Identification of Electric Vehicle Charging Stations Using an Optimum Energy Consumption Approach

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***Abstract*—An Electric Vehicle (EV) is a proven solution by car manufacturers to steadily replace the conventional vehicle with a more environmentally friendly option that will reduce our dependence on nonrenewable energies. One drawback is that an EV may take many hours to reach a full charge. Reducing the charging times for EVs are one of the leading challenges for promoting this type of vehicle. Also, the introduction of EVs into the power grid increases flow in the distribution network and as a result increases power flow congestion. Traffic conditions also play a key role in affecting EV battery consumption. Disturbed traffic conditions will result in increased energy consumption of the EV battery and negatively affect the overall performance of EVs. In this research, the problem of scheduling EV battery charging and the assignment of EVs to a Charging Station (CS) is formulated as an optimization problem and will be solved using a simulated annealing optimization method. The assignment of EVs to CSs will satisfy predetermined constraints related to CSs restrictions, the EV conditions, traffic conditions, etc. The proposed approach will be demonstrated using two different scenarios of the system, one where the EVs have homogeneous components and the second, where the EVs have heterogeneous components. From the results, it will be proven that the optimal assignment of an EV occurs when the State of Charge (SoC) of the EV battery remains at its highest possible percentage when arriving at the CS. Keeping the battery SoC at a high percentage results in reduced energy consumption and less charging time.**

***Index Terms*—Electric Vehicles, Charging Stations, Electricity Grid, State of Charge, EV Battery, intermittent energy sources, smart charging, simulated annealing optimization**

I. Introduction

The constant increase in environmental issues related to electricity is bringing new electricity demands to the market, which creates a huge incentive for Electric Vehicles (EVs). Because of the increase in awareness of the world population towards electricity and environmental problems, such as global warming, the use of electric vehicles is growing exponentially. Electric Vehicles can have different types of batteries, depending on the model and characteristics of a particular car. Some of these batteries include lead-acid batteries, lithium-ion/polymer, sodium/nickel chloride (also known as ZEBRA), nickel and cadmium, zinc-air batteries, lithium iron phosphate, among others. The most used battery in the U.S. is the lithium-ion battery. It is assumed that the EVs used in this research have lithium-ion batteries [1], [2]. The performance of an EV is directly related to its battery. The battery capacity, together with travel routes, use of electrical accessories, and driving mode, will provide the autonomy of an electric vehicle.

To recharge an EV battery that is close to its minimum state of charge, the vehicle must be driven to a Charging Station (CS). Therefore, CS's need to have complete infrastructure with multiple charging ports to be able to receive a large number of cars simultaneously [3]. At the same time, recharging an EV usually takes a different time for each vehicle. It could take from 30 minutes to about 24 hours for a vehicle to be fully charged. Because the recharging of an EV is still a long process, it often generates long queues and waiting times that are unbearable for most drivers. This issue is, one of the biggest problems when trying to introduce and promote EVs [4].

When driving an EV, one of the primary concerns to the driver is locating a CS that is closest in distance. Outside of locating the closest CS, the CS that is the most relevant and cost-effective are also important issues that need to be addressed. This requires the driver to find a route that minimizes distance and cost to reach the optimal charging station. Traffic conditions are always fluctuating and the access to ports at charging stations is variable as well [5]-[7]. The provision of adequate CS's for EVs will be fundamental for the future success and service of electric vehicles on the road.

In this research paper, a novel solution is proposed for the problem of locating the nearest CS for EVs. When an EV driver is driving, his most critical requirement would be to find the nearest CS if the EV runs out of charge. Moreover, while on the way to the CS, the EV must not be depleted of charge and stop midway which would further compound the issue. Hence it is necessary to arrive at the CS with as much charge as possible left in the EV. So, the problem here is to maximize the state of charge of an EV upon arrival in an available charging station. This will be carried out by formulating the arrival

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of EVs at a CS as an optimization problem under normal and disturbed conditions, which are affected by weather and traffic patterns. In addition, this research will also propose a solution to maximize the energy contained in the vehicle when the EVs are made up of (i) homogeneous components (a system where all EVs have the same model and characteristics) and (ii) heterogeneous components (EVs that have different characteristics including but not limited to battery type, make, and model). The charging scenarios can be further separated into slow charging and fast charging (type of CS) for charging of EV batteries. The study will include introducing different constraints on the charging system that will directly impact the result. The main contribution from our research that distinguishes our effort from that of previous researchers is the prioritization of EVs based on their state of charge. This means that the EV with a battery charge closest to their SoC_{min} will be treated as priority, and therefore will be first to be assigned to the closest and appropriate CS. The proposed approach will ensure that the SoC of all EVs will remain above their respective threshold values. The threshold will be determined based on the characteristics of each specific EV [8].

In this research, the problem of EV charge maximization is formulated as an optimization problem and Simulated Annealing (SA) is used to solve the optimization problem. SA is a very popular optimization technique and has many advantages over other optimization algorithms. Since there is a non-zero probability of accepting higher cost solutions in the search process, SA avoids becoming stuck at some local minima, unlike some greedy approaches. Also, the runtime of SA is controllable through the cooling schedule. This algorithm can be abruptly terminated by changing the parameter ending temperature in simulated annealing. Finally, there is always a best-known solution available know matter how little time has elapsed in the search process. With SA the user can always get a solution. In general, a longer run time would result in a better-quality solution. This flexibility explains SAs wide popularity [9].

The rest of this paper is arranged as follows: Section II, will present Literature Review and discuss the past methods proposed by researchers to solve the problem of EV charging management. Section III will present the proposed methodology to identify the CS that are close to the EVs so that the energy remaining in the EV is maximized while arriving at the CS. Section IV explains the problem formulation and the mathematical model that is used in this research to maximize SoC of the EV when arriving at the CS. This section introduces the reader to the various parameters and variables used in the proposed method. Section V undertakes the scenario of an EV fleet comprising of only homogeneous components and Section VI deals with an EV fleet comprising of heterogeneous components. Section V and VI illustrate the working of the proposed model by validating it on a test system and provide the results obtained for homogeneous and heterogeneous systems respectively. Section VII provides the conclusion and future scope of extending this research.

