Proposed Ranked Strategy for Technical and Economical Enhancement of EVs Charging With High Penetration Level

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\section*{ABSTRACT}
Car exhaust is one of the most common causes of ozone hole aggravation, electrical vehicles (EVs) represent a promising solution to avoid this problem. Despite the benefits of EVs, their random charging behavior causes some difficulties regarding the electric network performance, such as increased energy losses and voltage deviations. This paper aims to achieve the proper scheduling of the EVs charging process, avoid its negative impacts on the network, and satisfy the EVs users’ requirements. The EVs charging process is formulated as an optimization problem and solved using particle swarm optimization. The optimization problem formulation considers the EV arrival and departure times and the state of charge required by the user. Different strategies such as separated, accumulated, and ranked strategies with continuous or interrupted fixed charging have been applied to solve the uncoordinated EVs charging problem. These strategies are extensively tested on the modified IEEE 31 bus system (499-node network), using the combination of both Open DSS and MATLAB m-files. The simulation results confirm the effectiveness of the proposed accumulated ranked strategy with interrupted fixed charging in improving the overall power system performance. The achieved improvements include minimizing: the peak power consumed, the peak power losses, and the voltage drop. Moreover, the cost of the EVs charging in most of the feeders has been decreased to a satisfying value. A comparison between the proposed strategy and some previously reported strategies has been performed to ensure the technical and economic enhancement of the proposed strategy.

\section*{INDEX TERMS}
Charging cost, coordinated charging, electric vehicles (EVs), fixed charging, and multi-objective optimization.

\section*{I. INTRODUCTION}
Clean energy becomes necessary due to the significant worldwide trend to decrease fossil fuels consumption. The goal is to lessen pollution rates and carbon emissions to reduce global warming. Electric vehicles (EVs) have started to spread widely to decrease pollution problems as they are unobtrusive, non-pollutant, and odorless [1]. On the other hand, EVs cause technical and economic challenges due to their random charging behavior, such as increasing energy losses and voltage deviation. These problems occur because the infrastructure of the electric network is not designed to sustain a large number of EVs.

EVs have been the focus of many recent research studies in the last decade [2]–[22]. These studies discussed different essential topics such as EV charging/discharging [2]–[17], battery efficiency improvement [18]–[20], and charging cost reduction [21]–[23] as presented in Fig. 1.

Previous research studied the EVs in both the charging [2]–[10] and the discharging modes [9]–[15]. A coordinated charging schedule of EVs considering real-time data is proposed in [2] to satisfy customers. Besides, the achieved
optimization decreased the system load fluctuations to meet the grid requirements. Another EV charging technique is presented in [3]. It considers both the penetration of wind energy (as a renewable energy source (RES)) and the load fluctuations. Both [2] and [3] neglected the financial issues of EV charging. The study introduced in [4] investigated the effect of its proposed smart charging model on the transmission and distribution systems. A centralized control EVs charging algorithm is implemented in [5] to reduce the network technical problems such as high losses and voltage drop. Despite the importance of the studies [4], [5], they did not consider the end of charging time and the charging cost of each EV. Another technique is also applied in [6] to charge EVs and solve the high losses and high voltage deviation problems when capacitor switching and transformer tap changer are applied to improve the voltage drop. It offered a ranking for EV charging depending on charging slots without paying attention to departure time. On the other hand, [7] has presented coordinated charging techniques for charging EVs depending on the cost and the load level on the network. The applied charging strategies in both [6] and [7] may not be suitable for any model, as the departure time is taken at a very late time, which is not considered the actual real-time (each EV can charge in a long period as it parks from 9 to 14 hours). A route mapping for EVs is applied in [8] to the IEEE 33-bus system to estimate the state of charge (SOC) and the arrival time. In that study, 800 EVs are distributed on 7 parking lots using a hybrid interior-point optimization.

