which considered a nonlinear integer programming formulation, was developed and the objective of this model is to minimize the time cost of the driver of EVs [6]. A queuing model was used to determine the waiting time of EVs at the charging stations. The SCE-UA algorithm (or hybrid evolutionary algorithm), which is a heuristic algorithm is used to solve the optimization problem [6]. This method of solving is a commonly used method, and it is applied in different research studies [9, 10, 11]. Moreover, it is found out in a research that it is necessary to predict the driver charging behavior (charging at the nearest station or other one) before optimizing the location of charging stations [6].

2.2. Mixed-Integer Programming Optimization Models

An optimization model is developed to locate the charging stations to minimize the total construction cost using mixed-integer formulation [12]. To solve the model, different heuristic methods were proposed such as iterative mixed-integer linear pro-gram, greedy approach, effective mixed-integer linear program, and chemical reaction optimization. Several simulations were performed in the study using the four different solution methods [12]. It is found out that each method has advantages and disadvantages, and the choice of the appropriate method is based on the need. Moreover, in another research a mixed-integer non-linear optimization model is developed to minimize the sum of the land cost, charging station construction cost, and electric vehicles loss [13]. A genetic algorithm is used to solve the optimization model [13].

In addition, another model is developed to optimize the location of the charging stations. The objective of this model is to minimize the sum of the cost of investment at the beginning, the cost of operating the charging station and the cost of charging. The solution procedure adopted a hybrid-based particle swarm optimization. The number of the EVs is predicted in the study and the area is divided into smaller areas. After applying the model and solving it, the results indicated that seven charging stations are required as an optimal number of [14]. Moreover, a mixed-integer nonlinear optimization model was developed to minimize different costs such as the costs of charging stations (cost of constructing the charging station and or adding more chargers to an existing charging station), distribution network expansion, voltage regulation and protection device upgrade which is subjected to different constants. After convexifying all the problem constraints in the objective function, a data set was applied to evaluate the impact of each constraint on the objective function. Since the developed objective function developed is based on cost so it is applicable for different locations [15]. In addition, Chen et al. used mixed-integer linear programming model must develop an optimization model to locate the charging stations. The objective function considers two different costs including the investment cost and transportation cost of EVs to the charging station and the objective is to minimize the sum of the two costs. Similar to the previous research, a heuristic algorithm, which is an improved genetic algorithm was used to solve the optimization problem [16].

2.3. Other Optimization Models

Efthymiou et al. conducted a study to locate the charging infrastructure for EVs. No optimization model was developed in this study. To provide the best case for the number of charging stations and their locations, genetic algorithms were used based on the data collected for the city of Thessaloniki in Greece. It is found out that building 15 charging station will be enough to cover 80 percent of the charging demand of the city [17]. An improved genetic algorithm is proposed by Wang at al. [18] and it is called generic solution for multi-objective optimization problem. Different simulations were performed using MATLAB to validate the model and to check the im-proved genetic algorithm. After performing three different simulations, it is found out that the method of locating the charging station is practical [16]. An optimization objective function that includes two components, which are the investment and transportation cost, and the goal is to minimize the two costs was developed in another research. This model is solved using optimized genetic algorithm, which is called Optimized Location Scheme for electric charging stations (OLoCs), which gives a heuristic solution since the problem of locating the charging stations is an NP-hard or complex problem. To verify the model developed in the study it was applied to a case study of the Tapas Cologne town. The OLoCs locates 11 charging stations out of 16 proposed charging stations for this town [19].

2.4. Public Transport Electrification

An optimization model for the location of electric taxies' charging stations to maximize both the electric taxi service level and the charging service level was considered in some research [4]. Electric taxi service level is measured by the distance travelled by all the electric taxi with the longer distance means the better service. Furthermore, the charging service is measured by the total waiting time at all charging stations with lower waiting time means better service. In order to perform the optimization process, a maximization formulation is developed to maximize electric taxi service level and the charging service level. The objective function in the formulation includes the total distance travelled by all electric taxis and the total waiting time at all charging stations and the solution is achieved through applying a genetic algorithm.