II. Literature Review

The topic of charging management and scheduling for EVs is of great importance to many researchers as we continue to see success in EVs as an alternative to conventional gas-powered vehicles. Particularly, several research articles have focused on optimization of charging and discharging strategies of EVs. This section throws light on some of the related research work on management and optimal scheduling strategies of EVs.

In [10], [11] the authors presented a solution to the issue of managing and dispatching of electric vehicles with a Vehicle to Grid (V2G) approach. Their objective function includes minimizing load variance and cost of charging associated with EVs. Their proposed approach of Technique of Order of Preferences by Similarity of Ideal Solution (TOPSIS) was used to solve the scheduling problem and scheduling optimization was performed by a Grey Wolf Optimization (GWO) method. Results showed that with their TOPSIS approach, solutions obtained were favorable in terms of both scheduling and cost reduction.

In [12] the authors present a method to optimize EV charging by reducing and minimizing the cost associated with battery degradation. They approach this by solving the variable electricity cost using a simplified lithium-ion battery lifetime model. This model estimates both energy capacity fade and power fade due to its temperature, state of charge, and daily depth of discharge. An optimization method is also addressed in this paper [13], where the authors propose to solve the problem of determining the distance between EV and CS using the standard Microsoft Excel Solver to optimize SoC_f. This solver uses a basic implementation of the primal simplex method to solve linear programming problems.

The method of EV battery swapping verses EV battery charging was proposed by another researcher to reduce overall cost of EV battery charging. In [14] the authors aim to minimize the cost of EV battery charging by considering 3 factors in using a Battery Swapping Station (BSS): The incoming EVs battery will be replaced with a battery taken from stock, reducing the potential of charging damage encountered with the use of high-rate chargers, and reducing electricity cost to the grid by charging batteries during off peak time periods. This proposed approach works more efficiently if the EV driver makes advanced appointments to the BSS for swapping batteries, in that the BSS can prepare for incoming battery swaps. This approach would also need to account for the manual labor of swapping batteries by trained EV technicians and the real estate to build a BSS to allow for incoming EVs and battery storage. Although, the BSS method was able to obtain favorable results it would not fare well if there was a sudden influx of EVs into the grid and works best when EV owners are able to schedule requests with ample amount of time to allow the BSS to restock and prepare [15], [16].

Building upon overcoming the issue of reducing damage to the EV battery, in [17], [18] the authors propose a solution of using a real-time Battery Monitoring System (BMS) using a coulomb counting method for State of Charge (SoC) estimation and messaging. This approach can be easily implemented and has a less overall complexity. It aims to circumvent the possibility of damage to the EVs batteries by using a precise state of charge estimation to increase the lifespan.

In [19], [20] the authors discuss the importance and impact of the increase in electricity consumption on the power grid. They propose both a global scheduling optimization method and local scheduling optimization. The authors determined that the local scheduling optimization is more resilient to incoming EVs into the electric grid and performs better in terms of minimizing overall cost of the EVs. The next section explains the proposed methodology.

III. Proposed Methodology

One of the biggest problems when talking about electric vehicles is optimizing the time of recharging of an EV. The EV owner worries about how much time does an EV have to get a charging station, where is the closest charging station, as well as if that charging station is vacant and has the correct equipment necessary to recharge all different models of batteries and EVs [21].

The proposed solution will ultimately give the driver of the EV an increase in confidence while operating their EV. This will be done by ensuring the EV driver maintains a maximum state of charge for the EV battery. This solution will allow the EV driver to seamlessly connect to a network of predetermined charging stations while inside of their EV through use of an installed software program [22]. They will merely have to press a button to begin the proposed algorithm of searching for the optimal CS and this system will coincide with the internal navigation system of the EV to display to the route to the CS [23]. This will decrease the fear of EV drivers about losing battery charge while driving and allow for an increase in morale. As a result of this one can expect to see an increase of sales of EV's and EV's becoming much more practical, which will in turn have a positive benefit on the environment. To better understand the proposed solution to this problem, the methodology is explained using a flow chart shown in Fig. 1.