Some other researchers studied EVs scheduling in both charging and discharging modes. In [9], the study tends to make a charging/discharging schedule of EVs in a wide geographical area. This type of schedule is known as green scheduling of on-move EVs. It is done by using mobile edge computing (MEC) with the integration of RES to facilitate the charging/discharging of EVs, and the greedy-based algorithm is applied to choose the best charging station (CS) for EVs services. The most appropriate CS for each EV is chosen in [10] by using a decentralized technique taking into account the improvement of social welfare. In general, the discharging topic has been studied in different studies such as [11]–[17]. These studies classify the discharging into vehicle-to-vehicle (V2V), vehicle-to-grid (V2G), and vehicle-to-home (V2H) connections. V2G is considered a small distributed generation unit in EV discharging scheduling schemes in parking groupings. A management scheme of independent EV parking has been offered in [11] for exploiting the batteries to support numerous V2G facilities. Minimizing the electricity price and maximizing the profit for collectors in parking batches are discussed in [13] and [14]. A sophisticated strategy for optimal coordination of EVs and RESs is applied in [13] by executing effective demand response programs for residential loads. The approach encourages residential loads to discharge EVs at peak load periods with higher tariff prices to solve the energy deficit of RESs. The study in [15] has focused on the coordinated parking problem (CPP) and how the user could find the appropriate parking to facilitate the V2G services using mobile edge computing assisted green scheduling.

Reportedly, the allocations of EV parking lots on the grid are assessed in terms of voltage interruption, overall system consumption reduction, and peak system load. In the case of the V2H, the discharge/charge management as home energy management depends on human activity and the electricity tariff. Various studies have focused on home energy management systems (HEMS) incorporated with EVs, such as [16], [17] in the presence of photovoltaic (PV) energy as RES. The export of PV output remains on the grid at peak times to diminish the residential cost, and the home’s residential loads are energized from EV discharging. The investigators mainly concentrate on the house’s optimization, where the influence on the grid has not been well-judged as the synchronization between PV output and the grid is not considered.

Batteries manufacturers are continuously enhancing the efficiency of batteries [18]–[20]. An optimal charging model for EVs is proposed in [18] to reduce the losses in the lithium-ion batteries by changing their internal resistance as a function of their charge rate and state of charge. The applied strategy is achieved by selecting the best number of charging intervals to compromise the reduction of losses and the computational weight. The results indicate that the applied charging strategy decreases the battery charging losses (40.1%) for 34-Ah lithium/nickel/manganese/cobalt oxide battery compared to the conventional invariable current charging approach. Sodium/nickel chloride battery, known as ZEBRA, has been employed in [19] since it is cheaper than lithium-ion and owns equivalent specific energy. However, its weak specific power forces the researchers to incorporate ultra-capacitors to achieve high performance. The effect of charging or discharging power on the battery energy capacity is also studied in [20], it is concluded that the operational
charging approach was effective in decreasing both the reduced battery capacity and economic load on EV operators.

The challenge of reducing the charging costs of EVs is discussed in [8]. An approach for minimizing the charging costs of conventional and green EVs at PV-powered stations is presented in [21]. Minimizing the operational costs of the charging locations in EVs scheduling has been inspected in [22] in case of incorporating the energy storage system into the charging places. Intelligent control is used in [23] for EV charging to reduce the peak load and therefore the charging fees will be decreased. This occurred as the dynamic pricing scheme is used to motivate the customer to be subject to the applied charging schedule of EV.

This paper focuses on charging EVs at home while covering most of the mentioned concerns of the previous studies with the same research topic. So, the main objectives of the paper are to:

1) Deal with a large model for EVs load of a 63% penetration level with actual and reasonable data of EVs.
2) Minimize high consumed peak power, high power losses, and high voltage drop.
3) Decrease the charging cost of EVs from the owner’s point of view.
4) Evaluate four charging strategies and select the most proper one:
   - Separated strategy with continuous fixed charging (S-CFC) while each feeder is optimized separately, and then the summation of feeders’ results is done to get the final results.
   - Accumulated strategy with continuous fixed charging (A-CFC) while each feeder is optimized depending on the results of the prior optimized feeders.
   - Accumulated ranked strategy with continuous fixed charging (AR-CFC) similar to A-CFC, but the feeders here are ranked according to the separated approach from the highest to lowest of the peak power consumed to be optimized by this ranked strategy.
   - Accumulated ranked strategy with interrupted fixed charging (AR-IFC) which is considered the optimal proposed charging strategy.

The test results of the implemented strategies confirm the superiority of the recommended scheduling approach of the proposed ranked strategy with interrupted fixed charging (AR-IFC) in terms of decreasing the charging cost of EVs for the consumers and at the same time improving network performance.

The main contribution of this paper is summarized through the following points:

- Dividing the distribution network with high EVs penetration into a subgroup of feeders to get more accurate optimized results, where the number of variables decreased from 264 to 12 variables in each feeder. So, the proposed technique can be applied to any large network to get the best-optimized results.
- The gradient in the proposed strategies until reaching the proposed optimal strategy (AR-IFC) is extensively validated. The proposed strategy depends on ranking the feeders, and the diversity between continuous and interrupted fixed charging.
- Applying a multi-objective optimization (the reduction of power loss, the power consumed, and the charging cost), with adequate normalization between the three terms of the equation.