2.5. The Impact of Charging Stations and EVs on Traffic

Other studies were conducted to investigate the impact of EVs and charging stations locations on traffic. The existing car-following model, which is used nowadays to investigate the complex traffic phenomena cannot totally be used for testing EVs driving behaviors since it does not include one important feature of electric vehicle, which is the driving range unless it improved to include electric vehicles features. Firstly, a study proposed a new car-following model that includes the driving range feature of EVs to study the effect of driving range on the traffic flow [20]. There were several assumptions including EVs are distributed uniformly and there is a charging station along the road that serves one EV at one time. It is concluded that at short driving range, the increase in the driving range will increase the speed significantly (changing the driving range from 8 to 12 km will result in an increase in the average speed by 33%). However, at long driving range there will be an increase in the speed when increasing the driving range but at a lower rate (increasing the long driving range from 20 to 24 km, average speed only increases by 12%). Another study tried to evaluate the impact on the traffic with a large penetration of EVs into the road network [21]. A model of a road network was established and 30,000 EVs were simulated to drive in that road network that has 9 fast charging stations. It is found out that the roads with charging stations are more congested than the other roads with lower average speed and the congestion stays for a long time. The authors apply the shortest path for the EVs to choose the nearest charging station. It is found out that this strategy is not efficient in a network that has a high penetration of EVs since it will cause heavy traffic congestion around the charging stations location [21].

2.6. Charging Facilities Installation

Chen et al. [22] developed a model to offer means that describe how the charging lanes and stations work and how it will be installed. The research is conducted on a long corridor that has charging stations, which are uniformly distributed along the corridor and charging lanes. Charging lanes are not full lanes but they are provided in segments of different length. There are several assumptions such as drivers who choose to charge their EVs using the charging stations will experience some delay but for the drivers who choose to charge using the charging lanes will charge faster with-out any delay. Also, drivers who choose to charge using charging lanes need to add some devices in their cars that allow for charging from the charging lanes and need to pay more than charging in the stations. According to the results, people with high value of time will use to charge using charging lanes. The model includes a charging choice model, which has three types of drivers; high value of time and they choose to charge with the charging lanes, low value of time who choose to charge in the charging stations, and people who have no preference and they do not care whether to charge with charging stations or lanes. It was concluded that charging lanes are competitive compared to charging stations and drivers are charging their vehicles using charging lanes whether it is operated publicly or by private companies [22].

According to the previous literature, most of the research optimization models are concentrating on different costs and grid systems. However, limited research considers waiting time at the charging station as a decision variable in the optimization objective function. In addition, the vast majority of the reviewed research does not consider the traffic congestion as a factor in determining the charging stations' locations. Therefore, this paper presents an optimization model to optimize the location of EVs charging stations considering waiting and travel time to the charging station as decision variables. In addition, solution procedures are developed to solve the pro-posed optimization model.

3. Methodology

This section is divided into three parts. The first part is about the mathematical formulation of the optimization model, whereas the second part is about the simulation and the third part is about the solution procedure for the optimization model.

3.1. Problem Formulation

An optimization model is formulated in this section to satisfy the objective of this research, which is to optimize the location of EVs' charging stations. The problem formulation considers the following case:

In a city that has m possible locations for charging stations, it is required to select n ($n \leq m$) stations to be constructed to minimize the objective function:

$$\text{Min}\, z = \sum_s c_s + \sum_s \left(\sum_{vh} T_{(vh,s)}^{waiting} + \sum_{vh} T_{(vh,s)}^{travel}\right) * VT \tag{1}$$

The objective is to select the location of (n) charging stations that minimize the objective function. The objective function includes two different costs. One cost is for the charging station (c_s). This is the sum of three costs: infrastructure, distribution, and operation cost of the charging station. The other cost is the value of time (VT). This objective function is subject to several constraints. Some of these constraints are related to the battery consumption calculation [31]. Variability and uncertainty of EVs battery consumption will not be considered since the research will use the same battery consumption profile or function for all the EVs. The developed optimization model constraints are the following:

$$T_{(vh,s)}^{travel} = \frac{D_{(vh,s)}^{mile}}{v_{mile/h(q)}^{AVG}} \tag{2}$$

$$T_{(vh,s)}^{waiting} = \begin{cases} the\ time\ remaining\ for\ a\ charging\ pile\ to\ be\ avilable & NVs \geq Ps \\ 0 & otherwise \end{cases} \tag{3}$$