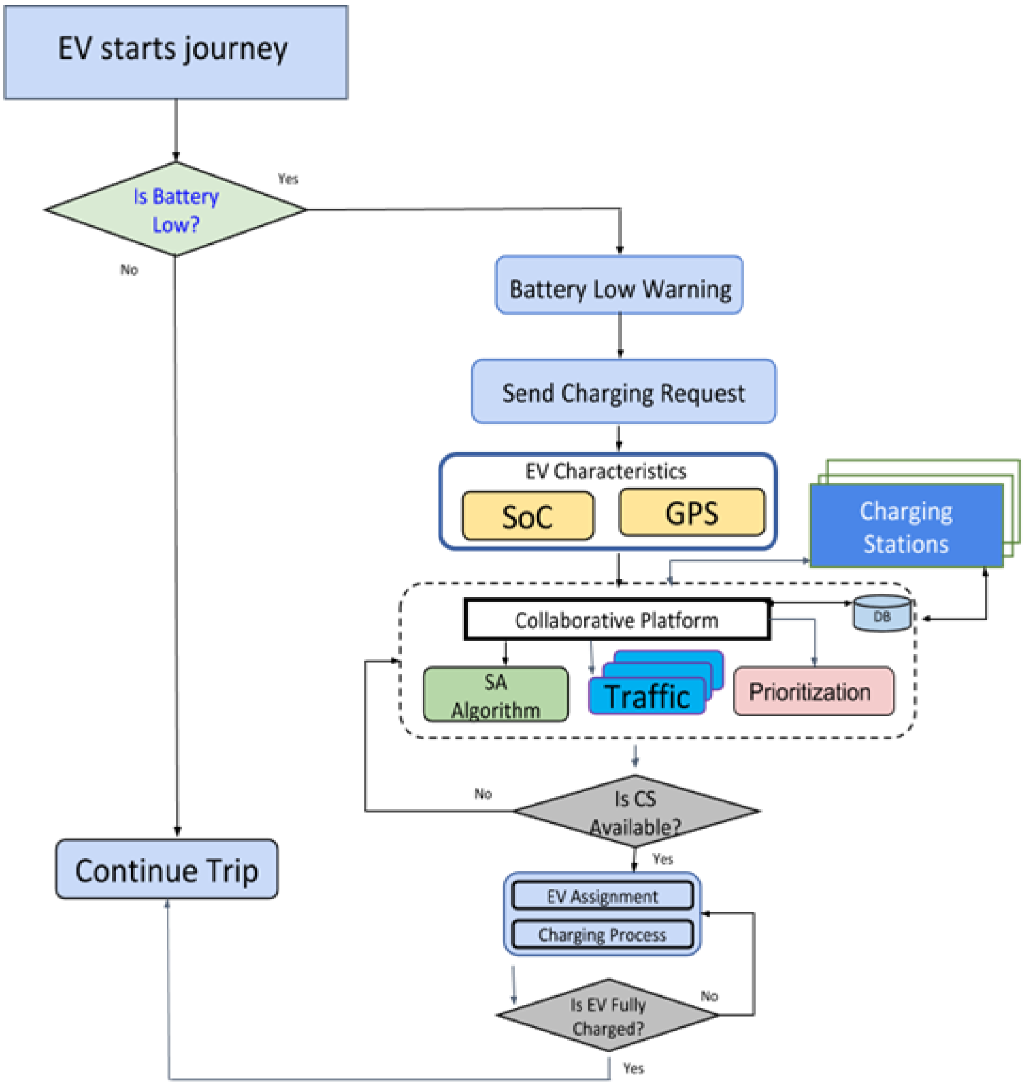

Figure 1. Outline of proposed approach.

As it can be observed in the flowchart, the system starts with analyzing the initial state of charge of the EV. If it is determined that the EV Battery needs a charge the program will display a warning to the driver alerting them that the battery is low. It will then record their state of charge at that time and sends a charging request to a collaborative system. This system will check with all the EV characteristics (GPS coordinates, SoC, etc.). It will then check the EV priority with other EVs on the road to place each EV in the queue based on EV needs and priority. The next step is to optimize the energy of the EV when it reaches the charging station [24], [25]. In this research, the simulated annealing algorithm is used for optimization. This optimization method will optimize (maximize) the final state of charge of each EV when it arrives at the charging station so that the EV is not depleted of charge on its way to the charging station. When the optimization is concluded, the program will then assign each EV to the optimal CS. When the EV has finished this charging process, it can continue its journey. The proposed approach is called Simulated Annealing based Charging Station Management (SAEVCM).

IV. Problem Formulation

Problem formulation and the equations used to arrive at the mathematical model are explained in Section IV.

A. Equations

As stated, the main goal of this research is for the EV battery's final state of charge SoC_f to be maximized upon reaching the charging station. Equation (1) calculates the final state of charge for the selected EV.

$$SoC_{f(i,j,t+T(i,j,t))} = SoC_{0(i,t)} - E_{cn(i,j,t+T(i,j,t))} \times Y_{(i,j,t)} \quad (1)$$

Parameter $Y_{(i,j,t)}$ depends on traffic conditions and it considerably impacts the energy consumption. Under normal conditions $Y_{(i,j,t)}$ is assumed to be 1.

$$Y_{(i,j,t)} = \int_{t+T(i,j,t)}^{t} v_{(i,j,s)} ds \quad (2)$$

EV speed based on traffic volume is equal to EV speed without the influence of traffic multiplied by 1 minus the product of average flow of vehicles between the EV and selected charging station and time divided by the product of time and density of traffic between the EV and the selected charging station.

$$v_{(i,j,t)} = v_{f(i,j,t)} \times \left(1 - \frac{q_{(i,j,t)} \times T_{(i,j,t)}}{d_{(i,j)} \times k_{jam(i,j,t)}}\right) \quad (3)$$

Time equals the distance traveled by the EV divided by speed.

$$T_{(ij,t)} = \frac{d_{(i,j,t)}}{v_{(i,j,t)}} \quad (4)$$

Energy consumed by the EV under normal conditions E_{cn} is equal to the rated capacity of the EV multiplied by distance to the charging station divided by the autonomy of the EV battery.

$$E_{cn(i,j,t+T(i,j,t))} = \frac{C_{n(i)} \times d_{(i,j)}}{A_{(i)}} \quad (5)$$

B. Main Objective

The primary goal of this research is for the EV battery's final state of charge SoC_f to be maximized between its original location and its destination, the CS.

An EVi is efficiently assigned to a CS when the variable $C_{(i,j,t)}$ takes on the maximum value. Keeping in mind the main objective of maximizing the battery final SoC, the assignment coefficient $C_{(i,j,t)}$ will be replaced in the assignment matrix by $SoC_{f(i,j,t+T(i,j,t))}$. This illustrates the final SoC of the battery of EVi when it arrives at the CS.