The paper’s organization will be as follows: the tested network and EVs data are discussed in Section II. In Section III, the base case of the system, without the penetration of EVs, is introduced versus the uncoordinated charging case. Then, the problem formulation is fully presented in Section IV. Afterward, the results of the applied coordinated charging strategies are demonstrated in detail in Section V. The last proposed optimal AR-IFC approach is evaluated in terms of voltage regulation, and cost analysis and also compared with some reported strategies in Section VI. Finally, conclusions are drawn in Section VII.

II. TESTED NETWORK AND EVs DATA

The four examined strategies are tested on the modified IEEE 31 bus 23 kV distribution network includes 6 lateral branches [24]. This network, shown in Fig. 2, consists of 22 low voltage residential feeders. Each feeder connects to 19 nodes (a, b, c, . . ., s) populated with residential loads through a 23/0.415 kV, 100 kVA distribution transformer [25]. For 63% penetration level, there are 12 EVs in each feeder in the system that can be connected/disconnected according to owners’ needs. It is worth mentioning that the modified IEEE 31 bus system is chosen here for two reasons:
- It is challenging because it is a large network close to real networks.
- It is used in several research studies [25]–[27], and thus the performance results of the applied strategies are compared to the published results of other schemes.

According to Fig. 2, the number of studied EVs is 264 for 63% penetration. Each EV has an arrival time (TArrival), departure time (TDeparture), an initial state of charge (SOC_{in.}), and a requested state of the battery charge (SOC_{req}). All these values are taken from [26]. Each EV also specifies the type of its charger and battery as follows:
- Charger rates: 3.3 kW, 6.6 kW, and 7.2 kW.
- Battery capacity: 6 kWh, 19.2 kWh, and 16 kWh.
- Slow charging type (charging at home).

All the simulations are performed using OpenDss and MATLAB. In addition, the cost of each feeder will be also studied according to the short-term market energy price (MEP) in Fig. 3 [26].
III. BASE CASE VERSUS UNCOORDINATED CHARGING

To discuss the difference between the base case and uncoordinated charging, the charging matrix of EVs must be created using the data of each EV by following some steps and equations.

Firstly, the charging energy of each EV ($CE_i$) is obtained as in (1), where ($E_i$) is the vehicle’s battery capacity, ($\eta_{Ch}$) is the charger efficiency, and ($i$) is the identity of an EV.

$$CE_i = \left[ SOC_{req_i} - SOC_{in_i} \right] \times \left[ \frac{E_i}{\eta_{Ch}} \right] \quad (1)$$

Then, the charging duration of the EV ($CD_i$) is calculated using (2), where $P_{Nominal_i}$ is the charger’s nominal power.

$$CD_i = \frac{CE_i}{P_{Nominal_i}} \quad (2)$$

Equation (3) depicts the conversion of time from hours to slots, where each hour is divided into 12 slots; each slot is 5 minutes long, giving a total of 288 slots for the 24 hours.

$$Number\ of\ Charging\ Slots_i (NCS_i) = CD_i \times \frac{60}{5} \quad (3)$$
Finally, the charging matrix has been created as in (4).

\[
\begin{array}{c|c|c|c|c|c|c|c|c|c|c}
\text{No. of Slots (288)} & \text{No. of EVs (204)} & \text{Power consumptions of EVs} & \text{Power losses} & \text{Voltage magnitude} \\
0 & 0 & P_{\text{base}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & P_{\text{uncoordinated}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & P_{\text{coordinated}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{array}
\]

\( (4) \)

\[\]

A. INVESTIGATING POWER CONSUMED, POWER LOSSES, AND VOLTAGE MAGNITUDE

Figure 4 shows the results for applying the base case in the absence of EVs during a day (black line). As shown, the maximum value of power loss was 26.35 kW, and the maximum value of consumed power was 0.8383 MW, while the minimum voltage value was 0.923 pu (higher than the minimum allowable value) at the bus 15J. This is logical because it is the furthest bus from the main feeder as illustrated in Fig. 2, and therefore the voltage bias is the highest possible. According to Fig. 3, the total cost of the residential load consumption on the whole system is estimated at 4560.3 $. It is also possible to observe that the peak demand period of the load is attained from 4 pm (16 h) till 8 pm (20 h).

