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A Framework for Day-ahead Optimal Charging Scheduling of Electric Vehicles Providing Route Mapping: Kowloon Case Study

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Abstract

With the ever-increasing growth of electric vehicles (EV)s in the power industry, their significance as a flexible load has increased drastically. On the other hand, uncontrolled charging of these vehicles can cause serious problems in the grid, such as a peak in demand, a decrease in the life expectancy of transformers and as a result, an increase in charging costs of EVs for the EV owners. In this paper, a framework for day-ahead optimal charging of EVs is proposed which through optimization of active and reactive power exchange at each time interval, could prevent the problems mentioned above and at the same time increase the benefit of EV owners and network operators simultaneously. Furthermore, taking into account the effective factors on electrical energy consumption of EVs and the driving pattern of their owners, a route mapping algorithm is developed based on the proposed framework, so as to provide the EV owners with better services. The simulations are carried out using a hybrid interior-point optimization approach, based on traffic and geographic data collected from the city of Kowloon and a standard IEEE 33 bus system is used. The simulation results show that integrating optimal charging of EVs with a route mapping algorithm into the proposed framework can reduce the loss costs of the network during the hours of EVs' presence in the framework and the selling price

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of electricity to EV owners by 24.93% and 33.6%, respectively in comparison with the uncontrolled mode. Also, the average life expectancy of power transformers is increased by 2.97% in the optimal charging mode compared to the uncontrolled mode.
Keywords: Day-ahead scheduling, Electric vehicles, Optimal charging, Route mapping, Transformers loss of life, Cloud storing and computing

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Nomenclature

Acronyms

EV	Electric vehicle
PL	Parking lot
EV2G	Electric vehicle to grid
G2EV	Grid to electric vehicle
EV2PL	Electric vehicle to parking lot
PL2EV	Parking lot to electric vehicle
PL2G	parking lot to grid
SO	System operator
PLO	Parking lot operator
CSC	Cloud storing and computing
LOL	Loss of life

Indices

k	Iteration index
n	EV index
t	Time interval
p	PL index
b	Bus index
l	Power line index
N	Set of all EVs
B	Set of all busses

$\cap$	Set of all power lines
	Parameters
$\overline{k}$	Maximum number of iterations
μ^{dep}	Average of EVs' departure times from PLs
σ^{dep}	Standard deviation of EVs' departure times from PLs
bc_n	Battery capacity of EV_n
K	Ratio of the transformer load to its nameplate rating, per unit
R	Ratio of the transformer load loss at the rated load to its no-load loss
m, n	Empirically derived exponents to calculate $\Delta\theta_{b,t}^{TO,U}$ and $\Delta\theta_{b,t}^{H,U}$ with changes in the load
τ_H/τ_{TO}	Top-oil/HST time constants (h)
ESL	Estimated shelf life of transformers
CC^T	Initial cost (purchase price) of transformers ($)
i_d	Discount rate
k_b	Wear of battery capacity per charge/discharge
E_n^{bat}	Nominal battery capacity of EV_n (kWh)
CC^B	Initial cost (initial purchase price) of the EV battery ($)
SV	Battery's salvage value at the end of its life cycle ($)
rel_b	Reliability of bus b
pr_t	Cost of electricity over the time interval t ($)
R_l	Resistance of line l (Ω)
$\overline{V}_b/\underline{V}_b$	Upper/lower bound for the voltage of bus b (V)
$\overline{I}_l$	Upper bound for the current of line l (A)
$\overline{SoC}/\underline{SoC}$	Upper/lower bound for the SoC (%)
$\overline{\gamma}_C/\underline{\gamma}_d$	Upper/lower bound for the rate of charge/discharge of EV battery (kWh)
v	EV speed (km/h)
g	Road grade (°)
θ^A	Ambient temperature (°C)
w	Wind speed (m/s)
$P_{n,t}^v$	Power consumption of EV_n over the time interval t with respect to vehicle speed (KW)

$E^{g}_{n,t}/E^{\theta}_{n,t}$	Percentage of change in electrical energy consumption of EV_n over the time interval t with respect to road grade/ambient temperature
$E^{w}_{n,t}$	Percentage of change in electrical energy consumption of EV_n over the time interval t with respect to wind speed
$t^{i}_{n,p}$	Time of departure from the origin for EV_n with destination PL_p
$t^{dri}_{n,p}$	Time spent on the road for EV_n with destination PL_p
$t^{ar}_{n,p}/t^{dep}_{n,p}$	Time of arrival/departure of EV_n at/from PL_p
SoC^{i}_{n}	Initial SoC of EV_n at the time of departure from the origin (%)
E^{dri}_{n}	Energy consumption of EV_n along its path (while driving) (kWh)
$SoC^{ar}_{n,p}$	SoC of EV_n at the time of its arrival at PL_p (%)
E^{dri}_{n}	Electrical energy consumption of EV_n while driving (kWh)
Y_{ba}	Admittance amplitude between buses a and b (℧)
θ_{ba}	Angle of voltage between buses a and b (°)
	Decision Variables
X^{k}	Location of search agents in iteration k
V^{k}	Speed of search agents in iteration k
$\Delta\theta^{TO,U}_{b,t}/\Delta\theta^{TO,R}_{b,t}$	Ultimate/rated top-oil temperature rise over ambient temperature for a transformer located on bus b over the time interval t (°C)
$\Delta\theta^{H}_{b,t}$	HST temperature rise over top-oil temperature for a transformer located on bus b over the time interval t (°C)
$\Delta\theta^{H,U}_{b,t}/\Delta\theta^{H,R}_{b,t}$	Ultimate/rated HST temperature rise over top-oil temperature for a transformer located on bus b over the time interval t (°C)
$\theta^{H}_{b,t}/\theta^{TO}_{b,t}$	HST/top-oil temperature of transformer located on bus b over the time interval t (°C)

F_{aa}	LOL rate of oil-immersed transformers
F_{EQA}	Equivalent LOL rate of transformers
dbw_n	Average daily battery wear of EV_n (kWh/day)
E_n^-	Electrical energy consumption of EV_n while in V2G mode (kWh)
N_n^{lfc}	Life cycle of the EV_n battery (days)
dwc_n	Daily wear cost of the EV_n battery ($)
$P_{b,t}/q_{b,t}$	Active/reactive power injected to bus b over the time interval t (kW/kVAR)
$v_{a,t}$	Voltage amplitude of bus a over the time interval t (V)
$\delta_{a,t}$	Phase of bus a over the time interval t (°)
$\delta_{b,t}$	Apparent power injected to bus b over the time interval t (°)
$I_{l,t}$	Current passing through line l over the time interval t (A)
$p_{n,t}^+/p_{n,t}^-$	Active power exchange from/to the network to/from the EV_n over the time interval t (kW)
$q_{n,t}^+/q_{n,t}^-$	Reactive power exchange from/to the network to/from the EV_n over the time interval t (kVAR)
$en_{n,t}$	Energy required to charge EV_n over the time interval t (kWh)
$SoC_{n,t}$	SoC of EV_n over the time interval t (%)
$U_{n,t}^-/U_{n,t}^+$	Binary variable that indicates if V2G/G2V is activated for EV_n over the time interval t
DLC	Daily energy loss cost of the grid ($)
DCC	Daily charging costs for EVs ($)

1. Introduction

The increase in greenhouse gas emissions, extensive climate change and most importantly shortage of fossil fuels has led to the development of alternatives to fossil-fueled vehicles [1]. The United States environmental protection agency published a report in 2018, which shows that transportation services and electricity generation sectors were two main greenhouse gas sources, releasing almost 55% of the total emissions in that year [2]. Due to low noise pollution, low greenhouse gas emissions and also low cost of maintenance, electric vehicles are rapidly expanding

as an alternative to fossil-fueled vehicles [3]. Predictions show that the production of EVs will rise by 2040 according to the laws adopted by the governments and people's interest in these vehicles will increase gradually [4]. Therefore, providing better services to EV owners must be more important than ever. Route mapping of EVs considering the lifespan of their batteries and the impact factors on their electrical energy consumption is an example of these services [3, 5, 6]. There are a lot of factors that affect the electrical energy consumption of EVs. Vehicle speed, ambient temperature, wind speed and road grade are among some of these important factors [7]. Electric vehicles are mainly considered as flexible loads in electrical networks. Therefore, they can be controlled in terms of charge/discharge at different time intervals, preventing peak of demand in the load profile [8]. Controlled charging can also increase the lifespan of power grid transformers and reduce electrical energy losses [9]. The benefit of EV owners should also be considered in the controlled charging schedule so that more EVs would want to participate in the schedule [10]. This benefit can be in the form of a reduction in the price of electricity paid for charging EVs, or in the form of an increase in the lifespan of their lithium-ion batteries [11].

Furthermore, [12] deals with the charging management of EVs, taking into account wind power and uncertainty in tariff, and utilizes a robust optimization approach in a model predictive framework. In [13] the optimal charging of EVs is performed based on EVs' preferences and concepts from economics. The paper uses the concept of pareto solution to solve a multi-objective optimization problem. [14] examines the benefits of participating in the primary frequency regulation markets for EVs, from the perspective of EV owners. A heuristic-based optimization process is proposed to find an optimized power bid based on local search algorithms. In [15] in addition to the power grid components, the EV transport system is also considered in the problem of charging EVs. A distributed trilayer multi-agent framework is proposed in [16] for optimal EV charging scheduling. The framework reduces the negative effects of EV charging demand on the electrical grids. In [17] parking lots placement is planned long term, considering the simultaneous benefits of the network and EV owners. The paper utilizes a multi-objective genetic algorithm to find

the optimal location and capacity of EV parking lots, along with the reinforcement plan of the distribution network. In [18] a two-stage approach is developed for EVs' parking lot allocation and DRR (distributed renewable resources), that benefits both the network and the parking lot owners. Moreover, genetic algorithm (GA) and particle swarm optimization (PSO) algorithm are used for the distribution network loss minimization purpose. Finally, in [19] a method is proposed to determine the optimal siting and sizing of EV parking lots, with the objective of maximizing the profit of electrical distribution companies.

Study of previous works in the field of charging and scheduling of EVs exhibit shortcomings (**Sh**) and weaknesses which are divided into the following categories:

- ✓ **Sh1**: day- ahead optimal charging scheduling is based solely on the profit of the EV owners and the benefit of the network operator is not taken into account [1, 3, 13, 14].
- ✓ **Sh2**: day- ahead optimal charging scheduling is based solely on the profit of the network operator and the benefit of the EV owners is not taken into account [4, 6, 9, 15, 16].
- ✓ **Sh3**: In the behavioral modeling of EVs, the SoC and arrival time of EVs at the parking lots are considered without route mapping [6, 12, 17–19].
- ✓ **Sh4**: in the route mapping of EVs, only vehicle speed is considered influential in vehicle's electrical energy consumption and other factors such as road grade, ambient temperature and wind speed are not considered [1, 3, 4].

In this paper, a framework for day-ahead optimal charging of EVs is presented based on the optimization of active and reactive power exchange between EVs and parking lots (denoted as EV2PL) and also between parking lots and the network (denoted as PL2G) at each time interval. Furthermore, the benefit of EV owners and system operator are considered simultaneously in this optimization framework. Route mapping is performed for EVs that want to participate in the day-ahead optimal charging program so as to bring the performance of the proposed framework closer to reality. The route mapping data are then sent to a central control system to communicate with parking lots. Finally, the proposed framework is able to provide services to EVs, PLs and providers in a suitable platform using cloud technology.

The main contributions of this paper are summarized as follows:

- ✓ Route mapping for EVs is performed based on four impact factors (vehicle speed, ambient temperature, road grade and wind speed) and as a result, the SoC and arrival time of EVs at the parking lots are determined accordingly (tackling **Sh3** and **Sh4**).
- ✓ Reactive power compensation is considered and subsequently, the loss costs of EVs during charging are reduced (tackling **Sh1**).
- ✓ An optimal charging framework is proposed considering the simultaneous profit of EV owners and system operators (tackling **Sh1** and **Sh2**).
- ✓ The lifespan of EV batteries and power transformers are taken into account in the optimal charging framework (tackling **Sh1** and **Sh2**).