S_j at time t + $T_{(i,j,t)}$, for i = 1, 2, . . ., n; j = 1, . . ., m; and at any time, t. The parameter $SoC_{f(i,j,t+T(i,j,t))}$ relies on system parameters correlated to the EVs and CS characteristics, road conditions and vehicle traffic on the road such as: $SoC_{0(i,t)}$, $d_{(i,j)}$, $q_{(i,j,t)}, T_{(i,j,t)}$, $k_{jam(i,j,t)}$, $v_{f(i,j,t)}$, $C_{n(i)}$ and $A_{(i)}$. These parameters are described in Table I. The objective function for the optimization model is given below:

$$Z(t) = \sum_{l=1}^{n} \sum_{j=1}^{m} SoC_{f(ij,t+T(i,j,t))} x_{(i,j,t)} \quad (6)$$

TABLE I. Nomenclature and Notations

Variable/Unit	Definition
n	number of EV's (EV1, . . ., EVn)
l	number of fast-charging EV's
K	number of slow-charging EV's
m	number of CS's (S1, . . ., Sm)
mj	number of charging ports available at the CS at Sj
R	subset of fast CS's
L	subset of slow CS's
i	index for selected EV
j	index for selected charging station
t	index for time
$c_{(i,j,t)}$	variable of EVi to Sj at time t
$v_{(i,j,t)}$	EV speed based on traffic volume (km/h)
$v_{f(i,j,t)}$	EV speed without traffic at time t (km/h)
$k_{jam(i,j,t)}$,	density of traffic between the EVi and Sj at time t
$q_{(i,j,t)}$	average flow of vehicles between EVi and Sj at time t (veh/h)
$d_{(i,j)}$	distance between the EVi and CS Sj (km)
$SoC_{0(i,t)}$	initial SoC of the EVi battery at time t
$dis_{(i,t)}$	distance with the remaining energy left related to SoC0(i, t) of the battery of EVi at time t (km)
$SoC_{f(i,j,t+T(i,j,t))}$	final SoC of the EVi battery at Sj at time t + T(i, j, t)
SoC_{min}	minimum limit for SoC of the EVi battery
$T_{(i,j,t)}$	required time to make the distance $d_{(i,j)}$ (h)
$E_{cn(i,j,t+T(i,j,t))}$	energy expended between EVi and the station Sj during normal conditions (kWh)
$E_{cd(i,j,t+T)}$	energy expended between the EVi and the station Sj during disrupted conditions (kWh)
$C_{n(i)}$	rated capacity of EVi battery (kWh)
$A_{(i)}$	autonomy of EVi battery(km)
$x_{(i,j,t)}$	binary variable. Equals 1 when the EVi is assigned to the Sj and equals 0 otherwise
$Y_{(i,j,t)}$	equals to 1 for normal traffic conditions and equal to the integral of velocities for disturbed traffic conditions

The constraints for the optimization problem are listed in equations (7), (8), and (9). In this research, SAEVCM will be used to solve the issue of managing and dispatching EVs to their respective Charging Station (CS). SAEVCM is used to optimize the objective function Z above in which it maximizes the final state of charge for the EV. The objective function will be solved in two different phases. In the first phase all EV's and CS's will have the same characteristics. EVs will share the same make, model and charging speed (homogeneous components) [26], [27]. In the second phase, the EV fleet is comprised of heterogeneous components, meaning that EV's will vary in make, model and charging speed. The approach will begin by working with a charging system under normal conditions, where $Y_{(i,j,t)}$ is assigned a value of 1. Charging system under disturbed conditions will be dealt with next. The value of $Y_{(i,j,t)}$ from Eq. (2) will have an impact on the total energy consumed by the EVi battery and the final SoC of the EVi battery.

V. Charging of EVs with Homogeneous Characteristics

A. Constraints Definition

The EV fleet is made up of homogeneous components and the following constraints will be considered:

- There will be a predetermined number of ports available at the charging stations and all ports will share the available charging power.
- EV's will share the same make and model characteristics (Tesla Model 3) but differing initial state of charges.
- Only one CS will be assigned to each EV.
- Each CS can charge EVi simultaneously up to the maxi- mum number of ports available.
- Prioritization of assignment of EV's to CS's is applied to the EV closest to its minimum threshold state of charge.

B. Constraints Formulation

During the optimization process the following constraints must be satisfied:

- Only one charging station will be assigned to each EVi at time t.

$$\sum_{j=1}^{m} x_{(i,j,t)} \quad (7)$$

- The remaining energy percentage of the EVi battery should be higher than the battery consumption it takes for the EVi to travel the distance to the CS.

$$d_{(i,j)} \geq dis_{(i,j)} \quad (8)$$

- There are a finite number of ports at each charging station and the proposed methodology will not allow an excess of EV's to be assigned to the charging stations at any time t.

$$\sum_{i=1}^{n} x_{(i,j,t)} \quad (9)$$

C. Simulated Annealing EV Charging Management Optimization Method

Simulated Annealing (SA) is a method for obtaining the optimal solution for a given problem. It is a meta-heuristic approach to solve optimization problem in a specified search space. It was made popular by the use of the traveling car salesman problem where the search space is large and discrete [28].

In this research, the problem of maximizing the energy remaining in the EV when it arrives at the CS will be solved using SA. This method will include the calculation of vehicle flow between the initial location of the EV and CS at time t, $q_{(i,j,t)}$. It will also calculate the final SoC for each EV battery upon reaching its destination.

The name Simulated Annealing came from the annealing of metals, a technique in which controlled heating and cooling of a metal is used to increase the size of its crystals and reduce their impurities. This technique of slow cooling is implemented into the SA algorithm and is interpreted as a gradual decrease in the probability of accepting worse solutions as the search space is explored. Accepting worse solutions is a crucial portion of meta-heuristics because it allows for a more detailed and extensive search for the optimal solution. The SA algorithm works in the following steps. At each time interval, the process randomly selects a solution close to the current one, measures its properties, and decides to move or to stay with the current solution. This is based on whether it has decided to choose the new solution as a better solution or worse solution than its current one. During each step, the temperature is slowly decreased from an initial positive value down to zero. The overall probability of transitioning to a new better solution will remain at 1 or a positive value and the probability of moving to a worse new solution is gradually moved towards zero.