Many studies discussed that the random charging of EVs causes several problems in the network as increasing power losses and clear voltage bias exceeding the \(\pm 10\%\) permissible limits [27]. It happens as the network infrastructure is not designed to withstand a lot of EVs. As shown in Fig. 4, when EVs are added to the tested network with a 63% penetration rate with uncoordinated charging [26], a noticeable increase in the peak losses (blue line) of approximately 110% (equivalent to 55.39 kW) occurs. An increase in the peak power consumption of 45.5% also happens besides the significant reduction in voltage value comprising only 0.81 pu (less than the minimum allowable value). In addition, the total charging cost reached 5604.6 $ with an increase of 23% from the base case cost.

Therefore, studying different EV charging strategies and comparing them to each other to reach the best charging method with the lowest negative impacts on the network will be the main objective of this paper.

B. INVESTIGATING LINES’ CURRENT CARRYING CAPACITIES

Six current transformers (CT 1, CT 2, CT 3, CT 4, CT 5, and CT 6) have been located at the six lateral branches in the system and another current transformer is located at the main feeder (Main CT) as shown Fig. 2 to check the current limits. Table 1 illustrates cable size and the current carrying capacity of the lines (according to the actual size of the cables of the tested network in [24]), the maximum daily currents for the base case without EVs, and also for the uncoordinated charging case.

As clearly observed, although the currents increased at the uncoordinated charging case to about 2.5 times the base case without EVs, they are still lower than the current-carrying capacity of the lines as the network is lightly loaded.

IV. PROBLEM FORMULATION

Charging EVs is controlled by choosing the appropriate time to start charging each EV to mitigate the problems that occurred in the electric network due to EVs’ penetration and their random charging. The optimization problem is solved using the particle swarm optimization (PSO) implemented by MATLAB m-file, where the PSO parameters are summarized as follows:

- Number of particles: 20
- Number of iterations: 90
- Number of runs: 20
- Velocities: \(C_1 = C_2 = 2\)
- Weights: maximum = 0.9, minimum = 0.4

The power system model was built in OpenDSS, and a link is accomplished between the two packages. The best solution for charging scheduling of EVs is achieved by 20 trials to ensure the reliability of the achieved results.

A. FORMULATION OF OBJECTIVE FUNCTION

Some researchers reported achieving optimal results using if-then techniques as introduced in [28]. Others solved the problem using different meta-heuristic techniques with different objective functions. For example, in [29], the multi-objective formulation is discussed. It includes three objectives, minimizing the operating cost, minimizing the pollutant treatment cost, and minimizing the carbon emission cost of a microgrid. These objective functions are converted easily to a single objective function by only inserting a weighting factor into each term; this approach is simple because all the terms have the same unit. On the contrary, another multi-objective function is presented in [30], but of different units and values far from each other. These objective functions were minimizing the operating cost, minimizing voltage over the limit of the mobile energy storage system, and maximizing the PV output. This problem can be skipped using the normalization method [31]; by multiplying each
In this study, the proposed multi-objective formulation will address both technical and economic factors. It consists of the summation of three functions: $f_1$, $f_2$, and $f_3$ as shown in (5).

$$\text{Objective Fun. (F)} = f_1 + f_2 + f_3$$

The objective of the first one is minimizing the peak consumed power to meet the maximum demand of the system, while the objective of the second is minimizing the peak power losses, and the target of the third one is minimizing the average cost at each feeder. This paper comprehensively considers peak-shaving and valley-filling. Since the three functions of (5) have different units and also different ranges, so according to [31], each part of them will be multiplied by a normalization factor ($n_1, n_2, n_3$) as follows:

1) Minimizing the maximum power consumed:

$$f_1 = w_1 \times n_1 \times \sum_{j=1}^{n} \sum_{i=1}^{m} p_{\text{Con, Peak}}^{i,j}$$

2) Minimizing the maximum power loss:

$$f_2 = w_2 \times n_2 \times \sum_{j=1}^{n} \sum_{i=1}^{m} p_{\text{Loss, Peak}}^{i,j}$$

3) Minimizing the average charging cost:

$$f_3 = w_3 \times n_3 \times \sum_{j=1}^{n} \sum_{i=1}^{m} \text{Cost}$$

Where $p_{\text{Con, Peak}}$ is the peak power consumed, $p_{\text{Loss, Peak}}$ is the peak power loss, Cost is the average charging cost, $n$ is the net number of feeders and $m$ is the net number of EVs.