$$E_{total(vh,t)}^{Cons} = E_{1(vh,t)}^{Cons} + E_{2(vh,t)}^{Cons} \quad \forall vh, t \tag{4}$$

$$bt_{(vh,t)} = \begin{cases} bt_{(vh,t)} - E_{total(v,t)}^{Cons} & \forall E_{total(vh,t)}^{Cons} < bt_{(vh,t)} \\ bt_{min(vh,t)} & \forall E_{total(vh,t)}^{Cons} \geq bt_{(vh,t)} \end{cases} \quad \forall vh, t \tag{5}$$

$$\mathrm{t}_{trip(vh,s)} = \begin{cases} T_{(vh,s)}^{waiting}, & T_{(vh,s)}^{travel} = 0 \\ T_{(vh,s)}^{travel} + T_{(vh,s)}^{waiting}, & T_{(vh,s)}^{travel} > 0 \end{cases} \tag{6}$$

$$\mathrm{t}_{trip(vh,s)} \leq \mathrm{t}_{trip\ MAX(vh,s)} \tag{7}$$

$$E_{1(vh,t)}^{Cons} = \begin{cases} \dfrac{\tau_{(vh)} \times D_{(m,d,h,vh)}^{mile}}{\eta_{BT} \times \eta_{PE} \times \eta_M \times \eta_A} & \forall \Theta_{min} \leq \Theta_{(t)} \leq \Theta_{max} \quad \forall vh, t \\ 0 & elsewhere \end{cases} \tag{8}$$

$$E_{2(vh,t)}^{Cons} = \begin{cases} E_{AC(vh,t)} & \forall \Theta_{AC} \leq \Theta_{(t)} \leq \Theta_{max} \\ E_{HT(vh,t)} & \forall \Theta_{min} \leq \Theta_{(t)} \leq \Theta_{HT} \quad \forall vh, t \\ 0 & elsewhere \end{cases} \tag{9}$$

$$E_{AC(vh,t)} = \begin{cases} P_{ST}^{AC} \times \dfrac{\mathrm{t}_{trip(vh,s)}}{60} & \forall \mathrm{t}_{trip(vh,s)} \leq 10 \\ 0.6 \times P_{ST}^{AC} + P_{CONT}^{AC} \times \dfrac{(\mathrm{t}_{trip(vh,s)} - 10)}{60} & \forall \mathrm{t}_{trip(vh,s)} > 10 \end{cases} \quad \forall vh, t \tag{10}$$

$$E_{HT(vh,t)} = \begin{cases} P_{ST}^{HT} \times \dfrac{\mathrm{t}_{trip(vh,s)}}{60} & \forall \mathrm{t}_{trip(vh,s)} \leq 10 \\ 0.6 \times P_{ST}^{HT} + P_{CONT}^{HT} \times \dfrac{(\mathrm{t}_{trip(vh,s)} - 10)}{60} & \forall \mathrm{t}_{trip(vh,s)} > 10 \end{cases} \quad \forall vh, t \tag{11}$$

$$\frac{\left(\sum_{vh} T_{(vh,s)}^{waiting} + \sum_{vh} T_{(vh,s)}^{travel}\right)}{N_{EV}} \leq \propto \tag{12}$$

Where:

c_s is the total cost of charging station (s) ($)

VT is the value of time ($/hour)

$T_{(vh,s)}^{waiting}$ is the time spent by vehicle (vh) at charging station (s) (this is the waiting time + charging time).

Nps is the number of chargers at station (s).

$T_{(vh,s)}^{travel}$ is the travel time of vehicle (vh) to reach station (s).

$D_{(vh,s)}^{mile}$ is the additional distance traveled by vehicle vh to reach station (s).

$E_{total(vh,t)}^{Cons}$ is the total energy consumed by vehicle (vh) in kWh.

$E_{1(vh,t)}^{Cons}$ denotes the total tractive energy required in kWh to overcome vehicle inertia, road resistance, and aerodynamics drag for the trip finished by vehicle (vh) at the end of time interval t.