D. Values of System Data

For the implementation of the SA, these are the parameters that were chosen:

- n = 50; Number of cycles
- m = 50; Number of trials per cycle
- na = 0.0; Number of accepted solutions
- p1 = 0.7; Probability of accepting worse solution at the start
- p50 = 0.001; Probability of accepting worse solution at the end
- t1 = -1.0/log(p1); Initial temperature
- t50 = -1.0/log(p50); Final temperature
- frac = $(t50/t1)^{(1.0/(n-1.0)}$; Fractional reduction every cycle

For the first focus of the optimization approach the following data is supplied:

- n = 6: sum of EV's
- m = 4: sum of CS's
- Initial locations of EV's and CS's are known
- Initial SoC of each EVi is randomized
- The time is started from t = t0 (where t0 is not equal to zero for calculations)
- Total number of charging ports at each CS are: m1 = 1, m2 = m3 = m4 = 2
- $k_{jam(i,j,t)}$ = 200 [veh/km]
- $v_{f(i,j,t)}$= 60 [km/h]

Table II displays the randomized values of the initial state of charge (SoC_0) and vehicle traffic on the road between EV and CS. Because this part of the focus is homogeneous, we only consider EVs of the same make and model. The Tesla Model 3 was chosen with the autonomy (An) of 354 [km] and the battery rated capacity (Cn) of 50 [kWh].

TABLE II. SYSTEM DATA: SOC0 , $d_{(i,j)}$ *and* $q_{(i,j,t)}$

		S1	S2	S3	S4
EV1: SoC_0 = 41	d	4	7	10	6
	q	1367	1761	1606	500
EV2: SoC_0 = 78	d	3	4	5	4
	q	1735	500	1721	1137
EV3: SoC_0 = 64	d	5	3	6	9
	q	629	1054	500	2209
EV4: SoC_0 = 52	d	6	7	3	2
	q	1434	1496	765	903
EV4: SoC_0 = 68	d	9	5	8	5
	q	2125	2400	549	2285
EV6: SoC_0 = 55	d	2	4	10	8
	q	1776	589	1551	709

TABLE III. ENERGY CONSUMPTION BY EV UNDER NORMAL AND DISTURBED CONDITIONS

Parameters of EVi		S1	S2	S3	S4
EV1	E_{cn}	0.57	0.9887	1.4124	0.8475
	E_{cd}	1.432	1.8478	4.6966	2.8622
EV2	E_{cn}	0.4237	0.57	0.7062	0.57
	E_{cd}	0.5414	0.7342	2.0282	1.1061
EV3	E_{cn}	0.7062	0.4237	0.8475	1.2712
	E_{cd}	1.3343	0.819	1.3134	3.8839
EV4	E_{cn}	0.8475	0.9887	0.4237	0.2825
	E_{cd}	1.131	2.1301	0.6131	0.3716
EV5	E_{cn}	1.2712	0.7062	1.1299	0.7062
	E_{cd}	3.1491	1.6093	1.8445	1.8913
EV6	E_{cn}	0.2825	0.57	1.4124	1.1299
	E_{cd}	0.4353	0.9149	2.8571	2.0451

E. Results, Discussions and Analysis

Using Eq. (1), the vehicle traffic on the road between the location of EVi and Sj can be calculated. Under normal conditions the parameter $Y_{(i,j,t)}$ is equal to 1. Using Eq. (5), the energy consumed by each EV upon reaching the charging station can be obtained. In the next step, optimization problem under disturbed conditions is considered. The variable of vehicle traffic is taken into consideration when energy consumption of EVs is calculated (E_{cn} multiplied by $Y_{(i,j,t)}$).

In this research, the initial SoC is randomized for each EV between 20% and 80%. This range is the normal day to day operating percentage charge for the Tesla Model 3 EV and has been found that staying in between these percentages prolongs the life of the EV battery. The SA optimization algorithm was executed multiple times to get an average data set and parameters for the EVs in terms of distance of charging station from EV, $d_{(i,j)}$, and the vehicle flow on the road between the charging station and EV at time t, $q_{(i,j,t)}$. Table II provides the results for this scenario. Using the data calculated from Table II, the SA algorithm was able to simultaneously account for energy consumed by each EV under both normal and disturbed conditions. The comparison between energy consumption under normal and disturbed conditions is displayed in Table III. The final value of SoC_f of each EV under normal and disturbed are given in Table IV. These results were further used to prioritize and assign the EV's with a charge closest to their respective SoC_{min} to the optimal CS. The results obtained from the SA algorithm in combination with the prioritization and assignment constraints was used to obtain the results displayed in Table IV.

F. Optimal Assignment

By implementing the proposed approach optimal solution was obtained, which maximizes the values of SoC_f using the SA optimization method. The calculated values representing the optimal assignment of EV's to CS's under normal conditions and disturbed conditions can be seen in the following figures (Fig. 2 and Fig. 3 respectively). It can be observed from these graphs that the optimal assignment of each EV associated with their optimal CS is color coordinated. It is evident that all constraints are met, and the main objective has been satisfied.

TABLE IV. OBTAINED SOC_F FOR ALL VEHICLES UNDER NORMAL AND DISTURBED CONDITIONS

Parameters of EV/Sj		S1	S2	S3	S4
EV1	Sof_n	40.43	40.01	39.59	40.15
	Sof_d	39.57	39.15	36.3	39.14
EV2	Sof_n	77.58	77.43	77.29	77.43
	Sof_d	77.46	77.27	75.97	76.89
EV3	Sof_n	63.29	63.58	63.15	62.73
	Sof_d	62.67	63.18	62.69	60.12
EV4	Sof_n	51.15	51.01	51.58	51.72
	Sof_d	50.87	49.97	51.39	51.63
EV5	Sof_n	66.73	67.29	66.87	67.29
	Sof_d	64.85	66.39	66.15	66.11
EV6	Sof_n	54.72	54.43	53.59	53.87
	Sof_d	54.56	54.09	52.14	52.95

- The total number of EV's assigned to each CS has not been exceeded. S1 has 1 port and S2, S3, and S4 all have 2 ports each.
- The prioritization constraint is upheld and those EV's that were the closest to their minimum threshold are assigned to CS's first, while still maintaining maximum SoC_f .
- Each assignment of EV's is reached while maximizing SoC_f. This minimizes the wait time of CS's, overall cost of operating an EV, and gets the driver of the EV back on the road as quickly as possible.