$n_1, n_2, n_3$ are the normalization factors, which are the inverse of maximum power consumed, the inverse of maximum power loss, and the inverse of average charging cost of EVs at uncoordinated charging respectively.

$w_1, w_2, and w_3$ are weighting factors for considering the network operator priority for the different objective functions, and they are considered here by the values 0.4, 0.3, and 0.3 respectively.

B. CONSTRAINTS

The objective function has the following three main constraints:

1) VOLTAGE CONSTRAINT

The voltage drop is considered a constraint (for all $n$ feeders) as not to exceed the permissible limits ($\pm 10\%$).

$$\Delta V_j = V_j - V_{\text{rated}} \leq \Delta V_{\text{max}}, \text{ for } j = 1, \ldots, n$$

In (9), $\Delta V_j$ is the per unit (pu) voltage deviation of the feeder $j$ which is limited to $\Delta V_{\text{max}} = 0.1$ pu in this paper.

It is worth mentioning that the voltage deviation for the tested system cannot be improved rather than a definite limit [27]. As will be discussed later in the voltage regulation section, some capacitor units should be installed at specific system locations to solve this issue.

2) STATE OF CHARGE LIMITS

The SOC limits of EVs batteries are considered one of the constraints for applying the proposed charging strategy as illustrated in (10).

$$SOC_{\text{ini, i}} \leq SOC_{\text{1st, i}} \leq SOC_{\text{req, i}}, \text{ for } i = 1, \ldots, m$$

where $SOC_{\text{ini, i}}$ and $SOC_{\text{req, i}}$ are the initial and required state of charges of EV (i) respectively. $SOC_{\text{1st, i}}$ is the state of charge at each time slot $\Delta t$. 
3) STARTING TIME OF CHARGING CONSTRAINT

This constraint is defined as continuous fixed charging (CFC) and interrupted fixed charging (IFC). As discussed earlier, CFC is applied in the charging strategies: S-CFC, A-CFC, and AR-CFC, while IFC is applied in the last proposed scheme, which is AR-IFC.

- For Continuous Fixed Charging (CFC):
  For this type, each EV charges continuously with its nominal charger power. Consequently, calculations are done through (11) and (12) to get the upper ($UB_i$) and lower ($LB_i$) bounds of the starting time of charge ($T_{st}$).

  Fig. 5 explains the idea of constructing (11) and (12); for EV ($i$) that arrived home at $T_{Arrival}$ and will leave home at $T_{Departure}$ as per customer requirements, consequently, the charging period must exist at this period.

  \[ LB_i \leq T_{st_i} \leq UB_i, \quad \text{for } i = 1, \ldots, m \]  
  \[ LB_i = T_{Arrival_i}, \quad UB_i = T_{Departure_i} - CD_i, \quad \text{for } i = 1, \ldots, m \]  

  where $m$ is the total number of EVs.

- For Interrupted Fixed Charging (IFC):
  IFC means that the charging period of each EV could be not continuous and divided into partitions, but each EV still charges with its charger nominal power. Table 2 explains an illustrative example of the interrupted fixed charging concept.

  Firstly, the EV No. $i$ is assumed to charge continuously with its nominal power without interruption in step 1. Then,

| Steps of Optimization | Time-line of EV No. $i$ |
|-----------------------|------------------------|
| **Step 1:** |
| - The first step is a detective step to determine the defective EVs (EVs charge in the peak period), blocked periods, and the No. of optimization steps required for each defective EV. |
| - The periods of peak power higher than the substation capacity limit (SCL), which is 0.84 MW [25], are considered blocked periods (BP) as charging is prohibited in them. |
| - To clarify the idea, the defective EV No. $i$ will be taken as an example, which is assumed to have a charging period (CHP) of continuous 16 slots (1.33 hours) from slot 28 to slot 43 (Green Period). |
| - 4 slots which are slot 30 and the slots from 36 to 38 are detected as blocked periods (Black Periods). |
| - According to the following equation, it can be concluded that the optimization will pass through five steps. No. of Optimization Steps = the step for detection + No. of BP Slots in the CHP |
| - By the end of this step, the charging period will be updated to be divided into only three partitions, from slot 28 to 29, from slot 31 to 35, and finally from slot 39 to 43. |

| **Step 2:** |
| - A new upper bound ($UB$) is re-estimated through the following equation, where $X$ is assumed here to be 1 slot, while other values may be assumed according to the optimizer: |
| \[ UB = T_{Departure} - X \]  |
| - Consequently, in this step, the optimization tool will relocate one slot from the blocked periods of the charging of EV No. $i$ to another permissible period of charging. It will be transferred to slot 9. |
| - By the end of this step, the partitions for charging are increased by another period from slot 9 to 10, which means that CHP increases one slot, and thus the BP decreases from one slot to be 3 slots (3 more steps are still required). |