$E_{2(vh,t)}^{Cons}$ denotes the energy in kWh required to maintain the cabin temperature comfortable for the vehicle driver and passengers during the trip finished by vehicle (vh) at the end of time interval t;

$bt_{(vh,t)}$ is the stored energy in kWh in vehicle (vh) at time t.

Θ_{max}, Θ_{min} denote the maximum and minimum temperature limits for battery usage in Battery Charge Depletion (BCD) mode, respectively.

Θ_{AC}, Θ_{HT} denote the average thresholds for A/C and HT operation, respectively.

$E_{AC(vh,t)}$, $E_{HT(vh,t)}$ denote the energies in kWh consumed by A/C and HT respectively, during the trip finished by vehicle (vh) at the end of time interval t;

$\mathrm{t}_{trip(vh,s)}$ denotes the duration in minutes of the trip of vehicle vh to reach charging station s.

$v_{mile/h}^{AVG}$ denote the average vehicle (vh) speed in mi/h.
P_{ST}^{AC}, P_{CONT}^{AC} denote the powers in kW consumed by A/C during starting and continuous operation, respectively.
P_{ST}^{HT}, P_{CONT}^{HT} denote the powers in kW consumed by heating during starting and continuous operation, respectively.
N_{EV} is the number of EVs that needed charging.
$\propto$ is the threshold for the maximum average waiting plus charging time per EV.

As it appears from the formulation, there is a need to evaluate the vehicle's travel time, which depends on the traffic congestion and network characteristics. In order to have accurate estimates of the travel times, traffic simulation will be utilized to estimate the travel times based on the prevailing traffic conditions in the network.

3.2. Simulating EVs

There are different traffic simulation models that can be used for the simulation purpose. According to the literature, these simulation models can be microscopic, mesoscopic, and macroscopic [24]. Microscopic simulation models are in-depth simulation models and consider each vehicle separately in which it includes several properties of vehicles such as speed, locations, fuel consumption and others [25]. Whereas macroscopic simulation is based on the evaluation of entire system not each vehicle separately in which it includes properties such as the average speed of all vehicles. On the other hand, mesoscopic simulation has the features of microscopic and macroscopic. The three traffic simulation models are also different in the amount of detail required for modeling purposes and the level of effort needed to model and simulate [26]. There are different traffic simulation tools that can be classified as microscopic simulation models such as TRANSIMS [27], SUMO [28], MAINSIM [29], Veins [30], MITSIMLab [31], VISSUM [32], Quadstone paramics [33], MITSIM [34], ITSUMO [35], Simtraffic[32], SIMWALK [36], and CORSIM [37]. Furthermore, examples of traffic simulation tools that can be classified as mesoscopic simulation models are MATsim [38], Dynameq [39], INTEGRATION [40], DynaMIT [41], and DYNASMART [42]. In addition, several examples of macroscopic traffic simulation tools will include NETFLO1 [43], FREQ 12 [44], Aurora [45], and JaamSim [46]. Each traffic simulation tool has advantages and disadvantages, and it can effectively be used in different simulation scenarios.

After reviewing the literature, a mesoscopic traffic simulation model was chosen to be used. The reason for using this simulation model is that it gathers the features of microscopic and macroscopic simulation models. It applies the microscopic features in intersection and macroscopic features on the links. DYNASMART traffic simulation tool will be used in this research due to its capabilities and functionalities. DYNASMART can show how the traffic flow will be in the network at different times and places and capable of providing a suitable route guidance to each user. These two capabilities are essential elements to dynamically assign traffic to a network, which is called descriptive and normative [47]. Another reason to use DYNASMART is that its source code is available to the research team, which will allow for modification.

In this research, DYNASMART will be used to simulate different traffic scenarios to the road network of the UAE. These scenarios include several penetration rates of EVs to the traffic stream such as 20, 40, 60, 80, and 100 percent. In addition, the travel demand will have three levels representing mild congestion, congested network and very congested network. The summary and detailed flowcharts for DYNASMART are provided in previous publication [42]. The simulation process within DYNASMART will be modified to take into consideration the EVs and the charging stations' locations and operation.

3.3. Proposed Solution Procedure

After formulating the optimization problem, the goal of this paper is to provide a procedure to decide on the optimal locations of electric vehicle charging stations, considering the prevailing traffic conditions. Similar to the previous research, all related optimization models cannot be solved using an exact algorithm since it is an NP-hard problem; so, a heuristic algorithm is used in the solution procedure.