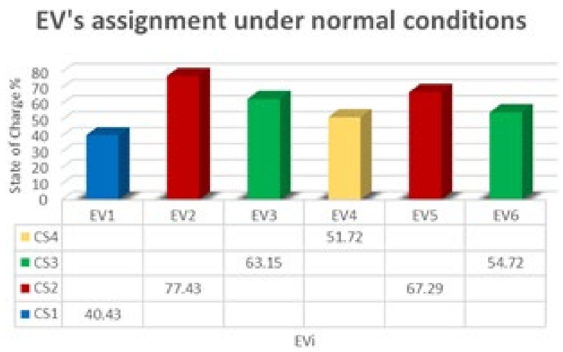

Figure 2. EV assignment under normal conditions using SAEVCM.

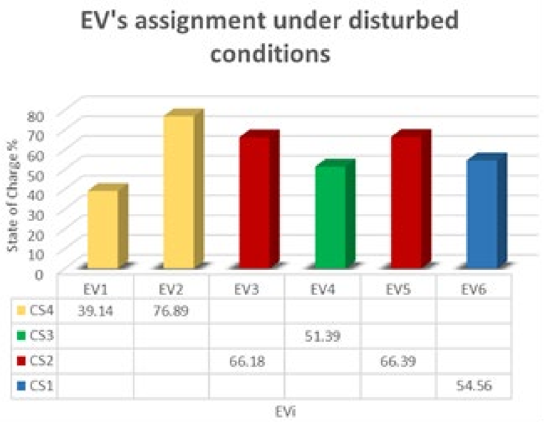

Figure 3. EV's assignment under disturbed conditions using SAEVCM.

VI. Heterogeneous Components

In this section, the proposed approach will be implemented on heterogeneous vehicles. Heterogeneous vehicles are those EVs that have different characteristics amongst them (they will have different capacities and autonomy's). The charging stations will also have different characteristics among themselves, allowing them to be divided into two categories: fast charging and slow charging. With all these elements, the main goal remains the same and it is to optimize the final state of charge of a battery, making it to be the largest possible value upon arriving at its destination [29]. SA will be used to obtain the optimal solution for this given problem.

A. Assumptions

Following the constraints that have already been observed in the homogeneous section, this section will consider the following in order to obtain the correct results:

1) A higher number of EVs are requesting for EV battery recharging

2) EVs will have varying charge speeds, meaning that some will need fast-charging, and some will need slow-charging.

3) Each CS will only provide one type of charging: fast or slow.

Table V displays the EV makes and models with their respective charging requirements. Note that most of the newer EV models offer both types of charging. Table VI details the characteristics of EVs used in this research.

TABLE V. Make, Model and Charging Requirements for EVs

EV	EV Make	EV Model	Charging Mode
EV1, EV6, EV12	Kia	2018 Kia Soul EV	Fast Charging
EV2, EV7, EV11	BMW	2018 BMWI3	Slow Charging
EV4	Nissan	2018 Nissan Leaf	Slow Charging
EV5, EV8	Tesla	Tesla Model 3	Fast Charging
EV3, EV9	Tesla	Tesla Model S	Fast Charging
EV10	Hyundai	Hyundai Ioniq EV	Slow Charging

TABLE VI. Characteristics of EV

EV Model	$C_{n(i)}$	A(Km)	EV Battery	SoC_{min}
2018 Kia Soul EV	32	164	Li-ion	20
2018 BMW I3	22	145	Li-ion	20
2018 Nissan Leaf	24	135	Li-ion	20
Tesla Model 3	50	354	Li-ion	20
Tesla Model S	85	400	Li-ion	20
Hyundai Ioniq EV	28	200	Li-ion	20

B. Problem Constraints

The following constraints are imposed:

- EV's declared as fast-charging will only be assigned to one fast-charging station at time t.

$$\sum_{j=1}^{R} x_{(i,j,t)} \tag{10}$$

- EV's declared as slow-charging will only be assigned to one slow-charging station at time t.

$$\sum_{j=R+1}^{l} x_{(i,j,t)} \tag{11}$$

- Final SoC of each EV battery must not exceed the minimum limit (SoC_{min}) set by the EV maker.

$$SoC_{f(ij,t+T(i,j,t))} \geq SoC_{\min(i)} \tag{12}$$

C. System Parameters

In the next stage, the proposed optimization approach was applied to heterogeneous components with the following data (also refer to Table IV):

- n = 12: total number of EV's
- m = 6: total number of CS's
- R = 3: sum of fast-charging stations (50 kW DC)

- L = 3: sum slow-charging stations (230V single-16A) (3 kW)
- Initial distances $d_{(i,j)}$ and EV locations are given
- Initial SoC of each vehicle EVi $SoC_{0(i,t)}$ are randomized
- The number of charging ports within each CS are: n1 = 1, n2 = n3 = n4 = 2, n5 = 4, n6 = 3, n7 = 5
- $k_{jam(i,j,t)}$ = 200 [veh/km]
- $v_{f(i,j,t)}$= 60 [km/h]

D. Energy Consumption

The energy consumption E_{cd} of all electric vehicles, can be evaluated by calculating the difference between the SoC initial and SoC final of the EV. These results can be observed in Fig. 4. In Fig. 5, all the final state of charges for each EV, that were calculated using Eq. 1 are illustrated.

E. Optimal Assignment

The optimal solution for the problem represented by Eq.6 is presented and solved with a SA algorithm using MATLAB. Fig. 4 demonstrates the optimal assignment of each EV to their respective charging station. Fig. 5 demonstrates a comparison between the each EVs initial state of charge and their final state of charge, further illustrating EV battery consumption. It is evident that all constraints are met, and the main objective has been satisfied.

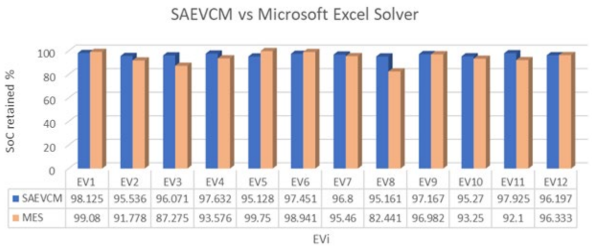

Figure 4. SAEVCM vs MES.