2. System framework

In this paper, a framework for optimal charging of EVs is presented based on cloud storing and computing. Several stakeholders can be involved in this framework. The main stakeholders and the possible benefits that the proposed framework can provide for them are discussed below.

- ✓ EV user: EV owners who are interested in participating in this program can reap the benefits of this program, including services to find the optimal route to reach their destination, increasing the battery life of EVs and also reducing their charging costs.
- ✓ System Operator (SO): SO is a centralized unit that must have the required authority to retain information received from EV users and PLOs and meet privacy concerns. SO can be a DSO and participating in this program can help reduce the loss costs of EVs during charging and also extend the lifespan of power transformers.
- ✓ Parking lot operators (PLO): PLOs can benefit from this program with the intent to provide services for EVs. As a matter of fact, by encouraging PLOs to participate in the program, SO allocates part of the profit from reduction of electricity losses to parking lot owners as a privilege. Furthermore, each

parking lot can improve the quality of its service by providing information (such as capacity, selling price, etc.) to EV owners. Moreover, through better participation in the competitive power market and deployment of different modes of EVs, PLOs can determine the price of their services such that they can provide services to more EVs and as a result, their final profit is increased. There are several modes for EVs:

- ✓ Electric vehicle to grid (EV2G)
- ✓ Grid to electric vehicle (G2EV)
- ✓ Vehicle to parking lot (EV2PL)
- ✓ PL to vehicle (PL2EV)

These modes cause more EVs to interact with the grid and thus provide more control over this flexible load. In order to coordinate and enable data exchange between the involved stakeholders for day-ahead optimal charging, a framework is proposed, as shown in Figure 1.

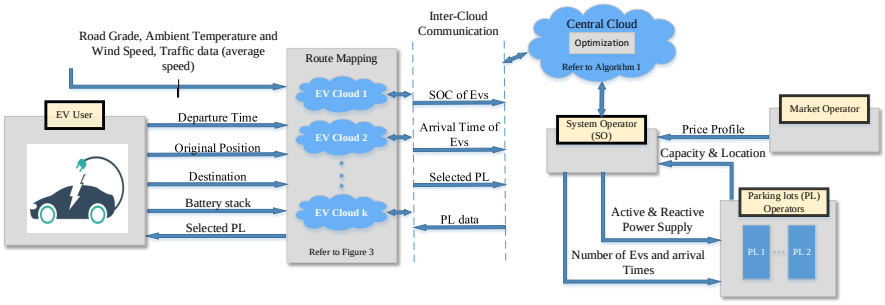


Figure 1: Proposed framework for day-ahead optimal charging of EVs

In this framework, the urban network is partitioned into k separate areas and each area is assigned a cloud to store and process EV data. Moreover, SO receives relevant and important information from PLOs (such as parking lot location, capacity, etc.) and from the market operator (the forecasted day-ahead price profile based on the load profile), and sends this information to a central cloud. First, EV owners who want to participate in this program send their origin, destination and time of departure to the EV cloud. This data is sent to one of the area clouds based

on the location of EVs throughout the city. Then, according to the destinations specified by the EV owners and the information from the parking lots (capacity, location, etc.), route mapping is performed and the appropriate parking lot for each EV and the proposed route is sent to the EV owners. The appropriate parking lots are selected with respect to travel distance. In other words, the nearest parking lot, with available spots, to the destination specified by each EV is determined for that EV via route mapping. In addition, based on the performed route mapping, the estimated SoC of each EV and its estimated arrival time at the selected parking lot(s) are sent to the central cloud. Once this is done for all EVs participating in the day-ahead program, taking into account the benefit of SO and EV owners simultaneously, as well as the constraints related to the charging of EVs, an optimization problem is solved in the central cloud for the next day, using a hybrid interior-point method, so as to determine the optimal active and reactive power exchange between the EVs and the grid at each time interval. Finally, the optimized power and the number of EVs that intend to participate in this program are announced to the PLOs by the SO. EV owners' preferences are also taken into consideration in that the nearest parking lot to their destination is selected for them, which reduces their travel distance and consequently, their travel time and energy consumption are reduced as well. Furthermore, EV drivers determine their arrival/departure times to/from the parking lots and the optimal charging program is developed in such a way that EVs will leave the parking lots with full charge.

2.1. Cloud Storing and Computing (CSC)

This section explains in detail how CSC works. As shown in Figure 2, in general, cloud storing and computing is a model that allows easy and quick access to a shared pool of configurable computing resources (such as networks, servers, storage, applications and services) with minimal management or service provider interaction [20]. These resources are accessed via the internet, which is metaphorically referred to as a "cloud". The focus of this model is to provide on-demand resources for the users, without the need for the user to have special equipment for processing or even be aware of the location of the processing [21].

Cloud-based computing allows the user to take advantage of a huge virtual space for storing data and processing them quickly. In addition, it provides a suitable platform for quick bidirectional exchange of data between different units [20]. On the other hand utilization of cloud storing and computing, poses some challenges such as information security, ease of access and data management. Cloud data security is usually provided using encryption protocols. This would allow encrypted data to be sent to the cloud. Hence computations in the cloud are performed only on encrypted data and the results are obtained by decrypting the output sent back from the cloud. However, encryption methods are limited in terms of the types of computation they can support; therefore, alternative methods such as transforming the original computational problem, introducing noise into the problem and splitting the original problem and solving each subproblem in a different cloud platform are presented [22]. Confidentiality and integrity of communications to and from the cloud, and within the cloud can also be ensured by standard cryptographic protocols such as IPSec or TLS. The issue of access and management of large amounts of data can also be solved by distributing the data and computations between multiple independent clouds. Additionally, the multi-instance architecture minimizes the impact of possible outages and security breaches, since in the case of such occurrences, not all EVs' data would be compromised. However, this approach results in higher costs for data maintenance and management of each cloud [23]. In this paper, due to the presence of multiple units and the need for communication and processing of large amounts of data, the proposed framework for day-ahead optimal charging of EVs utilizes cloud storing and computing.

Each unit in this framework is able to send or receive real-time information to or from the cloud server using an application. To this end, each EV user is able to log in to the application through a pre-assigned user id and password, and share its required information such as type of battery and its capacity, SoC of the battery, vehicle speed, etc. with the cloud. The cloud then uses this information, along with the information it receives from the operators of other units (PLOs), to provide the EV users with the closest parking lot and the suggested route to the selected parking lot, through the application.

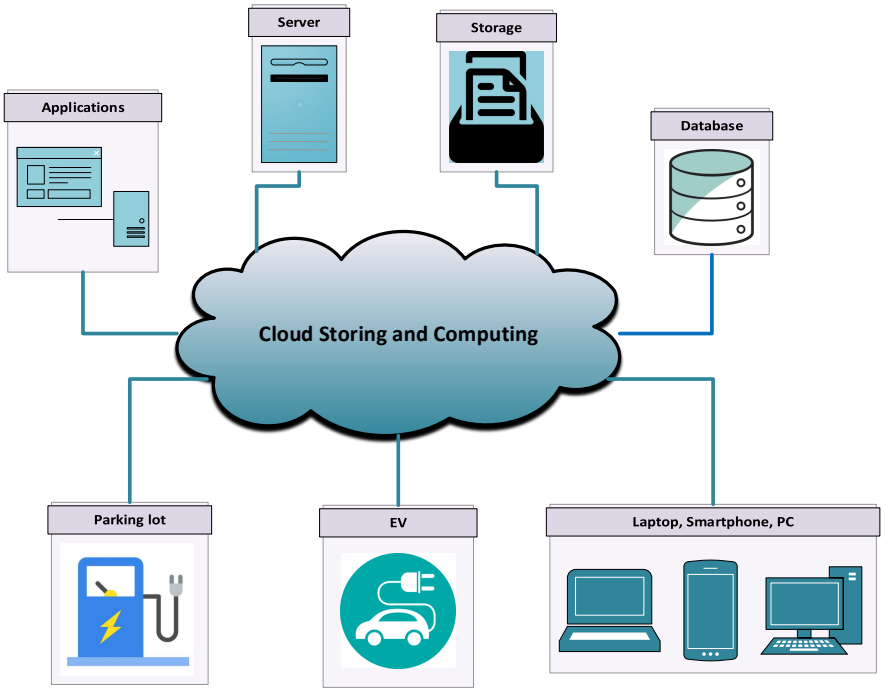


Figure 2: Cloud storing and computing

2.2. Route Mapping

In this section, the route mapping performed in the EV cloud is discussed. Route mapping of EVs, as one of the main future means of transportation, is a very important issue and faces many challenges (such as limited capacity of EV batteries, sparse availability of charging stations and time-consuming process of charging EVs) [24]. Therefore, several route mapping approaches consider optimizing energy consumption explicitly. However, energy optimal routes often greatly increase travel time and so optimizing energy consumption as single criterion is helpful only in special cases, e.g., when the battery SoC is very low. In practice, users would be more interested in taking routes that form a convenient trade-off between travel time and energy consumption.

It should also be noted that in reality, in most urban environments, EVs constitute the minority of vehicles and most of the urban traffic is made up of conventional

cars. Therefore, the route mapping in this paper is performed taking into account the presence of these conventional vehicles. Furthermore, the proposed framework for optimal charging of EVs can also be extended to conventional vehicles, where the drivers of these vehicles can participate in a similar program where they can be informed of the nearest gas station to their destination, gas station capacity, fuel costs, etc.

Dijkstra's algorithm is one of the most widely used routing algorithms, which is utilized in this paper. In 1959, Dijkastra developed an algorithm for the shortest path problem that appeared to be considerably more efficient and required less data storage space compared to the previous methods. This algorithm is a mature classical shortest path of single source algorithm and it is used for calculating the shortest path from one node to all other nodes in non-negative weights graphs [25]. In 1968 [26] developed a search strategy called A^* to find the path with the minimum cost. This algorithm is different from other methods since it utilizes an estimate of the cost of "path-completion" and it finds the optimal path for certain classes of estimating functions. In [27], a comparative study was done regarding the performance of Dijkastra and A^*. The results indicated that A^* can outperform Dijkastra's algorithm with respect to run time when spatial coordinated are present. However, as mentioned earlier, A^* requires a function for estimating the completion cost of a path and therefore is not suitable for many shortest path applications. Another famous method of the shortest path algorithm is the Floyd algorithm. [25] investigates the online real-time path planning abilities of Floyd, Dijkasta and A^* under two conditions: the threat of fixed obstacles and sudden threats. Although all three can handle fixed and sudden threats, Dijkastra's algorithm is better in terms of the run time, complexity and path length of the three algorithms [25]. Even though Dijkastra is one of the earliest developed shortest path algorithms, it remains to this day one of the best approaches for optimally solving the simple shortest path problem when all arcs have non-negative lengths and a lot of research is being conducted to improve and extend Dijkastra [28–30]. Therefore, this algorithm has been applied in many domains and applications, the most famous of which is Google Maps.

In this paper, using Dijkstra's algorithm, the shortest path is obtained with re-

spect to travel time and then the electrical energy required for traveling the chosen path is calculated according to four impact factors. Vehicle speed is one of the most important impact factors that influence the energy consumption of EVs. In addition, some environmental factors such as wind speed, road grade and ambient temperature can significantly affect EV's energy consumption [7]. This paper takes into account the aforementioned impact factors in determining the required electrical energy consumption for each path so as to calculate energy consumption more accurately and improve vehicle fuel economy.

2.2.1. The proposed algorithm for Route Mapping of EVs

This section provides an algorithm based on DIjkstra's method for the route mapping of EVs. The flowchart of the proposed algorithm is shown in Figure 3.