The goal of the procedure is to select the least number of charging stations (n) from a large number (m). These (m) possible locations are determined based on the electrical network grid in the considered study area. The selection of the stations is an iterative procedure. At the initial iteration, all possible locations are considered as charging stations. The study area network is simulated, and two values for waiting times are obtained, the total waiting time (tot_w_st), at the charging stations, and the average waiting time (w_avg), at the charging stations, for all EVs in the network. The process continues by ranking all the stations based on the total waiting time at each station (tot_w_st), removing all stations with zero (tot_w_st) and one station with the lowest (tot_w_st) based on the ranking, then simulating the traffic network with the new number of charging stations. The optimization process stops when the average waiting time exceeds a threshold value ($\propto$). Otherwise, until the condition is reached, the process will continue by removing one station at each step based on the ranking. The described solution procedure is illustrated in Fig. 1.

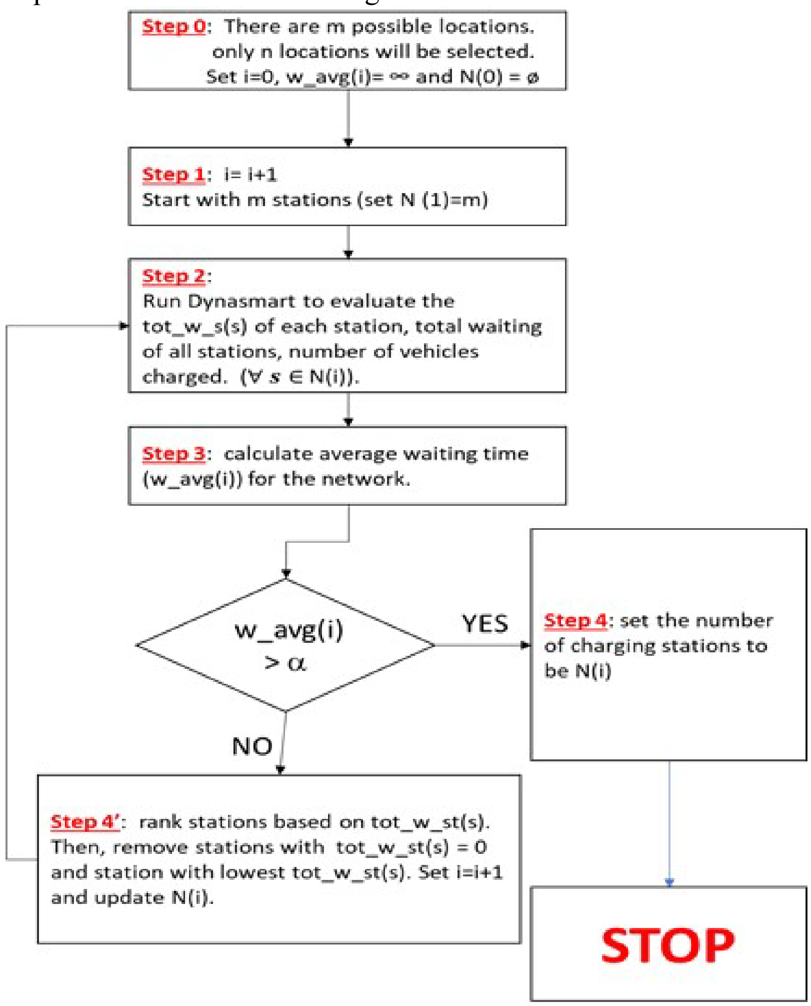

Fig. 1: The optimization procedures.

4. Conclusions

The planet is facing a problem of a significant increase in the amount of harmful gases produced by vehicles due to the increase in the number of vehicles. Therefore, alternatives to conventional vehicles need to be considered. EVs are one of these alternatives that need to be taken into consideration due to their advantages in reducing the amount of harmful gases released. As previously mentioned, governments started promoting EVs and plan for this new type of vehicles. Since EVs need to be recharged, one of the important planning tasks is to build charging stations. In the literature, most of the research optimization models are concentrating on different costs and grid systems. However, no research considers waiting time at the charging station as a decision variable in the optimization objective function. In this research, DYNASMART will be used to simulate EVs within the traffic stream and an optimization model was developed to optimize the location of EVs charging stations considering waiting and travel time to the charging station as decision variables. The developed optimization model is a complex problem that cannot be solved for the exact solution. However, this research developed solution procedures which are used to find the optimal solution. The proposed optimization model and the solution procedure developed might be modified or improved during the actual application if needed.