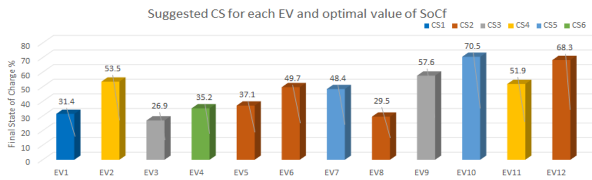

Figure 5. EV assignment using SAEVCM optimization.

The number of EV's assigned to each CS has not exceeded set constraints. The assignment of EV's follows the queue determined by the prioritization constraint. For each EV battery state of charge, their SOC_{min} has not been reached Battery state of charge for each EV has been optimized. EV's with models Kia Soul EV, Tesla Model 3 and Tesla Model S are assigned only to fast-charging stations. EV's with models BMW I3, Hyundai Ioniq EV and Nissan Leaf are assigned only to slow-charging stations.

F. Comparison Results

Displayed in Fig. 6 is the comparison of the results of this study using the SAEVCM optimization method against a similar study conducted in [13] using a Microsoft Excel Solver. From Fig. 6 it can be seen that the results using the SAEVCM optimization method are more favorable in maximizing and maintaining a higher SoC_f overall for the EV. SAEVCM was able to retain a higher percentage of initial state of charge in 7 of 12 of the EVs with an average retained of 96.54% and Microsoft Excel Solver had an average state of charge retained of 93.91%.

TABLE VII. SYSTEM DATA

Data EVi		S1	S2	S3	S4	S5	S6
EV1: SoC0 = 32	d	5	4	3	6	8	10
	q	1293	700	1402	1046	1420	700
EV2: SoC0 = 56	d	2	5	4	7	6	8
	q	1799	732	1211	2266	968	902
EV3: SoC0 = 28	d	5	9	10	6	1	7
	q	700	700	1266	1304	878	1269
EV4: SoC0 = 38	d	7	6	5	9	3	2
	q	2300	1511	1493	1640	1245	2368
EV5: SoC0 = 39	d	2	5	7	6	9	1
	q	1469	700	2011	1857	1601	1746
EV6: SoC0 = 51	d	9	5	8	4	2	7
	q	1927	700	814	700	1765	700
EV7: SoC0 = 50	d	6	8	9	4	2	1
	q	700	2114	700	1250	2198	2269
EV8: SoC0 = 31	d	8	5	2	4	7	6
	q	1157	1758	1909	2400	700	2377
EV9: SoC0 =60	d	1	2	5	7	6	8
	q	700	1159	700	1330	1817	2400
EV10: SoC0=74	d	6	10	7	2	4	1
	q	1806	1279	1907	1229	1563	1598
EV11: SoC0=53	d	2	4	5	6	10	7
	q	1666	700	1191	2223	891	2345
EV12: SoC0=71	d	5	6	7	3	2	9
	q	700	1544	2256	2014	1700	2197

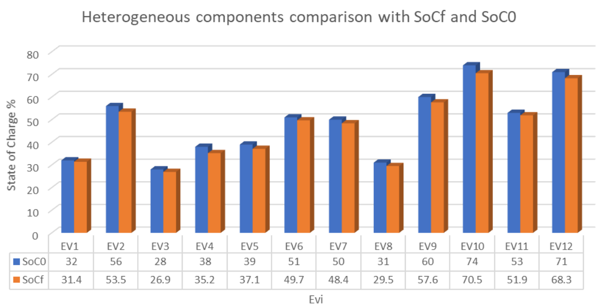

Figure 6. SoC_f comparison using SAEVCM optimization.

VII. CONCLUSION

In conclusion, this research paper used the simulated annealing optimization process to assign electrical vehicles to the most suitable charging station. The proposed optimization method takes into consideration a number of different constraints to be able to achieve the main objective. In theory, the system considers the minimum SoC of each electric vehicle, the initial SoC, the conditions of the road, the traffic density, the priority queue based on the prioritization constraint, and distance between the electric vehicle and charging station. It also accounts for the energy consumption for the EV to reach its destination CS. The main objective of this research is solved in two different scenarios: the use of strictly homogeneous components and the use of heterogeneous components. For the homogeneous case, the results were given under two different instances: all of the electrical vehicles were being driven under normal road conditions (without the additions of traffic density) and the second scenario, allocating all of the electric vehicles into a system with disturbed conditions. Upon observation of the results, it is observed that the final state of charge of each electric vehicle was much higher in normal conditions compared against disturbed condition, leading to lower energy consumption during normal conditions.

For the heterogeneous section of the research, the system was only under disturbed conditions with addition of different makes and models of electric vehicles, which have different baselines for minimum state of charge and differing charging modes. Optimal results and assignments were obtained while simultaneously satisfying all the constraints detailed previously. Using this proposed approach, as each EV reached its destination charging station, minimum energy was consumed and the SoC of the battery was maximized. Proposed models and numerical examples during this research demonstrate the effectiveness of the results obtained by the Simulated Annealing optimization approach and parameters. Comparing the proposed SAEVCM method to an already existing technique using Microsoft Excel Solver, it is observed that SAEVCM is easily scalable for larger systems with higher number of EVs and CSs. The future scope of this research work includes validating and testing the feasibility of SAEVCM on large scale test systems and by considering random behaviors of drivers.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Christian Anthony Rosa: Background research, Software development, research on literature review, data analysis, results review, paper writing.

Dr. Bhuvana Ramachandran: Mentoring the undergraduate student Mr.Christian on understanding technicalities of the project, Technical assistance with software development, data analysis, results review, review paper and provide comments.

REFERENCES

[1] Tesla. Model 3. [Online]. Available: https://www.tesla.com/model3

[2] Tesla. Charging-90-question. [Online]. Available: https://forums.tesla.com/forum/forums/charging-90-question

[3] X. Hu, S. J. Moura, N. Murgovski, B. Egardt, and D. Cao, "Integrated optimization of battery sizing, charging, and power management in plug-in hybrid electric vehicles," *IEEE Transactions on Control Systems Technology*, vol. 24, no. 3, pp. 1036-1043, May 2016.