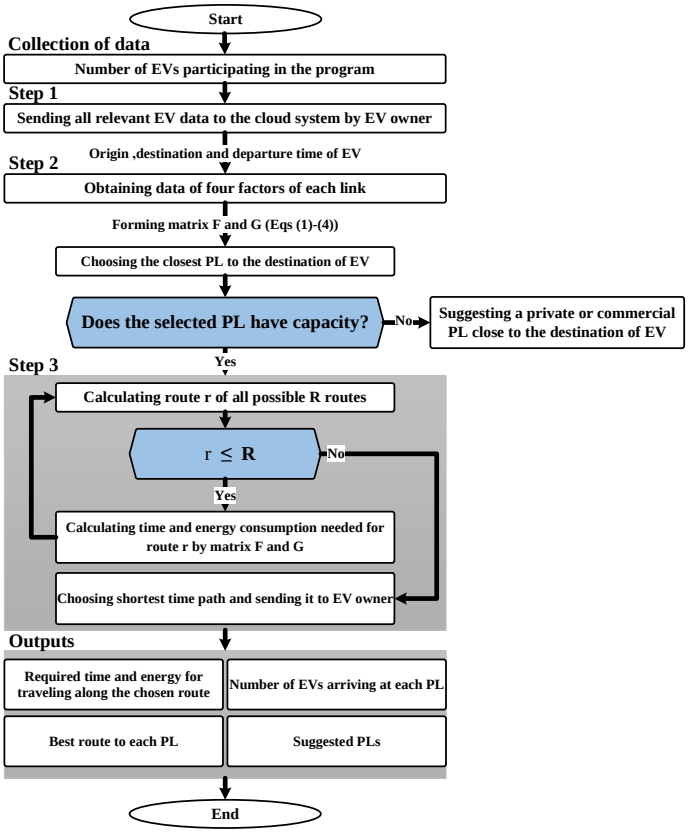


Figure 3: Flowchart of the proposed algorithm for route mapping performed in the EV cloud based on Dijkstra's algorithm

An urban network is constituted of a number of links and intersections. First, the urban network is modeled as a graph in which each link represents a street and each node represents the intersection of the city's main streets. **Step 1**- **Step 3** are implemented to utilize the proposed algorithm. These steps are described as follows:

- ✓ **Step 1**: the information about a driver (including the departure time, origin and destination) that wants to participate in the day-ahead optimal charging program is sent to the EV cloud so that the appropriate parking lot and the suggested route to that parking lot are provided for the driver.
- ✓ **Step 2**: given the average speed of EVs in each link and also the length of each

link, the estimated time required for traveling each link is obtained and as a result, matrix $F_n = [f_{n,ij}]_{s\times s}$, which is the travel time matrix of each link is formed; Where s is the number of nodes in the graph and $f_{n,ij}$ is the required time for EV_n to reach node j from node i. similarly, the electrical energy consumption required for each EV to pass through each link is calculated based on available data and Eqs (5)- (8). Finally, matrix $G_n = [g_{n,ij}]_{s\times s}$ which is the electrical energy consumption matrix passing through each link is formed. Where s is the number of nodes in the graph and $g_{n,ij}$ is the required energy for EV_n to reach node j from node i. for example, given s= 2 and n= 2, matrices F and G are formed as follows:

$$F_1 = \begin{pmatrix} 0 & f_{1,12} \\ f_{1,21} & 0 \end{pmatrix} \tag{1}$$

$$F_2 = \begin{pmatrix} 0 & f_{2,12} \\ f_{2,21} & 0 \end{pmatrix} \tag{2}$$

$$G_1 = \begin{pmatrix} 0 & g_{1,12} \\ g_{1,21} & 0 \end{pmatrix} \tag{3}$$

$$G_2 = \begin{pmatrix} 0 & g_{2,12} \\ g_{2,21} & 0 \end{pmatrix} \tag{4}$$

where $f_{1,12}$, $f_{2,12}$, $f_{1,21}$ and $f_{2,21}$ are the required time for EV_1 and EV_2 to reach node 2 from node 1 and vice versa respectively. Similarly $g_{1,21}$ and $g_{2,12}$ are the required electrical energy for EV_1 and EV_2 to reach node 2 from node 1 respectively. And $g_{1,21}$ and $g_{2,21}$ are the required electrical energy for EV_1 and EV_2 to reach node 1 from node 2 respectively. It's evident that the diagonal entries of F_n and G_n are zero.

✓ **Step 3**: at this stage, all possible routes to reach the destination specified by the EV owner, are obtained. Assuming that there are R possible routes, the shortest time path is identified and the travel time and energy consumption of EVs along the chosen route are calculated based on Eqs (5)-(8). Also, the suggested parking lot and the best route to each parking lot are presented to

each EV accordingly. Furthermore, the number of EVs and their arrival times to each parking lot are announced to the PLOs. It is worth noting that since the capacities of the PLs are limited, in a case where the selected parking lot for some EVs is full, the algorithm suggests another private or commercial parking lot which is close to the destination of those EVs. Nevertheless, those EVs are not included in the proposed charging program of this paper. This is because due to the partitioning of the urban network, the parking lots are located relatively far apart, and suggesting another parking lot in the program, could move some EVs away from their destination.

For instance, Figure 4 demonstrates an urban network containing 6 nodes $\{a_i\}_j = 1:6$ and 8 links $\{e_i\}_j = 1:8$. As shown in the figure, the EV driver is supposed to travel from a_1 to a_6. There is a total of 8 different routes between the two nodes and according to the algorithm demonstrated in Figure 3, the shortest time route (the red route) and the time and energy required to travel along this route are obtained.

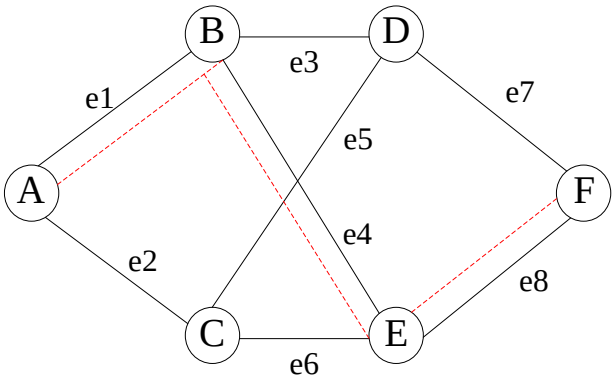


Figure 4: Path graph for EVs to travel from a_1 to a_6

3. Problem Formulation

3.1. Factors influencing the electrical energy consumption of EVs

Several factors affect the electrical energy consumption of EV batteries. The most important of these factors are vehicle speed, ambient temperature, road grade and wind speed [7, 31]. In the following, each factor is examined separately.

3.1.1. Vehicle speed

The first and most important factor that influences the energy consumption of EVs is vehicle speed. As illustrated in Figure 5, there is a direct relationship between the two parameters of energy consumption and speed of EVs. This relationship is modeled by a third order polynomial function according to Eq (5) [7].

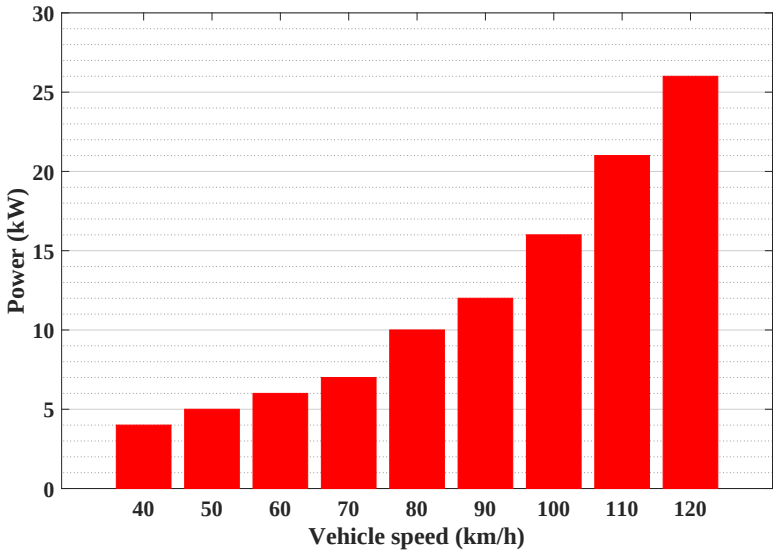


Figure 5: Relationship between energy consumption and speed of EVs

$$P^{v}_{n,t} = 2.247\times10^{-5}v^{3}_{n,t} - 0.002205v^{2}_{n,t} + 0.1547v_{n,t} + 0.04653 \qquad \forall t \in T\ ,\ \forall n \in N \tag{5}$$

3.1.2. Road grade

Road grade is another important factor that has a significant effect on the energy consumption of EVs. The relationship between road grade and the energy consumed by EVs is illustrated in Figure 6. Moreover, this relationship is modeled by a third order function according to Eq (6) [7].

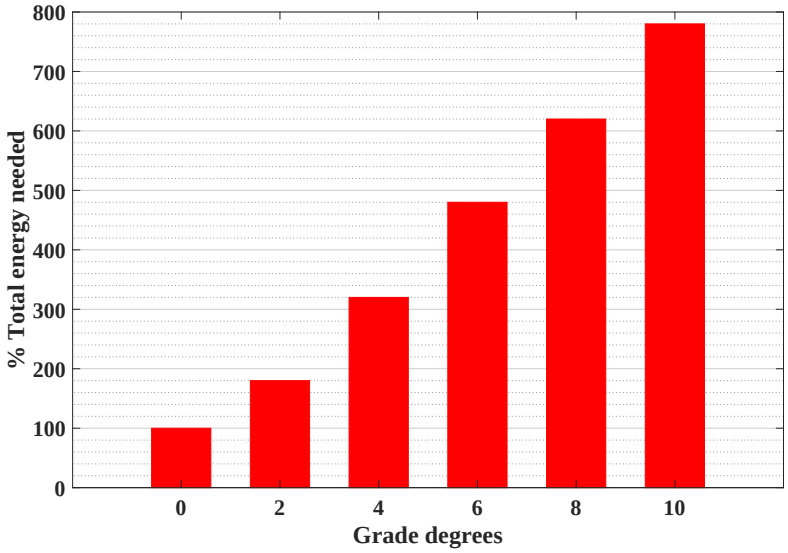


Figure 6: Relationship between percentage of changes in electrical energy consumption of EVs and road grade

$$E^{g}_{n,t} = -0.3067 g^{3}_{n,t} + 6.721 g^{2}_{n,t} + 31.77 g_{n,t} + 97.54 \quad \forall t \in T \ , \forall n \in N \quad (6)$$

3.1.3. Ambient temperature

The next factor that influences the energy consumption of EVs is ambient temperature. This factor indirectly impacts the electrical energy consumption of EVs by affecting the use of their cooling and heating systems. At ideal temperatures (20°C), the EV owners do not usually see the need to use cooling and heating systems, but with changes in temperature, the need to use these systems is gradually felt. The relationship between ambient temperature and energy consumption of EVs is shown in Figure 7 and modeled by a third order function according to Eq (7)

[31].