| **Step 3:** |
| - In this step and without deviating the LB & UB, another shifting occurs where another charging slot for the EV No. $i$ is shifted from the blocked period to slot No. 46 (the last slot between updated UB and $T_{Departure}$). |
| - Consequently, the BP decreased to be 2 slots (2 more steps are still required), and the CHP increased by another slot. |
TABLE 2. (Continued.) Example on the charging period of EV no. \(i\) by interrupted fixed charging.

| Step 4: | Step 5: |
|---|---|
| - By repeating the previous step, another charging slot is transferred from the blocked period to a permissible charging slot to be slot 10.  
- By the end of this step, the BP will be only one slot, and the ChP increases one more slot. | - By the last step, the charging period of EV No. \(i\) is divided into several partitions (5 partitions) to get away from the blocked periods. The four charging slots of EV No. \(i\) which were in the blocked periods, in Step 1, are correctly shifted from slots No. 30, 36, 37, and 38 in blocked periods to slots No. 9, 46, 10, and 11 respectively. |

Finally, by studying the current-carrying capacity limit of the system lines as discussed in Section III.b, it was concluded that it is a lightly loaded network even in an uncoordinated charging case. Thus, the current constraint is not taken into consideration. Otherwise, if the system is highly loaded near the thermal capacity of the lines, a current constraint must be taken into consideration for all the lines as follows:

\[
I_k \leq I_{\text{max}}^k, \quad \text{for } k = 1, \ldots, \text{no. line sections} \tag{13}
\]

where \(I_k\) is the current flowing in the line section \(k\), while \(I_{\text{max}}^k\) denotes the maximum current carrying capacity of line section \(k\).

V. COORDINATED CHARGING STRATEGIES

The optimum solution of coordinated charging is reached after several steps. These steps are presented through different applied strategies. As discussed at the end of Section I, four different strategies are applied. The results of each strategy have been compared with both the base case and the uncoordinated charging case to evaluate its effectiveness.

A. SEPARATED STRATEGY (STANDALONE) WITH CONTINUOUS FIXED CHARGING (S-CFC)

Due to the high number of variables in the tested network, since the number of EVs is 264, it was troublesome to get the steps tabulated in Table 2 are consequently carried out for applying IFC to achieve better results.

Finally, by studying the current-carrying capacity limit of the system lines as discussed in Section III.b, it was concluded that it is a lightly loaded network even in an uncoordinated charging case. Thus, the current constraint is not taken into consideration. Otherwise, if the system is highly loaded near the thermal capacity of the lines, a current constraint must be taken into consideration for all the lines as follows:

\[
I_k \leq I_{\text{max}}^k, \quad \text{for } k = 1, \ldots, \text{no. line sections} \tag{13}
\]

where \(I_k\) is the current flowing in the line section \(k\), while \(I_{\text{max}}^k\) denotes the maximum current carrying capacity of line section \(k\).
optimal results when optimizing the whole system. As a result, the network was divided into a group of feeders to apply the separated strategy with continuous fixed charging per feeder as demonstrated in Fig. 6.

Accordingly, 22 feeders are optimized individually, where each feeder has 12 EVs, and thus the number of variables is reduced from 264 to 12 only, making it easier and faster to find a solution for the optimization problem.

Fig. 7 summarizes the results of the whole system when optimizing each feeder independently. As a result of optimizing Feeder No.1 only, the peak power losses of the overall system reached 1.209 MW. Then, as a result of optimizing Feeder No.2 only, the peak power losses of the whole system reached 1.19 MW and so on (as shown in Fig 7-a).

Fig. 7-a shows that the least peak power consumed by the overall system (1.1794 MW) is achieved when optimizing Feeder No.18 only (other feeders are not optimized, but their uncoordinated data are taken into consideration), which is a reasonable value compared to the maximum power consumed in the uncoordinated charging (1.22 MW). Also, we can notice that the highest peak power consumed is 1.2197 MW while the highest average cost is 5598 $ when optimizing Feeder No.15 (other feeders are not optimized, but their uncoordinated data is considered) as shown in Fig. 7-d. It occurs since most of the charging periods of the EVs at that feeder happen at the peak period of the curve.