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References

[1] Z.-J. M. Shen, B. Feng, C. Mao, and L. Ran, (2019) "Optimization models for electric vehicle service operations: A literature review," Transportation Research Part B: Methodological, vol. 128, pp. 462-477, 2019, doi: https://doi.org/10.1016/j.trb.2019.08.006.

[2] International Energy Agency, (2015) "Energy and climate change," World Energy Outlook Special Report, France.

[3] B. Yacitekin, M. Uzunolu, and A. Karaka, (2016) "A new deployment method for electric vehicle charging infrastructure," Turkish Journal of Electrical Engineering and Computer Sciences, vol. 24, no. 3, pp. 1292-1305, doi: 10.3906/elk-1311-221.

[4] W. Tu, Q. Li, Z. Fang, S.-l. Shaw, B. Zhou, and X. Chang, (2016) "Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach," Transportation Research Part C: Emerging Technologies, vol. 65, pp. 172-189, doi: https://doi.org/10.1016/j.trc.2015.10.004.

[5] Z. Li and M. Ouyang, (2011) "The pricing of charging for electric vehicles in China—Dilemma and solution," Energy, vol. 36, no. 9, pp. 5765-5778, doi: https://doi.org/10.1016/j.energy.2011.05.046.

[6] Z. Tian, W. Hou, X. Gu, F. Gu, and B. Yao, (2018) "The location optimization of electric vehicle charging stations considering charging behavior," SIMULATION, vol. 94, no. 7, pp. 625-636, 2019/10/18, doi: 10.1177/0037549717743807.

[7] J. Ma and L. Zhang, (2018) "A Deploying Method for Predicting the Size and Optimizing the Location of an Electric Vehicle Charging Stations," Information, vol. 9, no. 7, doi: 10.3390/info9070170.

[8] R. Romero and A. Monticelli, (1994) "A zero-one implicit enumeration method for optimizing investments in transmission expansion planning," IEEE Transactions on Power Systems, vol. 9, no. 3, pp. 1385-1391, doi: 10.1109/59.336126.

[9] B. Yao, P. Hu, X. Lu, J. Gao, and M. Zhang, (2014) "Transit network design based on travel time reliability," Transportation Research Part C: Emerging Technologies, vol. 43, pp. 233-248, doi: https://doi.org/10.1016/j.trc.2013.12.005.

[10] S. Lee and T. Kang, (2016) "Analysis of Constrained Optimization Problems by the SCE-UA with an Adaptive Penalty Function," Journal of Computing in Civil Engineering, vol. 30, no. 3, p. 04015035, doi: 10.1061/(ASCE) CP.1943-5487.0000493.

[11] J.-H. Jeon, C.-G. Park, and A. B. Engel, (2014) "Comparison of Performance between Genetic Algorithm and SCE-UA for Calibration of SCS-CN Surface Runoff Simulation," Water, vol. 6, no. 11, doi: 10.3390/w6113433.

[12] A. Y. S. Lam, Y. Leung, and X. Chu, (2014) "Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions," IEEE Transactions on Smart Grid, vol. 5, no. 6, pp. 2846-2856, doi: 10.1109/TSG.2014.2344684.

[13] P. Sadeghi-Barzani, A. Rajabi-Ghahnavieh, and H. Kazemi-Karegar, (2014) "Optimal fast charging station placing and sizing," Applied Energy, vol. 125, pp. 289-299, doi: https://doi.org/10.1016/j.apenergy.2014.03.077.

[14] Z. Tang, C. Guo, P. Hou, Y. Fan, and D. Jia, (2013) "Optimal Planning of Electric Vehicle Charging Stations Location Based on Hybrid Particle Swarm Optimization," Advanced Materials Research, vol. 724-725, pp. 1355-1360, doi: 10.4028/www.scientific.net/AMR.724-725.1355.