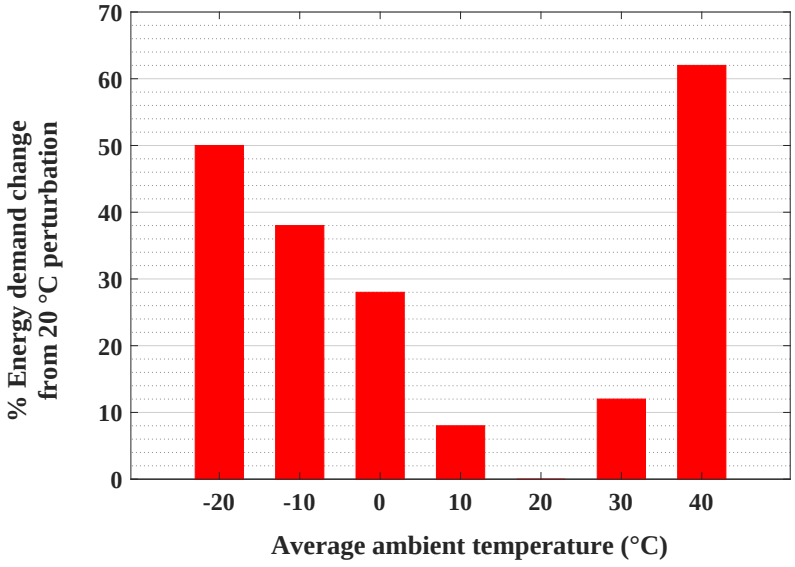


Figure 7: Relationship between percentage of changes in electrical energy consumption of EVs and ambient temperature

$$E^{\theta}_{n,t} = 1.875\times10^{-3}\theta^{3}_{n,t} - 3.532\times10^{-3}\theta^{2}_{n,t} - 1.951\theta_{n,t} + 25.33 \quad \forall t \in T, \forall n \in N \quad (7)$$

3.1.4. Wind speed

Wind speed and direction is another factor that influences the energy consumption of EVs. By moving in the direction of the wind, the consumption of electrical energy is decreased whereas moving in the opposite direction has the opposite effect. The relationship between wind speed and energy consumption of EVs is illustrated in Figure 8, and modeled by a third order function according to Eq (8) [7].

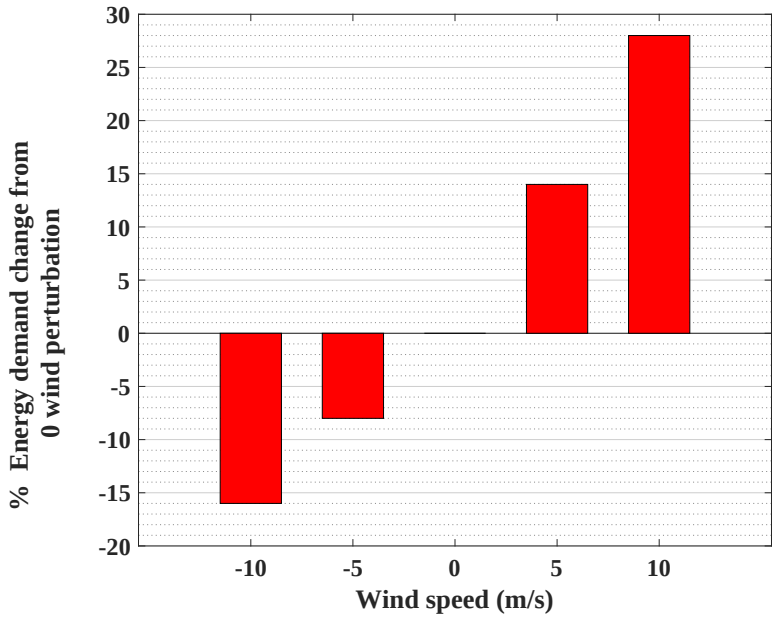


Figure 8: Relationship between percentage of changes in electrical energy consumption of EVs and wind peed

$$E^{w}_{n,t} = 6.77 \times 10^{-18} w^{3}_{n,t} + 0.06857 w^{2}_{n,t} + 2.2 w_{n,t} + 0.177 \quad \forall t \in T, \forall n \in N \quad (8)$$

3.2. Modeling the presence of EVs in parking lots

To model the presence of EVs in the parking lots (PLs), in order to schedule for the optimal exchange of active and reactive power, Eqs (9), (10) and (11) are used for the calculation of arrival and exit times and SoC of EVs when entering the PLs, respectively. It should be noted that the departure time of EVs, both from their origin and from the PLs, are known and sent to the cloud by EV owners beforehand. In the simulations, however, these values were modeled using the Gaussian model. The arrival time of EVs to the parking lots, on the other hand, is obtained via route mapping as was mentioned in step 3 of the route mapping algorithm of section 2.2.1. Furthermore, it is assumed that the EVs are charged from night till morning and move towards the PLs at full charge (i.e., with an SoC of 80%).

$$t^{ar}_{n,p} = T^{dri}_{n,p} + t^{i}_{n,p} \quad (9)$$

$$t_{n,p}^{dep} = \mu^{dep} + \sigma^{dep} N_1 \tag{10}$$

$$SoC_{n,p}^{ar} = SoC_n^i - E_n^{dri}/bc_n \tag{11}$$

3.3. Modeling the thermal behavior of transformers

Thermal transformers are one of the main components of power networks and this section is dedicated to obtaining a thermal model for them [32]. At each time interval the ultimate top-oil temperature rise, as well as the ultimate HST (hottest spot temperature) rise for the transformers of bus 'b' are calculated from the load level at that instant according to Eqs (12) and (13). Then from the ultimate top-oil temperature rise and the ambient temperature at each time interval, the increment in the top-oil temperature is calculated using Eq (14). The increment in the HST rise can also be calculated according to Eq (15).

$$\Delta\theta_{b,t}^{TO,U} = \Delta\theta_{b,t}^{TO,R} \times \left(\frac{K^2R+1}{R+1}\right)^n \quad \forall b \in B, \quad \forall t \in T \tag{12}$$

$$\Delta\theta_{b,t}^{H,U} = \Delta\theta_{b,t}^{H,R} \times K^{2m} \qquad \forall b \in B, \quad \forall t \in T \tag{13}$$

$$\tau^{TO}\frac{d\theta_{b,t}^{TO}}{dt} = \left(\Delta\theta_{b,t}^{TO,U} + \theta_t^A\right) - \theta_{b,t}^{TO} \quad \forall b \in B, \quad \forall t \in T \tag{14}$$

$$\tau^{H}\frac{d\Delta\theta_{b,t}^{H}}{dt} = \left(\Delta\theta_{b,t}^{H,U} - \Delta\theta_{b,t}^{H}\right) \qquad \forall b \in B, \quad \forall t \in T \tag{15}$$

Finally, in order to obtain the HST, the top-oil temperature and the HST rise are added according to Eq (16).

$$\theta_{b,t}^{H} = \theta_{b,t}^{TO} + \Delta\theta_{b,t}^{H} \qquad \forall b \in B, \quad \forall t \in T \tag{16}$$

According to ANSI/IEEE standard, the LOL rate of oil-immersed transformers can be calculated using Eq (17).

$$F_{aa} = \exp\left(\frac{15000}{383} - \frac{15000}{\theta_H + 273}\right) \tag{17}$$

According to this standard Eq (18) is used to obtain the equivalent LOL rate.

$$F_{EQA} = \frac{\sum_{t=1}^{t} F_{aa_t}\Delta t_t}{\sum_{t=1}^{T}\Delta t_t} \tag{18}$$

As a result, the transformers loss of life (LOL) is calculated using Eq (19).

$$LOL_T = \frac{ESL}{F_{EQA}} \tag{19}$$

Now, with the help of engineering economics formulas, the daily operational cost of transformers is modeled according to Eq (20).

$$DOC = \frac{\left((1+i_d)^{\frac{1}{365}}-1\right)(1+i_d)^{LOL_T}}{\left((1+i_d)^{LOL_T}-1\right)(1+i_d)^{1/365}} \times CC_T \tag{20}$$

3.4. Modeling of EVs' batteries

Another component that has been modeled in this work is the lifespan of EV batteries based on their energy exchange with the grid network. This modeling is based on the equations in [33]. It should be noted that according to [34], the effect of the current rate at charge rates below 1C, is less than that of the SoC and can be neglected. Since in the simulations performed, the maximum charge rate is considered to be 5kWh, which is equivalent to 0.5C, the current rate is not considered in the modeling of battery lifespan. It is also assumed that all EVs move from their origin to the parking lots at full battery charge, and eventually their battery charge reaches its full value when leaving the parking lots, in which case the average daily wear of EV batteries is modeled using Eq (21).

$$dbw_n = k_b((1+e)E_n^{dri} + 2E_n^- \quad (kW.h)/day \tag{21}$$

where k_b is the wear of battery capacity per charge/discharge in (KWs); which is equal to 0.0015 (kWh/kWh) according to [33]. i.e. for each charge or discharge of 1 KWh, the capacity of lithium-ion batteries is reduced by 0.00015 kW.h. Moreover, due to the fact that the energy exchanged in V2G mode must eventually be replenished by recharging, E_n^- is multiplied by 2. The weighing factor e is considered due to the higher energy discharge during driving compared to the V2G mode, which according to [35] equals 2.22.

According to [33], EV batteries reach the end of their lifespan as they lose 20% of their original nominal capacity and hence the approximate battery life for each EV is modeled using Eq (22).

$$N_n^{lfc} = \frac{0.2E_n^{bat}}{dbw_n} \quad (days) \tag{22}$$

Now based on engineering economics formulas, the daily cost due to EV battery wear is calculated using Eq (23). In this equation, the difference between the initial

cost of batteries and their salvage value are spread over the batteries' life cycle, with the incorporation of i_d. i_d acts as the inflation rate and has to be accounted for to compare the initial cost and salvage value, in a realistic way.

$$dwc_n = \frac{i_d\,(CC^B(1+i_d)^{N_n^{lfc}} - SV)}{(1+i_d)^{N_n^{lfc}} - 1} \quad \frac{US\$}{day} \tag{23}$$

3.5. Cost function

The cost function consists of two parts. The first part (OF_1) concerns the profit of EV owners in the day-ahead optimal charging program which includes minimizing the cost of charging EVs and increasing the lifespan of their batteries whereas the second part of the cost function (OF_2) concerns the profit of network operators. These profits include reducing losses and improving the lifespan of the network's power transformers.

$$minOF = OF_1 + OF_2 \tag{24}$$

$$OF_1 = \sum_{b\epsilon B}\sum_{t\epsilon T}\sum_{n\epsilon N} rel_b.(en_{n,t}.pr_t) + \sum_{n\epsilon N} dwc_n \tag{25}$$

$$OF_2 = \sum_{t\epsilon T}\sum_{l\epsilon \cap} R_l I_{l,t}^2.pr_t + \sum_{b\epsilon B} DOC_b \tag{26}$$

$$P_{b,t} = \sum_{a\epsilon B} V_{b,t}.V_{a,t}.Y_{ba}.\cos(\theta_{ba} - \delta_{b,t} + \delta_{a,t}),\ \forall b \in B;\ \forall t \in T \tag{27}$$

$$q_{b,t} = \sum_{a\epsilon B} V_{b,t}.V_{a,t}.Y_{ba}.\sin(\theta_{ba} - \delta_{b,t} + \delta_{a,t}),\ \forall b \in B;\ \forall t \in T \tag{28}$$

$$P_{b,t} + jq_{b,t} = S_{b,t}, \quad \forall b \in B;\ \forall t \in T \tag{29}$$

$$\underline{V_b} \leqslant V_{b,t} \leqslant \overline{V_b}, \quad \forall b \in B;\ \forall t \in T \tag{30}$$

$$I_{l,t} \leqslant \overline{I_l}, \quad \forall l \in \cap;\ \forall t \in T \tag{31}$$

$$\underline{SoC} \leqslant SOC_{n,t} \leqslant \overline{SoC}, \quad \forall t \in T\ ,\ \forall n \in N \tag{32}$$

$$p_{n,t}^{+} \leqslant \overline{\gamma_c}\ \ , \quad p_{n,t}^{-} \leqslant \overline{\gamma_d}\ \ \forall t \in T \tag{33}$$

$$q_{n,t}^{+} \leqslant \overline{\gamma_c}\ \ , \quad q_{n,t}^{-} \leqslant \overline{\gamma_d}\ \ \ \forall t \in T\ ,\ \forall n \in N \tag{34}$$

$$U_{n,t}^{+} + U_{n,t}^{-} \leqslant 1\ \ , \quad U_{n,t}^{+} + U_{n,t}^{-} \leqslant 1\ \ \forall t \in T\ ,\ \forall n \in N \tag{35}$$

Eqs (27)- (31) represent the load distribution constraints and Eqs (32)- (35) on the other hand, represent the charge/discharge constraints of EVs.