The voltage magnitude is around 0.8132 pu and 0.8137 pu, while the highest magnitude was achieved when optimizing
Feeder No. 14 which reached 0.8202 pu, although all of the values did not reach the permissible limit as clearly shown in Fig. 7-c.

Concerning the results presented in Fig. 7, some notes should be addressed; why the Feeder No. 15 is the worst in the peak power consumed with an average cost, but not in the maximum power losses? Why Feeder No. 18 has the highest decrease in the peak power consumed but not the same in the average cost or the peak power loss? It takes place due to the slight difference between the power consumed curve and the tariff curve, as shown in Fig. 3, and the difference in the weighting factor of each term in the objective function.

By accumulating the achieved results for optimizing all feeders to reach the final solution, as revealed in Fig. 8, the result was not satisfying. On the contrary, optimizing each feeder individually gives better results. Rationally, because the optimum solution is found for each feeder alone without considering others, the charging period for each EV is chosen to be at the bottom of the curve. Consequently, if all the charging periods for all EVs are summed up in all the feeders, a new peak is created in the curve at another time that differs from that of the uncoordinated charging. The maximum power consumed by all feeders has reached 1.2593 MW at an approximate time ranging from 2.5 pm (14.5 h) to 4.5 pm (16.5 h), as revealed in Fig. 8-a. It is also worth mentioning that such a peak is also higher than the SCL of the network (0.84 MW). The same issue occurs in the power losses in Fig. 8-b as the peak losses reached 75 kW.

B. ACCUMULATED STRATEGY (INTEGRATED) WITH CONTINUOUS FIXED CHARGING (A-CFC)

According to the previous results of the separated strategy with continuous fixed charging (S-CFC), it can be deduced that it was not effective as the result of each feeder does not depend on the other feeders. It caused another peak instead of peak shaving. So, the accumulated strategy is applied here to overcome this vital problem. This strategy ensures that the optimized result of each feeder should be considered in the optimization of the next feeder and so on until reaching the final feeder as illustrated in Fig. 9.

Fig. 10 shows the results of applying the accumulated strategy with continuous fixed charging (A-CFC). The result of each feeder represents the accumulative results from the first feeder until the last feeder. So, the result of the final feeder (Feeder No. 22) is the final result of all feeders (the whole system). It can be observed from the scale of the Y-axes in Fig. 11 that the results of cost, power consumed, power losses, and voltage drop are improved significantly.

Fig. 11-a shows that the maximum power consumed decreased by 29% from its value at uncoordinated charging, but this value is still higher than the SCL of the network. Also, Figs. 11-b and 11-c illustrate that the maximum power loss decreased to reach 29 kW and the voltage magnitude increased compared with the uncoordinated charging case to reach 0.85 pu but still does not reach the permissible limits. The voltage drop problem will be solved in the voltage regulation part.

C. ACCUMULATED RANKED STRATEGY WITH CONTINUOUS FIXED CHARGING (AR-CFC)

The previously discussed results of the accumulated strategy are similar to or a little bit better than the results of [26], which applied a coordinated aggregated PSO-based scheme. A more effective strategy is still required to improve these results.

The proposed ranked strategy depends on the previous strategies (S-CFC, A-CFC strategies), where an accumulated optimization is repeated but with the achieved ranking of the feeders according to the results obtained from the S-CFC strategy. As shown in Fig. 12, optimized feeders will proceed by ranking them from the best result to the worst result based on the separated strategy.

Table 3 shows the ranking of all feeders to be taken into account when applying the proposed ranked strategy. For example, the rank of the Feeder No. 18 is 1 (the first one to be optimized here) while the rank of Feeder No. 7 is 2 (the second one to be optimized while considering the result of the first one), and so on.

The achieved results of this strategy are much better than that of the accumulated one, as shown in Fig. 13. Figs. 14-a and 14-b illustrate the results of applying the proposed ranked strategy. The consumed and losses powers are evaluated against both base case and uncoordinated charging. These results are a little bit better than the integrated strategy results. Also, the maximum power consumed has...
the power consumed is still higher than the maximum load capacity of the network. The results of the ranked strategy can be further improved through interrupted fixed charging to avoid exceeding the network capacity (0.84 MW), as will be shown in the next section.

D. ACCUMULATED RANKED STRATEGY WITH INTERRUPTED FIXED CHARGING (AR-IFC)

To achieve the best economical and technical results, the AR-IFC is implemented. In which, the EVs that charge at peak periods are detected to be re-optimized using Interrupted Fixed Charging (IFC) as illustrated in detail in Table 2 (Section IV.b).