[15] Q. Cui, Y. Weng, and C. Tan, (2019) "Electric Vehicle Charging Station Placement Method for Urban Areas," IEEE Transactions on Smart Grid, pp. 1-1, doi: 10.1109/TSG.2019.2907262.

[16] S. Chen, Y. Shi, X. Chen, and F. Qi, (2015) "Optimal location of electric vehicle charging stations using genetic algorithm," in 2015 17th Asia-Pacific Network Operations and Management Symposium (APNOMS), 19-21 Aug. 2015, pp. 372-375, doi: 10.1109/APNOMS.2015.7275344.

[17] D. Efthymiou, K. Chrysostomou, M. Morfoulaki, and G. Aifantopoulou, (2017) "Electric vehicles charging infrastructure location: a genetic algorithm approach," European Transport Research Review, vol. 9, no. 2, p. 27, doi: 10.1007/s12544-017-0239-7.
[18] D. T. Wang, L. F. Ochoa, and G. P. Harrison, (2011) "Modified GA and Data Envelopment Analysis for Multistage Distribution Network Expansion Planning Under Uncertainty," IEEE Transactions on Power Systems, vol. 26, no. 2, pp. 897-904, doi: 10.1109/TPWRS.2010.2057457.
[19] S. Mehar and S. M. Senouci, (2013) "An optimization location scheme for electric charging stations," in 2013 International Conference on Smart Communications in Network Technologies (SaCoNeT), 17-19 June 2013, vol. 01, pp. 1-5, doi: 10.1109/SaCoNeT.2013.6654565.
[20] T.-Q. Tang, L. Chen, S.-C. Yang, and H.-Y. Shang, (2015) "An extended car-following model with consideration of the electric vehicle's driving range," Physica A: Statistical Mechanics and its Applications, vol. 430, pp. 148-155, doi: https://doi.org/10.1016/j.physa.2015.01.014.
[21] Y. Luo, T. Zhu, K. Cao, and K. Li, (2013) "The Impacts of Large Scale Electric Vehicles Charging Behaviour on Distribution System and Local Traffic System," IFAC Proceedings Volumes, vol. 46, no. 21, pp. 651-657, doi: https://doi.org/10.3182/20130904-4-JP-2042.00081.
[22] Z. Chen, W. Liu, and Y. Yin, (2017) "Deployment of stationary and dynamic charging infrastructure for electric vehicles along traffic corridors," Transportation Research Part C: Emerging Technologies, vol. 77, pp. 185-206, doi: https://doi.org/10.1016/j.trc.2017.01.021.
[23] M. F. Shaaban, Y. M. Atwa, and E. F. El-Saadany, (2013) "PEVs modeling and impacts mitigation in distribution networks," IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 1122-1131, doi: 10.1109/TPWRS.2012.2212467.
[24] D. F. Allan and A. M. Farid, (2015) "A Benchmark Analysis of Open Source Transportation-Electrification Simulation Tools," in 2015 IEEE 18th International Conference on Intelligent Transportation Systems, 15-18 Sept. 2015, pp. 1202-1208, doi: 10.1109/ITSC.2015.198.
[25] P. Jaworski, T. Edwards, K. Burnham, and O. Haas, (2012) "Microscopic traffic simulation tool for Intelligent Transportation Systems," in 2012 15th International IEEE Conference on Intelligent Transportation Systems, 16-19 Sept. 2012, pp. 552-557, doi: 10.1109/ITSC.2012.6338659.
[26] S. Lang, T. Reggelin, and T. Wunder, (2017) "Mesoscopic Simulation Models for Logistics Planning Tasks in the Automotive Industry," Procedia Engineering, vol. 178, pp. 298-307, doi: https://doi.org/10.1016/j.proeng.2017.01.118.
[27] S. G. Eubank and S. Eubank, (1999) "What makes a simulation useful? [TRANSIMS]," Los Alamos: IEEE Transc., vol. 4, p. 640.
[28] Z. Liang and Y. Wakahara, (2013) "City traffic prediction based on real-time traffic information for Intelligent Transport Systems," in 2013 13th International Conference on ITS Telecommunications (ITST), 5-7 Nov. 2013, pp. 378-383, doi: 10.1109/ITST.2013.6685576.
[29] J. Dallmeyer and I. Timm, (2012) "MAINSIM-Multimodal Innercity Simulation," Conference on Artificial Intelligence (KI-2012), September 2012, pp. 24.-27.
[30] H. Noori (2012) "Realistic urban traffic simulation as vehicular Ad-hoc network (VANET) via Veins framework," in 2012 12th Conference of Open Innovations Association (FRUCT), 5-9 Nov. 2012, pp. 1-7, doi: 10.23919/FRUCT.2012.8122092.
[31] J. Sanchez-Medina, M. Moreno, and E. Rubio, (2008) "Evolutionary Computation Applied to Urban Traffic Optimization," book chapter in Advances in Evolutionary Algorithms, DOI: 10.5772/6119.
[32] K. Shaaban and I. Kim, (2015)"Comparison of SimTraffic and VISSIM Microscopic Traffic Simulation Tools in Modeling Roundabouts," Procedia Computer Science, vol. 52, pp. 43-50, doi: https://doi.org/10.1016/j.procs.2015.05.016.
[33] Y. Gao (2019) "Calibration and Comparison of the VISSIM and INTEGRATION Micro-scopic Traffic Simulation Models," Master of Science Thesis in Civil Engineering, Virginia Tech. University.
[34] M. Hasan, M. Jha, and M. Ben-Akiva (2002) "Evaluation of ramp control algorithms using a microscopic traffic simulation laboratory, MITSIM," Transp. Res. – Part C: Emerging Technologies, 10(3), pp 229-256.