3.6. Optimization algorithm

In this section, steps of the proposed algorithm for obtaining the optimal active and reactive power exchange between the EVs and the grid, in the day-ahead optimal charging program, are illustrated in detail using Algorithm 1. In this algorithm, a hybrid interior-point approach is adopted. The interior-point method, which is a gradient-based optimization algorithm, was used due to the superior performance compared to heuristic optimization approaches [36]. Interior-point methods are very efficient search approaches. However, they require a good starting point in order to end up in the global optimum instead of a local optimum [37]. Thus, whale optimization (WO) algorithm was combined with the interior-point method to provide an initial point and help speed up the search. In this hybrid approach, first the WO algorithm, which is a heuristic, is launched and the problem is solved until a termination criterion is met [38]. One possible stopping criterion is a specified maximum number of iterations [39]. The solution is then passed on to the interior-point method as the initial point. Due to the sensitivity of interior-point methods to the starting point, this hybrid approach increases the chance of finding the problem's most likely global solution. The aim of Algorithm 1 is managing the values of p_t^* and q_t^*, which represent the optimal active and reactive power respectively, such that (24) is minimized. Based on the proposed framework of section 2 and the charging constraints of (27)-(35), EVs are charged using this algorithm.

Algorithm 1: The proposed algorithm

Input Route mapping data, EVs characteristics, the forecasted ambient temperature, and electricity price.

Output: Optimal active and reactive power exchange $(p_t^*,\ q_t^*)$, between EVs and the grid at each interval

Providing the solution obtained by the WO method as the initial point

while $|OF_{k+1} - OF_k| > \epsilon$ **do**

  for *each test point* $i \in N_{Pop}$ **do**

    Updating p_t **and** q_t

    for *each time step* $t \in \tau$ **do**

      Performing power flow subject to constraints using Eqs (27)- (33)

      Obtaining F_{aa}^t **using Eq (17)**

$$F_{aa}^{daily} \longleftarrow F_{aa}^{daily} + \frac{F_{aa}^t \cdot \Delta t_n}{\sum_{n=1}^{T} \Delta t_n} \tag{36}$$

      for *each power line* $l \in \cap$ **do**

$$DLC \longleftarrow DLC + pr_t \cdot R_l I_{l,t}^2 \tag{37}$$

      end

      for *each EV* $n \in N$ **do**

$$SoC_{n,t} \longleftarrow SoC_{n,t} + \frac{p_t}{bc_n} \tag{38}$$

        for *each bus* $b \in B$ **do**

$$DCC \longleftarrow DCC + rel_b \cdot (en_{n,t} \cdot pr_t) \tag{39}$$

        end

      end

      Calculating dwc_t **using Eq (23)**

$$OF_i \longleftarrow DCC + DLC + DCC + dwc_t \tag{40}$$

      if $OF_{k+1} > OF_i$ **then**

$$OF_{k+1} \longleftarrow DOC + DLC + DCC + dwc_t \tag{41}$$

      end

    end

  end

  Forming a new point

end

4. Case study

4.1. Input data

In this section, the proposed framework for the day-ahead optimal charging of EVs is implemented with the utilization of Kowloon traffic and weather data

[40, 41]. As mentioned in Section 2.2.1, for the route mapping of EVs, a number of nodes are assigned to the intersections of Kowloon's main streets as shown in Figure 9. Furthermore, it is assumed that a total of 7 parking lots are located in different parts of the city and 800 EVs are willing to participate in the day-ahead optimal charging program.

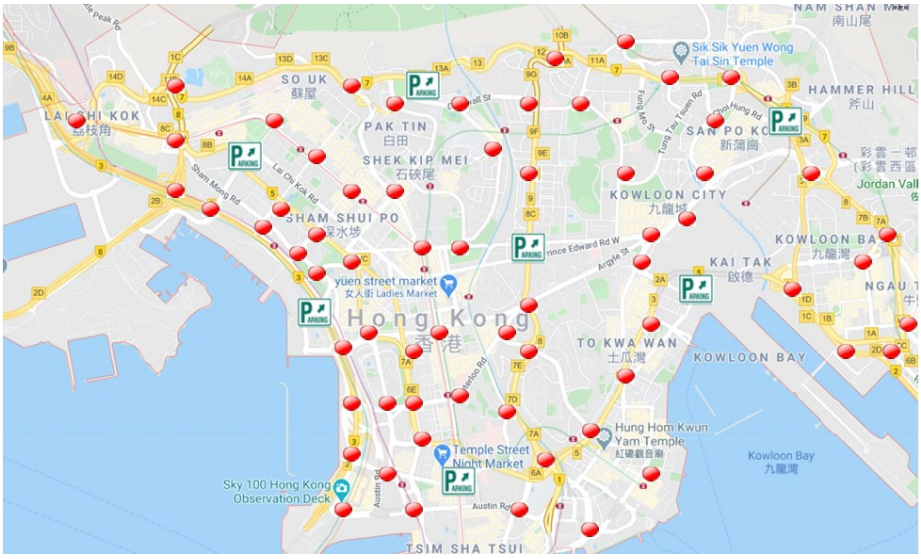


Figure 9: Kowloon city map

In order to model the Kowloon power grid, the standard IEEE 33 bus system is used. The electric power grid diagram and the location of the parking lots on the buses are shown in Figure 10. Located on each of these buses is a thermal transformer, whose lifespan is affected by factors such as overload and ambient temperature. Data on thermal transformers and their prices are given in [42].

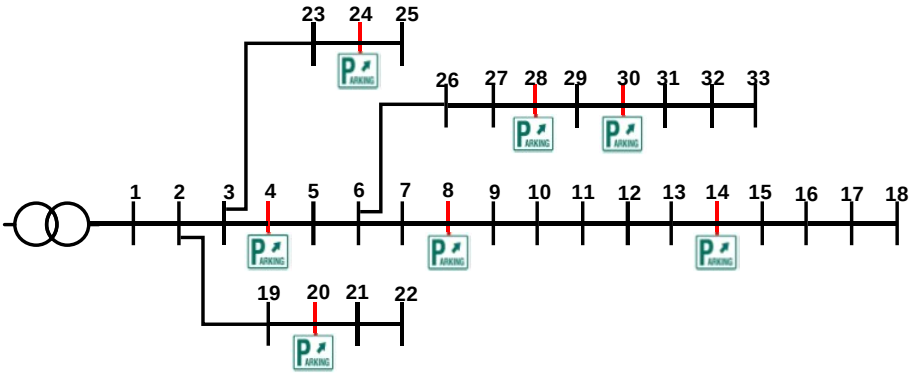


Figure 10: IEEE 33 bus system and the location of PLs

The market share percentage of EVs, based on their class specifications is displayed in Table 1. Furthermore, according to [43], the price of lithium ion batteries is estimated at 175 $/kWh.

Table 1: Market share percentage of EVs based on their class specifications

EV Class	β(kWh)	Market Share
1	10	0.2
2	12	0.3
3	16	0.3
4	21	0.2

The data related to the modified electricity price profile based on time of use (TOU), for warm and cold seasons are collected from [44] and [45] respectively, and the load profile, for cold and warm seasons are derived from [46]. Moreover, the electricity price profile is shown in Figure 11.

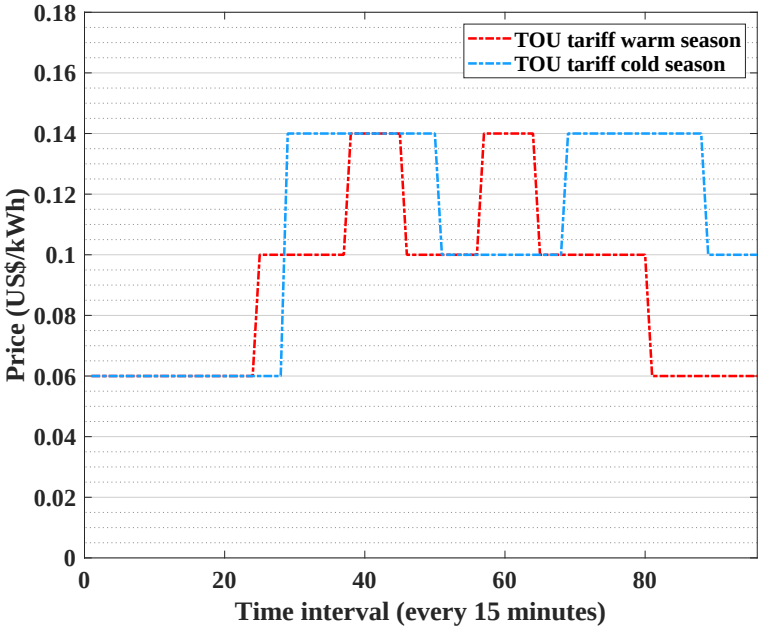
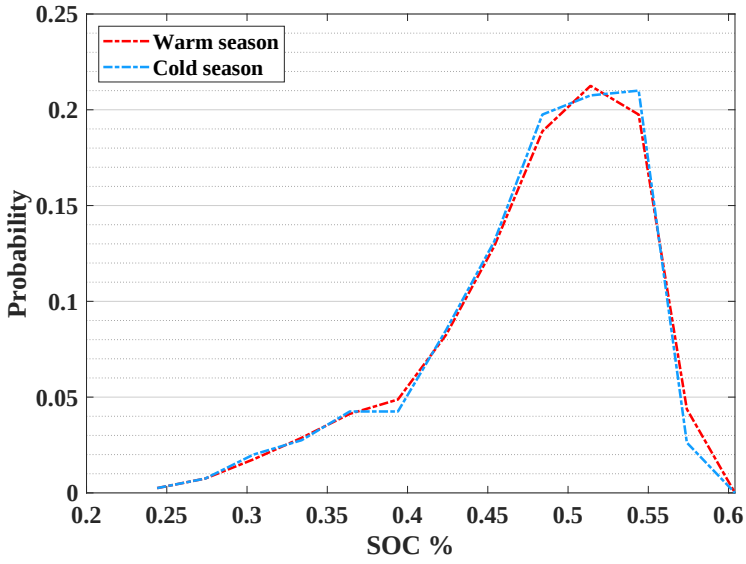


Figure 11: Electricity tariffs

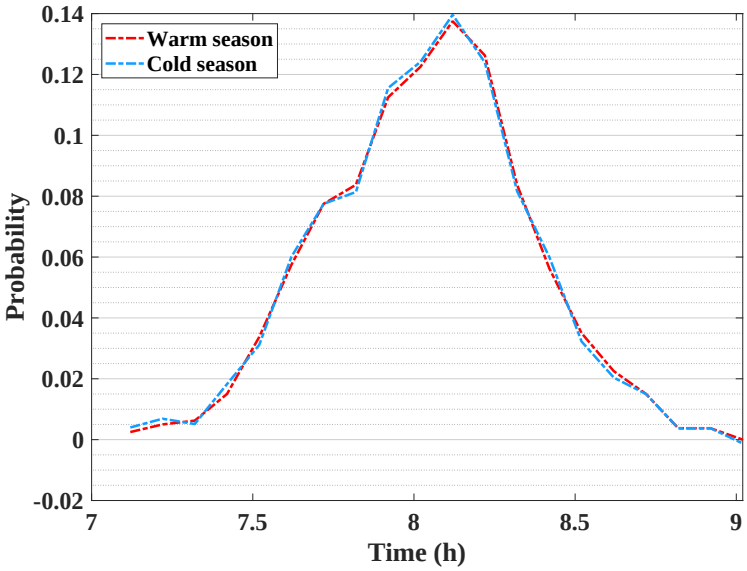
As demonstrated in Figure 11, the electricity pricing varies by TOU. In this paper, prices of 0.06 US$/kWh, 0.1 US$/kWh and 0.14 US$/kWh are categorized as low, moderate and high respectively. In the simulations, it is assumed that EVs are charged at level 2. Charging of EVs is generally divided into 2 levels [47]. Level 1 charging is commonly used at homes and can charge EVs up to 1.92 KW depending on the equipment used, whereas level 2 charging is mostly used in PLs and has the ability to charge EVs up to 19.2 KW depending on the equipment used. In this paper, 5kWh is considered as the maximum charge rate. To increase the accuracy of the simulations, optimization time intervals of 15 minutes are considered. i.e. the charge and discharge rate of the active and reactive power varies every 15 minutes.