[4] Z. Rezvani, J. Jansson, and J. Bodin, "Advances in consumer electric vehicle adoption research: A review and research agenda," *Transportation Research Part D: Transport and Environment*, vol. 34, pp. 122-136, 2015.

[5] C. Elmas, U. Guvenc, and M. U. Dogan, "Tire-Road friction coefficient estimation and experimental setup design of electric vehicle," *Balkan Journal of Electrical & Computer Engineering*, vol. 3, no. 4, pp. 202-207, 2015.

[6] C. Sun, F. Sun, X. Hu, J. K. Hedrick, and S. Moura, "Integrating traffic velocity data into predictive energy management of plug-in hybrid electric vehicles," in *Proc. American Control Conference*, Chicago, IL, USA, 2015, pp. 3267-3272.

[7] C. Ma, J. Rautiainen, D. Dahlhaus, A. Lakshman, C. Toebermann, and M. Braun, "Online optimal charging strategy for electric vehicles," *Energy Procedia*, vol. 73, pp. 173-181, June 2015.

[8] S. G. Li, S. M. Sharkh, F. C. Walsh, and C. N. Zhang, "Energy and battery management of a plug-in series hybrid electric vehicle using fuzzy logic," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 8, pp. 3571-3585, Oct. 2011.

[9] D. Bertsimas and J. Tsitsiklis, "Simulated annealing," *Statistical Science*, vol. 8, no. 1, pp. 10-15, 1993.

[10] J. Singh and R. Tiwari, "Multi-Objective optimal scheduling of electric vehicles in distribution system," in *Proc. 20th National Power Systems Conference*, Tiruchirappalli, India, 2018, pp. 1-6.

[11] K. Qian, C. Zhou, Y. Yuan, and M. Allan, "Temperature effect on electric vehicle battery cycle life in Vehicle-to-grid applications," in *Proc. 2010 CICED*, Nanjing, China, 2010, pp. 1-6.

[12] A. Hoke, A. Brissette, D. Maksimović, A. Pratt, and K. Smith, "Electric vehicle charge optimization including effects of lithium-ion battery degradation," in *Proc. IEEE Vehicle Power and Propulsion Conference*, Chicago, IL, USA, 2011, pp. 1-8.

[13] R. Mkahl, A. Nait-Sidi-Moh, J. Gaber, and M. Wack, "A linear optimization approach for electric vehicles charging," in *Proc. 3rd International Renewable and Sustainable Energy Conference*, Marrakech, Morocco, 2015, pp. 1-6.

[14] H. Wu, G. K. H. Pang, K. L. Choy, and H. Y. Lam, "An optimization model for electric vehicle battery charging at a battery swapping station," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 2, pp. 881-895, Feb. 2018.

[15] S. Li, H. He, Y. Chen, M. Huang, and C. Hu, "Optimization between the PV and the retired EV battery for the residential Microgrid application," *Energy Procedia*, vol. 75, pp. 1138-1146, August 2015.

[16] O. Sassi and A. Oulamara, "Electric vehicle scheduling and optimal charging problem: Complexity, exact and heuristic approaches," *International Journal of Production Research*, vol. 55, no. 2, pp. 519-535, 2017.

[17] M. Asaad, F. Ahmad, M. S. Alam, and Y. Rafat, "IoT enabled electric vehicles battery monitoring system," in *Proc. the 1st EAI International Conference on Smart Grid Assisted Internet of Things*, 2017.

[18] K. Liu, K. Li, Q. Peng, and C. Zhang, "A brief review on key technologies in the battery management system of electric vehicles," *Frontiers of Mechanical Engineering*, vol. 14, no. 1, pp. 47-64, 2019.

[19] Y. He, B. Venkatesh and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1095-1105, Sept. 2012.

[20] Z. Qu, *et al.*, "Optimization model of EV charging and discharging price considering vehicle owner response and power grid cost," *J. Electr. Eng. Technol.*, vol. 14, pp. 2251-2261, 2019.

[21] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 940-951, May 2013.

[22] A. Bhattacharjee, "Design and comparative study of three photovoltaic battery charge control algorithms in MatLab/Simulink environment," *International Journal of Advanced Computer Research*, vol. 2, no. 3, pp. 129-135, 2012.

[23] C. Musardo, G. Rizzoni, and B. Staccia, "A-ECMS: An adaptive algorithm for hybrid electric vehicle energy management," in *Proc. the 44th IEEE Conference on Decision and Control*, Seville, Spain, 2005, pp. 1816-1823.

[24] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, and J. Li, "An optimized EV charging model considering TOU price and SOC curve," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 388-393, March 2012.

[25] C. Wang and R. Power. (2019). Modeling and simulating battery performance for design optimization. [Online]. Available: https://www.mathworks.com/company/newsletters/articles/modeling-and-simulating-battery-performance-for-design-optimization.html
[26] O. Sundstrom and C. Binding. (2019). Optimization methods to plan the charging of electric vehicle fleets. [Online]. Available: https://www.zurich.ibm.com/pdf/csc/EDISON_ccpe_main.pdf
[27] O. Sundstrom and C. Binding, "Flexible charging optimization for electric vehicles considering distribution grid constraints," *IEEE Transactions on the Smart Grid*, vol. 3, no. 1, pp. 26-37, March 2012.
[28] O. Sassi and A. Oulamara, "Electric vehicle scheduling and optimal charging problem: Complexity, exact and heuristic approaches," *International Journal of Production Research*, vol. 55, no. 2, pp. 519-535, 2017.
[29] Z. Yang, K. Li, A. Foley, and C. Zhang, "Optimal Scheduling Methods to Integrate Plug-in Electric Vehicles with the Power System: A Review," *IFAC Proceedings Volumes*, vol. 47, no. 3, pp. 8594-8603, 2014.

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