[35] A. L. Bazzan, M. d. B. do Amarante, T. Sommer, and A. J. Benavides, (2010) "ITSUMO: an agent-based simulator for ITS applications," in Proc. of the 4th Workshop on Artificial Transportation Systems and Simulation. IEEE.

[36] R. A. Raslan, A. F. Bakr, and H. A. Ayad, (2011) “Simulation of Pedestrian Behaviour in Urban Spaces. A Case Study of “Sidi Gaber” Public Space, Alexandria, Egypt” Proceeding Real Corp 2011, pp. 863-872.

[37] B. E. Sandoval and P. Rudy Malfabon, (2012) "CORSIM Modeling Guidelines," Nevada Department of Transportation.

[38] M. Galus, R. Waraich, F. Noembrini, K. Steurs, G. Georges, K. Axhausen, and G. Anders-son, (2012) "Integrating Power Systems, Transport Systems and Vehicle Technology for Electric Mobility Impact Assessment and Efficient Control," IEEE Transactions on Smart Grid, vol. 3, no. 2, pp. 934-949, doi: 10.1109/TSG.2012.2190628.

[39] W. Burghout, (2005) "Mesoscopic simulation models for short-term prediction," PREDIKT project report CTR2005, vol. 3.

[40] M. Van Aerde, B. Hellinga, M. Baker, and H. Rakha, (1996) "INTEGRATION: An over-view of traffic simulation features," Paper presented at the 1996 Transportation Research Board Annual Meeting, Washington DC.

[41] S. A. Boxill and L. Yu, (2000) "An evaluation of traffic simulation models for supporting its," Development Centre for Transportation Training and Research, Texas Southern University, Houston, TX.

[42] M. Roelofsen, (2012) "Dynamic modelling of traffic management scenarios using DYNASMART," Master Thesis, University of Twente, Auckland, New Zealand.

[43] M. Iliescu and D. Barbinta, (2013) "Aspects Regarding Road Traffic Simulation," Indian Journal of Applied Research, vol. 3, no. 4, doi: 10.36106/ijar

[44] D. May and L. Leiman, (2005) "Freeway Analysis Manual: Parts 1 and 2," California PATH Research Report UCB-ITS-PRR-2005-17.

[45] A. H. F. Chow, G. Gomes, A. A. Kurzhanskiy, and P. Varaiya, (2009) "Aurora Arterial Modeler – A Macroscopic Tool for Urban Traffic Signal Control," IFAC Proceedings Volumes, vol. 42, no. 15, pp. 361-366, doi: https://doi.org/10.3182/20090902-3-US-2007.0067.