4.2. Results of the route mapping

According to the route mapping performed for EVs, the probability distribution of their SoC and arrival times at the PLs, for cold and warm seasons are shown in Figure 12.



(a) probability distribution of EVs' SoC



(b) probability distribution of EVs' arrival time

Figure 12: Probability distribution of EVs' SoC and arrival times

4.3. Scenario description

In this section, 5 different scenarios (SC) are considered for the day-ahead optimal charging program.

- ✓ Scenario 1 (**SC1**): no EVs participate in the day-ahead optimal charging program. (base scenario)
- ✓ Scenario 2 (**SC2**): EVs are charged at a constant rate of 1 KW as soon as they enter the PLs (uncontrolled charging).
- ✓ Scenario 3 (**SC3**): the active power exchange between EVs and the grid is optimized and only the benefit of EV owners is taken into account (the cost function is OF_1).
- ✓ Scenario 4 (**SC4**): the active power exchange between EVs and the grid is optimized and only the benefit of SO is taken into account (the cost function is OF_2).
- ✓ Scenario 5 (**SC5**): the active and reactive power exchange between EVs and the grid is optimized taking into account the simultaneous benefit of EV owners and SO.

4.3.1. Daily profile of the network's active and reactive power, losses and power factor

Figure 13 shows the daily active power profile of the network under study. In **SC1**, the daily load of the network is shown without the presence of EVs. In **SC2**, it is demonstrated that EVs are charged as soon as they enter the PLs, creating a morning peak which causes problems with meeting network demand. The network demand peak in this scenario is increased by about 8.97% in the warm season and by about 13.42% in the cold season, compared to the base scenario (i.e. **SC1**). Furthermore, the energy exchange between the EVs and the grid is limited to the early hours of EVs being present at the PLs, which leads to the incapability of using the full capacity of this flexible load in the charging program. In **SC3**, in the warm season, considering the benefit of the EV owners, charging is done during the hours when the average price of electricity is moderate, which creates a larger peak in the electricity network. In the cold season however, when EVs reach the parking lots, the electricity price is high, as a result, EVs wait until the price of electricity

goes down and then start charging. In this scenario, the network demand peak has increased by about 24.5% in the warm season. This significant increase in the network demand peak in the warm season, causes problems such as difficulty meeting network demand by the SO and damage to power equipment. Due to the negative impact of V2G power exchange on the battery of EVs and consequently a decrease in the battery lifespan and considering the price profile, V2G power exchange does not occur at the network demand peak in this scenario. In **SC4**, charging of EVs is done in line with the benefit of the SO and thus, In the warm season, EVs are charged during the hours when the electricity price is moderate and are discharged during peak hours of the load and electricity price. Therefore, network losses and costs are reduced during these hours, and then to compensate for the discharge power and reach the desired SoC when leaving the PLs, EVs are charged again during the hours of low network demand. This will create a peak in the network in the upcoming hours. This increase in the network demand peak is about 4.73%, in the warm season, compared to the base scenario. In the cold season, when the EVs reach the parking lots, due to the high electricity price, they discharge subject to certain constraints. This injection of active power from EVs into the grid is done in an effort to reduce network losses. Then, when the price of electricity goes down, EVs start charging, subject to charging constraints. In **SC5**, charging of EVs is done taking into account the simultaneous benefit of EV owners and the SO. Therefore, in both cold and warm seasons, EVs are charged during hours of moderate electricity price and also the exchange of active and reactive power continues until the last hours of EVs' presence at the PLs. As a result, the new peak created in the network is very small compared to the base scenario (about 0.81% in the warm season), which has a positive effect on reducing losses and meeting network demand. Furthermore, the charging of EVs is more uniform, which in turn can improve the lifespan of network transformers.

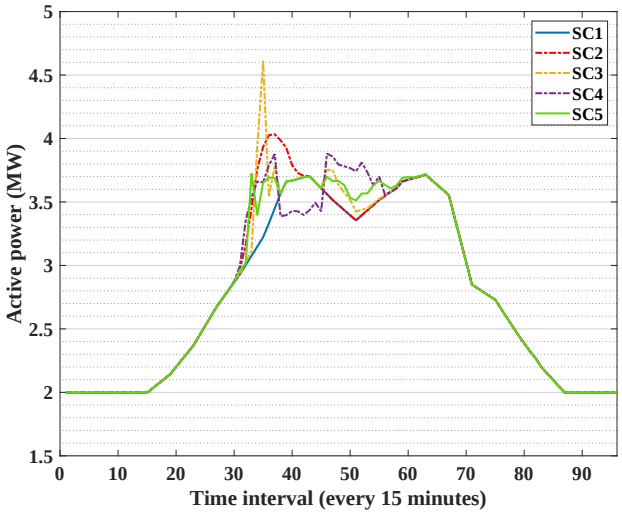
In the cold season, charging of EVs occurs during the hours of lowest demand, therefore, the demand peak remains unchanged in **SC3**- **SC5** compared to the base scenario. Moreover, the lowest network demand peak in the warm season (about 0.27%, compared to the base scenario) belongs to **SC5**. **SC2** and **SC5** indicate the

worst and best scenarios, respectively in terms of demand response. Moreover, the average daily active power of the network is the same in **SC2**- **SC5** (since the network load is constant and 800 EVs must be charged subject to charging constraints) and has increased by about 1.42% and 1.46%, in the warm and cold seasons respectively, compared to the base scenario.

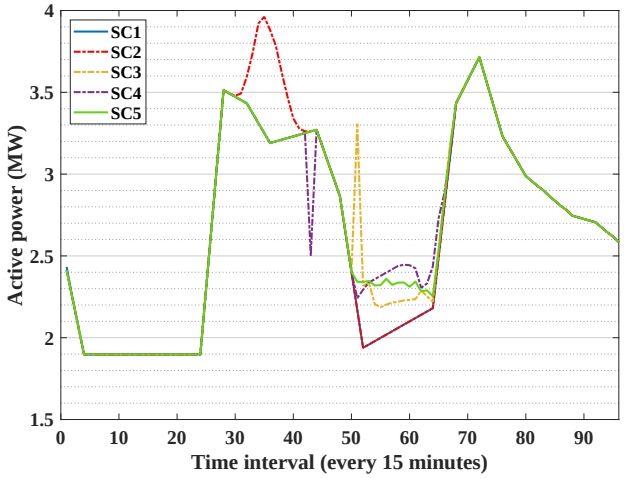
Figure 14 demonstrates the daily reactive power profile. As mentioned before, the exchange of reactive power between EVs does not occur in **SC2**- **SC4** and therefore the reactive power profile in these scenarios is the same as that of **SC1** (i.e. the base scenario). However, in **SC5** reactive power is injected to the grid by EVs, in both warm and cold seasons. Therefore the average daily reactive power has decreased by about 19.94% and 23.11%, in the warm and cold seasons, respectively, compared to the base scenario. This decrease in the reactive power exchange not only reduces the costs of reactive losses but also improves network voltage.

Figure 15 shows the profile of daily network losses. These losses include the sum of active and reactive power losses of the network. As can be seen, in **SC1**- **SC4** this profile is similar to the active power profile (Figure 13), since in these scenarios no exchange of reactive power with the grid occurs and the loss profile is only a function of the active power profile. Therefore it is observed that the average daily losses, in warm and cold seasons, have increased by about 2.94% and 3.15%, respectively, in **SC2**- **SC4** compared to the base scenario. (The average daily losses are the same in **SC2**- **SC4**, however the average cost of losses varies in each scenario depending on the price profile, which is discussed later in Table 3). In **SC5** however, the situation is different and due to the injection of reactive power from the EVs to the grid, the average daily network losses have decreased by about 8.04% and 8.32%, in warm and cold seasons, respectively, compared to the base scenario.

Finally, the network's daily power factor (PF) profile is demonstrated in Figure 16. PF describes the ratio of network's active power to its apparent power. As this value approaches 1, the network's performance becomes more efficient. As can be seen in Figure 16, in **SC5** the PF is close to 1 during the hours of EVs' presence at the PLs which is due to the decrease in the reactive power during those hours.

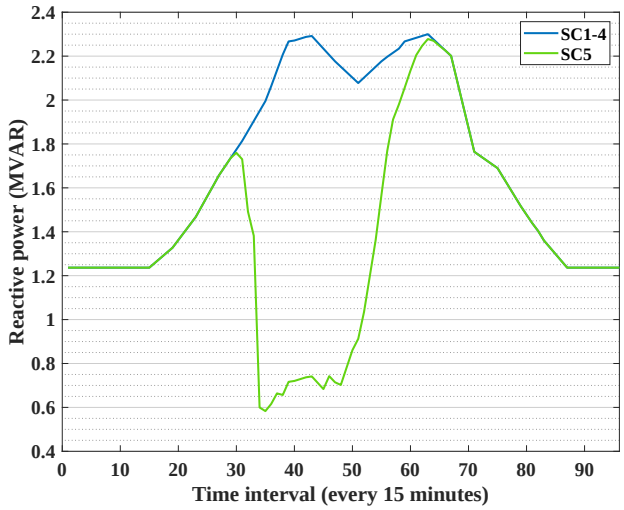


(a) Warm season

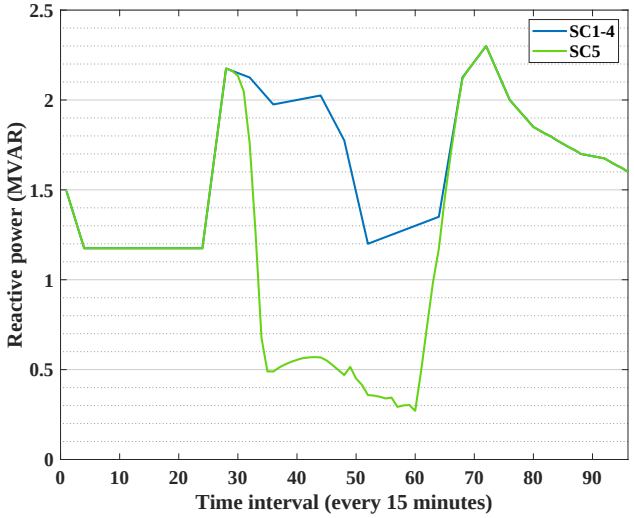


(b) Cold season

Figure 13: Daily active power profile

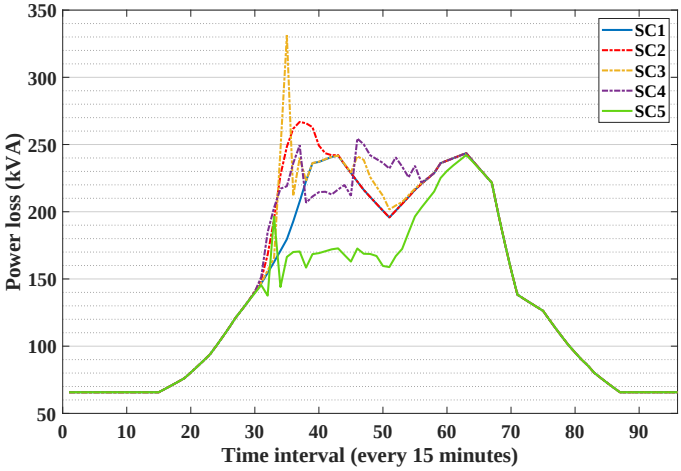


(a) Warm season

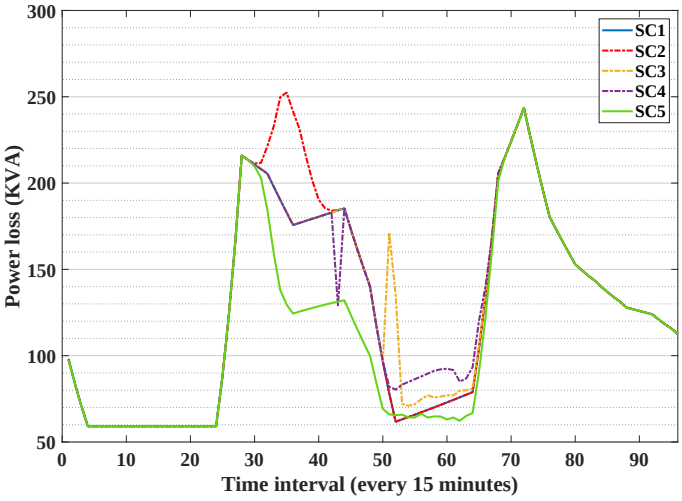


(b) Cold season

Figure 14: Daily reactive power profile

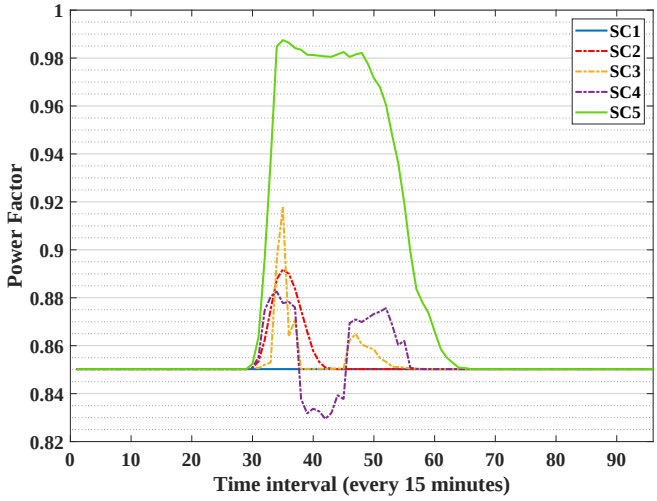


(a) Warm season

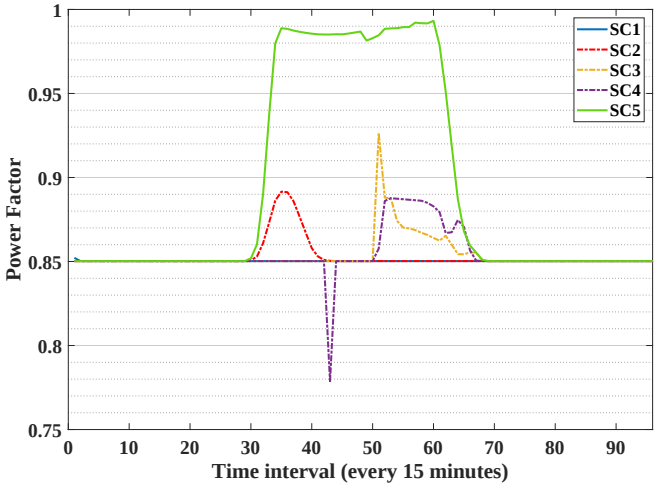


(b) Cold season

Figure 15: Daily network losses profile



(a) Warm season



(b) Cold season

Figure 16: Daily power factor profile

4.3.2. Examining the benefits of EV owners in different scenarios

In this section, the benefits of the EV owners can be studied in terms of the two following categories:

1. Charging costs
2. Battery wear costs

The importance of battery wear costs is that EV owners would have to replace their batteries whenever their EV battery life expires. Therefore, the EV owners would reap more benefits if these batteries lasted longer. It should be noted that all costs discussed for examining the benefits of the EVs and SO, are specific to the time of EVs' presence in the framework.

Costs of EV battery wear: In **SC2**, **SC3** and **SC5**, considering the fact that EVs do not inject active power into the grid, the cost of battery wear is only related to charging EVs and is almost the same in these three scenarios. However, in **SC4**, due to the injection of active power into the grid, the cost of battery wear is increased by 26.66% and 10.12% in warm and cold seasons, respectively, compared to the other three scenarios.

Costs of charging EVs: in **SC2**, given that EV charging is partly done at the peak of electricity price, the charging costs are the highest in this scenario and are increased in the warm season by 15.6%, 39.3% and 15.46%, and in the cold season by 50.84%, 56.97% and 50.58% compared to **SC3**, **SC4** and **SC5**, respectively. Meanwhile, in **SC4**, EVs inject active power into the grid; in fact in this scenario, EVs sell power to the grid at the peak of electricity price and are recharged later when the prices drop. Therefore their charging costs are improved over **SC2**, **SC3** and **SC5** respectively by 28.21%, 17.02% and 17.12% in the warm season and by 36.29%, 3.91% and 4.07% in the cold season.

Regarding the total costs of EV owners, it can be noted that in **SC3**, the optimization is done based solely on the benefits of the EV owners. Therefore the lowest costs for EV owners result from this scenario which compared to **SC2**, **SC4** and **SC5** show an improvement of 4%, 13.15% and 0.03%, respectively in the warm season and the results obtained from the load profile of the cold season indicate an improvement of 11.82%, 6.03% and 0.05% respectively. It can be observed that despite the lower charging costs, the highest costs for EV owners, results from **SC4**, which indicates that with the defined electricity tariff and the price of lithium batteries, participating in the V2G market is not in the interest of EV owners. The costs related to charging EVs and their battery wear in **SC2**- **SC5** are demonstrated in Table 2 for the load profiles of cold and warm seasons.

Table 2: Costs related to charging EVs and their battery wear in **SC2**-5 in cold and warm seasons

		SC2	**SC3**	**SC4**	**SC5**
Warm Season	Battery cost ($)	1043.4	1043.4	1321.54	1043.4
	Electricity cost ($)	439.4	380.11	315.43	380.58
	Total cost ($)	1482.8	1423.51	1638.97	1423.98
Cold Season	Battery cost ($)	1036.4	1036.4	1141.3	1036.4
	Electricity cost ($)	559.99	371.25	356.75	371.89
	Total cost ($)	1596.39	1407.65	1498.05	1408.29

4.3.3. Examining the benefits of the SO in different scenarios

Regarding the operating costs of transformers, it can be stated that in **SC5**, the load profile is more smooth and the network demand peak is lower compared to the other scenarios. Therefore, in this scenario, for the warm season, the operating costs of transformers are decreased by 0.9%, 0.86% and 1.74%, compared to **SC2**, **SC3** and **SC4**, respectively. In the cold season, this value is decreased by 2.97%, 2.1% and 32%, respectively.

The cost of losses in **SC4**, through optimizing the active power exchange is reduced by 2.35% in the warm season and by 4.62% in the cold season compared to the uncontrolled case (**SC2**). This is because the optimization in **SC4** is done in line with the benefits of the SO. Meanwhile, in **SC5**, with simultaneous optimization of the active and reactive power exchange between EVs and the grid, the cost of losses is reduced by 16.72%, 16.36% and 14.72% in the warm season and by 24.93%, 21.87% and 21.29% in the cold season respectively, compared to **SC2**, **SC3** and **SC4**.

Regarding the total costs of the SO, it can be observed that **SC5** yields the lowest costs, which compared to **SC2**, **SC3** and **SC4** is decreased by 15.42%, 15.08% and 13.6% respectively in the warm season. In the cold season this value is decreased by 22.28%, 19.42% and 18.71% respectively. The operating costs of transformers and loss costs for the SO in **SC2**- **SC5** are demonstrated in Table 3 for cold and warm seasons.

Table 3: Operating costs of transformers and cost of daily losses for SO in **SC2**-5 in cold and warm seasons

		SC2	**SC3**	**SC4**	**SC5**
Warm Season	Loss cost ($)	259.54	258.42	253.44	216.14
	Transformer cost ($)	23.34	23.33	23.54	23.13
	Total cost ($)	282.88	281.75	276.98	239.27
Cold Season	Loss cost ($)	188.87	181.47	180.14	141.79
	Transformer cost ($)	25.91	25.68	25.22	25.14
	Total cost ($)	214.78	207.15	205.36	166.93

4.3.4. Sensitivity analysis of the performed optimization to the number of participating EVs

In this section, sensitivity analysis to the number of EVs for the load profile of the cold season is discussed. In 4 different cases, different numbers of EVs are considered and **SC2** and **SC5** are compared in terms of battery, electricity, loss and transformer costs. The results are demonstrated in Table 4 and all costs are specific to the time of EVs' presence in the framework. Based on the results of this table, the costs in **SC2** (uncontrolled scenario) are higher than those of **SC5**. In both scenarios, due to the lack of active power injection from the EVs into the grid, battery degradation cost only exists when the batteries are charging and therefore, this cost is the same in both scenarios for all cases. In Cases 1, 2, 3 and 4 the cost of electricity in **SC5** is decreased by 33.37%, 34.09%, 33.59% and 33.88%, respectively, compared to **SC2**. This is because in **SC2**, Evs are charged when the price of electricity is high. In **SC5**, the loss cost for the network in cases 1, 2, 3 and 4, is decreased by 7.28%, 16.13%, 24.93% and 28.48% compared to **SC2**, due to the reactive power injection from EVs into the grid. Transformer costs are also higher in **SC2**, since in **SC5**, EVs are charged evenly and without peaks, as peaks reduce the lifespan of network transformers. The decrease in the transformer cost in **SC5** is 1.66%, 2.42%, 2.97% and 2.73% for the four cases, respectively. Moreover, the total costs in sc5 are reduced by 10.12%, 12.47%, 13.03% and 13.11% in cases 1,

2, 3 and 4, respectively.

Table 4: Sensitivity analysis for the load profile of cold season

Number of EVs	Scenarios	Battery Cost ($)	Electricity Cost ($)	Loss Cost ($)	Transformer Cost ($)	Total Costs ($)
Case1: 200 EV	**SC2**	262.29	140.87	178.81	25.35	607.32
	SC5	262.29	93.86	165.8	24.93	545.88
Case2: 400 EV	**SC2**	515.86	278.84	182.02	25.63	1002.35
	SC5	515.86	183.79	152.66	25.01	877.32
Case3: 800 EV	**SC2**	1036.4	559.99	188.87	25.91	1851.17
	SC5	1036.4	371.89	141.79	25.14	1575.22
Case4: 1000 EV	**SC2**	1302.6	691.66	192.36	26.04	2213.02
	SC5	1302.6	461.18	142.10	25.33	1931.21

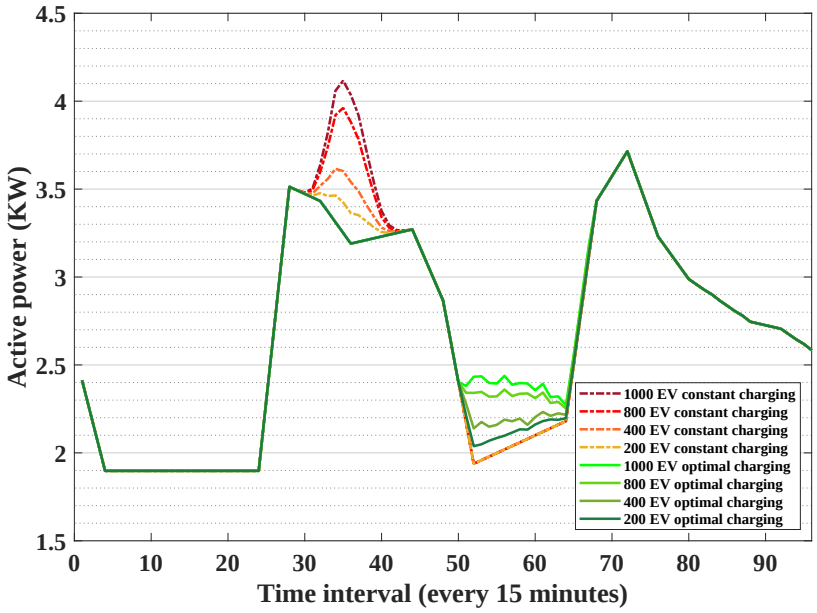


Figure 17: Sensitivity analysis for the load profile of cold season

5. Conclusion

In this paper, a framework for day-ahead optimal charging of EVs has been presented. Firstly, considering four effective factors on electrical energy consumption

of EVs, including vehicle speed, ambient temperature, wind speed and road grade, a route mapping algorithm has been implemented so as to provide better services to EV owners. Next, based on the performed route mapping and time of arrival at the selected PLs for each EV, a method has been proposed for the optimal charging of EVs, through optimizing active and reactive power exchange between EVs and the grid, using a hybrid interior-point optimization approach. Moreover, this method considered the simultaneous benefit of EV owners, PLOs and SO. The simulations have been carried out utilizing traffic information from the city of Kowloon and a standard IEEE 33 bus system. Different scenarios have been investigated for load profiles of cold and warm seasons, which show that the proposed scenario yields a better performance than the uncontrolled scenario. In the optimal charging method, the cost of charging EVs and network losses during the hours of EVs' presence in the framework, were reduced up to 33.6% and 24.93% respectively compared to the uncontrolled scenario. Furthermore, the lifespan of the power transformers has improved up to 2.97% compared to the uncontrolled scenario. The main results obtained from this paper can be summarized as follows:

1. Providing a new framework for day-ahead optimal charging of EVs
2. Presenting a new route mapping algorithm with the utilization of cloud systems to provide EVs with better services
3. Introducing an optimal method of charging EVs, considering the benefits of the EV owners and SO simultaneously.

The proposed framework was able to significantly reduce the costs of losses and charging EVs, which could play an important role in reducing the costs of the SO and EV owners in the future.

References

[1] Z. Wang, P. Jochem, W. Fichtner, A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand, Journal of Cleaner Production 254 (2020) 119886.

[2] M. Ahrabi, M. Abedi, H. Nafisi, M. A. Mirzaei, B. Mohammadi-Ivatloo, M. Marzband, Evaluating the effect of electric vehicle parking lots in transmission-constrained ac unit commitment under a hybrid igdt-stochastic approach, International Journal of Electrical Power Energy Systems 125 (2021) 106546.

[3] H. Jahangir, H. Tayarani, A. Ahmadian, M. A. Golkar, J. Miret, M. Tayarani, H. O. Gao, Charging demand of plug-in electric vehicles: Forecasting travel behavior based on a novel rough artificial neural network approach, Journal of Cleaner Production 229 (2019) 1029–1044.

[4] M. Li, H. He, L. Feng, Y. Chen, M. Yan, Hierarchical predictive energy management of hybrid electric buses based on driver information, Journal of Cleaner Production 269 (2020) 122374.

[5] H. Guo, X. Wang, L. Li, State-of-charge-constraint-based energy management strategy of plug-in hybrid electric vehicle with bus route, Energy Conversion and Management 199 (2019) 111972.

[6] P. Aliasghari, B. Mohammadi-Ivatloo, M. Alipour, M. Abapour, K. Zare, Optimal scheduling of plug-in electric vehicles and renewable micro-grid in energy and reserve markets considering demand response program, Journal of Cleaner Production 186 (2018) 293–303.

[7] P. Khayyer, J. Wollaeger, S. Onori, V. Marano, Özgüner, G. Rizzoni, Analysis of impact factors for plug-in hybrid electric vehicles energy management, in: 2012 15th International IEEE Conference on Intelligent Transportation Systems, 2012, pp. 1061–1066.

[8] W. Chiu, J. Hsieh, C. Chen, Pareto optimal demand response based on energy costs and load factor in smart grid, IEEE Transactions on Industrial Informatics 16 (3) (2020) 1811–1822.

[9] H. Nafisi, Investigation on distribution transformer loss-of-life due to plug-in

hybrid electric vehicles charging, International Journal of Ambient Energy 0 (2019) 1–19.

[10] N. T. Milas, E. C. Tatakis, Charging station selection through the analytic hierarchy process enabled by opc-ua for vehicle-to-grid communications, in: 2019 21st European Conference on Power Electronics and Applications (EPE '19 ECCE Europe), 2019, pp. P1–P10.

[11] R. Das, Y. Wang, G. Putrus, R. Kotter, M. Marzband, B. Herteleer, J. Warmerdam, Multi-objective techno-economic-environmental optimisation of electric vehicle for energy services, Applied Energy 257 (2020) 113965.

[12] M. Tavakoli, F. Shokridehaki, M. Marzband, R. Godina, E. Pouresmaeil, A two stage hierarchical control approach for the optimal energy management in commercial building microgrids based on local wind power and pevs, Sustainable Cities and Society 41 (2018) 332 – 340.

[13] J. Chen, X. Huang, S. Tian, Y. Cao, B. Huang, X. Luo, W. Yu, Electric vehicle charging schedule considering user's charging selection from economics, IET Generation, Transmission Distribution 13 (15) (2019) 3388–3396.

[14] N. Bañol Arias, S. Hashemi, P. B. Andersen, C. Træholt, R. Romero, Assessment of economic benefits for ev owners participating in the primary frequency regulation markets, International Journal of Electrical Power & Energy Systems 120 (2020) 105985.

[15] Y. Luo, T. Zhu, S. Wan, S. Zhang, K. Li, Optimal charging scheduling for large-scale ev (electric vehicle) deployment based on the interaction of the smart-grid and intelligent-transport systems, Energy 97 (2016) 359–368.

[16] B. Khaki, C. Chu, R. Gadh, Hierarchical distributed framework for EV charging scheduling using exchange problem, Applied Energy 241 (2019) 461–471.

[17] M. Mozaffari, H. Askarian Abyaneh, M. Jooshaki, M. Moeini-Aghtaie, Joint expansion planning studies of ev parking lots placement and distribution network, IEEE Transactions on Industrial Informatics 16 (10) (2020) 6455–6465.

[18] M. H. Amini, M. P. Moghaddam, O. Karabasoglu, Simultaneous allocation of electric vehicles' parking lots and distributed renewable resources in smart power distribution networks, Sustainable Cities and Society 28 (2017) 332–342.

[19] M. A. Kazemi, M. Sedighizadeh, M. J. Mirzaei, O. Homaee, Optimal siting and sizing of distribution system operator owned ev parking lots, Applied Energy 179 (2016) 1176–1184.

[20] D. S. Markovic, D. Zivkovic, I. Branovic, R. Popovic, D. Cvetkovic, Smart power grid and cloud computing, Renewable and Sustainable Energy Reviews 24 (2013) 566–577.

[21] M. Mierau, S. Fey, R. Kohrs, C. Wittwer, Communication solutions for a cloud-based charging management system for a fleet of shared-use electric vehicles, in: 2013 World Electric Vehicle Symposium and Exhibition (EVS27), 2013, pp. 1–11.

[22] V. Chang, M. Ramachandran, Towards achieving data security with the cloud computing adoption framework, IEEE Transactions on Services Computing 9 (1) (2016) 138–151.

[23] M. M. Hussain, M. S. Alam, M. S. Beg, Plug-in electric vehicle to cloud data analytics for charging management, International Journal of Engineering & Technology 9 (2017) 361–370.

[24] M. Baum, J. Dibbelt, A. Gemsa, D. Wagner, Towards route planning algorithms for electric vehicles with realistic constraints, Computer Science - Research and Development 31 (2017) 361–370.

[25] Z. He, L. Zhao, The comparison of four uav path planning algorithms based on geometry search algorithm, in: 2017 9th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Vol. 2, 2017, pp. 33–36.

[26] P. E. Hart, N. J. Nilsson, B. Raphael, A formal basis for the heuristic determination of minimum cost paths, IEEE Transactions on Systems Science and Cybernetics 4 (2) (1968) 100–107.

[27] W. Zeng, R. Church, Finding shortest paths on real road networks: The case for a, International Journal of Geographical Information Science 23 (2009) 531–543.

[28] Yin Chao, Wang Hongxia, Developed dijkstra shortest path search algorithm and simulation, in: 2010 International Conference On Computer Design and Applications, Vol. 1, 2010, pp. V1–116–V1–119.

[29] H. I. Kang, B. Lee, K. Kim, Path planning algorithm using the particle swarm optimization and the improved dijkstra algorithm, in: 2008 IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application, Vol. 2, 2008, pp. 1002–1004.

[30] Z. Fuhao, L. Jiping, An algorithm of shortest path based on dijkstra for huge data, in: 2009 Sixth International Conference on Fuzzy Systems and Knowledge Discovery, Vol. 4, 2009, pp. 244–247.

[31] T. Yuksel, J. J. Michalek, Effects of regional temperature on electric vehicle efficiency, range, and emissions in the united states, Environmental Science & Technology 49 (6) (2015) 3974–3980.

[32] S. M. Agah, H. A. Abyaneh, Distribution transformer loss-of-life reduction by increasing penetration of distributed generation, IEEE Transactions on Power Delivery 26 (2) (2011) 1128–1136.

[33] H. Farzin, M. Fotuhi-Firuzabad, M. Moeini-Aghtaie, A practical scheme to involve degradation cost of lithium-ion batteries in vehicle-to-grid applications, IEEE Transactions on Sustainable Energy 7 (4) (2016) 1730–1738.

[34] S. Han, S. Han, H. Aki, A practical battery wear model for electric vehicle charging applications, Applied Energy 113 (2014) 1100 – 1108.

[35] S. B. Peterson, J. Apt, J. Whitacre, Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization, Journal of Power Sources 195 (8) (2010) 2385–2392.

[36] S. S. K. Madahi, H. Nafisi, H. A. Abyaneh, M. Marzband, Co-optimization of energy losses and transformer operating costs based on smart charging algorithm for plug-in electric vehicle parking lots, IEEE Transactions on Transportation Electrification, Advance online publication, (2020). doi:10.1109/TTE.2020.3020690.

[37] M. Gertz, J. Nocedal, A. Sartenar, A starting point strategy for nonlinear interior methods, Applied Mathematics Letters 17 (8) (2004) 945–952.

[38] L. Jourdan, M. Basseur, E.-G. Talbi, Hybridizing exact methods and metaheuristics: A taxonomy, European Journal of Operational Research 199 (3) (2009) 620–629.

[39] B. Mansoornejad, N. Mostoufi, F. Jalali-Farahani, A hybrid ga–sqp optimization technique for determination of kinetic parameters of hydrogenation reactions, Computers Chemical Engineering 32 (7) (2008) 1447–1455.

[40] https://data.gov.hk., `https://data.gov.hk/en-data/dataset/hk-td-sm_1-traffic-speed-map`, accessed: 2018-07-01.

[41] Kowloon, hong kong 14 day weather forecast., `https://www.timeanddate.com/weather/china/kowloon/ext.`, accessed: 2018-07-01.

[42] M. R. Sarker, D. J. Olsen, M. A. Ortega-Vazquez, Co-optimization of distribution transformer aging and energy arbitrage using electric vehicles, IEEE Transactions on Smart Grid (2017).

[43] A. Gailani, M. Al-Greer, M. Short, T. Crosbie, Degradation cost analysis of li-ion batteries in the capacity market with different degradation models, Electronics 9 (1) (2020).

[44] K. Liu, X. Hu, Z. Yang, Y. Xie, S. Feng, Lithium-ion battery charging management considering economic costs of electrical energy loss and battery degradation, Energy Conversion and Management 195 (2019) 167 – 179.

[45] Q. Tan, M. Wang, Y. Deng, H. Yang, R. Rao, X. Zhang, The Cultivation of Electric Vehicles Market in China: Dilemma and Solution, Sustainability 6 (2014).

[46] Y.-J. Ma, M.-Y. Zhai, Day-ahead prediction of microgrid electricity demand using a hybrid artificial intelligence model, Processes 7 (6) (2019).

[47] M. Muratori, Impact of uncoordinated plug-in electric vehicle charging on residential power demand, Nat. Energy 3 (2018) 193–201.