The results of applying the AR-IFC strategy, in Fig. 15-a, confirm the effectiveness of such a method where the peak power consumed has decreased to 0.8383 MW which is less than the SCL (0.84 MW). Also, Fig. 15-b indicates that the peak losses reached 27.85 kW, which is 50% of the losses decreased by 3% from the outcomes of [26] to reach 0.8563 MW, and the power loss reached 29 kW. As noticed,

| Feeder Rank (i) | Feeder No. (j) | Feeder Rank (i) | Feeder No. (j) |
|-----------------|----------------|-----------------|----------------|
| 1               | 18             | 12              | 3              |
| 2               | 7              | 13              | 20             |
| 3               | 2              | 14              | 8              |
| 4               | 11             | 15              | 16             |
| 5               | 12             | 16              | 10             |
| 6               | 19             | 17              | 1              |
| 7               | 21             | 18              | 6              |
| 8               | 17             | 19              | 9              |
| 9               | 22             | 20              | 14             |
| 10              | 4              | 21              | 5              |
| 11              | 13             | 22              | 15             |
from the uncoordinated charging method. Furthermore, the voltage magnitude of the weakest bus has increased to 0.8552 pu, which is significantly higher than the AR-CFC strategy shown in Fig. 15-c. Therefore, this proposed strategy is considered the optimal charging strategy for EVs.

E. FLOWCHART
The flowchart demonstrated in Fig. 16 summarizes the steps for applying the four charging strategies described in Section I (S-CFC, A-CFC, AR-CFC, and AR-IFC).
- It starts with reading the system data and illustrating the base case (without EVs). It comprises running the load flow analysis through OpenDSS to get the consumed apparent power ($S_{Cons}$), apparent power losses ($S_{Loss}$) of the whole system and voltage magnitude ($V_{magnitude}$) at each feeder to be sent to MATLAB.
- Consequently, from these values, the consumed active power ($P_{Cons}$), active power losses ($P_{Loss}$), voltage drop (V.D), and the average cost of each feeder are calculated.
- After implementing the stage of the base case, EVs are connected to the system and different strategies are applied for charging them as will be explained in Section V. Each strategy is described briefly with its optimization sequence in the flowchart.
- In the end, the achieved results are extensively compared to determine the most proper strategy for charging EVs. Also, the voltage drop results are studied to decide whether the system needs another compensation method (i.e. capacitors and transformer tap changers) to improve that drop or not.

VI. OVERALL EVALUATION OF THE PROPOSED AR-IFC STRATEGY
After discussing each of the implemented strategies in detail, it is concluded that the strategy which achieved the best system performance is the AR-IFC. The proposed AR-IFC significantly improved the network performance as the peak power consumed and the peak power loss decreased by 31.2% and 50% respectively, compared to the uncoordinated charging. Consequently, an overall evaluation is done for the AR-IFC strategy regarding voltage regulation, current carrying capacities, and economic aspects. The effect of considering the uncertainty in EVs behavior has also been investigated. Finally, a comparison will be conducted between the results achieved by AR-IFC and the results of some other published schemes.

A. VOLTAGE REGULATION
According to [27], voltage regulation is achieved for the tested system by inserting five capacitors on buses 4, 14, 16, 20, and 27 with 50, 100, 100, 50, 50 kVAR respectively. In addition, if the voltage drop is still more than 10%, the substation transformer taps are used to reach the required value of voltage magnitude. The transformer has five tap positions of $[-2 - 1012]$ which vary the voltage magnitude by ±5%. Therefore, when implementing the proposed ranked accumulated strategy with interrupted fixed charging (AR IFC) in the presence of the compensating methods, the least voltage magnitude is recorded throughout the whole day, as illustrated in Fig. 17. The voltage drop was successfully reduced within the permissible range of 10% to reach 0.9 pu.

B. CURRENT CAPACITY LIMITS
As a part of evaluating the proposed strategy, the maximum readings of the main and six CTs, located in the system as shown in Fig. 2, were illustrated in Fig. 18.

It is clear from the graph that the current values in the coordinated proposed strategy are still less than the maximum current carrying capacity limits described in Table 1.

C. ECONOMIC EVALUATION
A detailed study was conducted on EV charging costs when applying the proposed strategy AR-IFC. This study was carried out to estimate the reduced cost for each customer, as shown in Fig. 19. It can be noticed that EV No. 150 has the highest cost reduction percentage of 78.3%. Table 4 summarizes the results where the charging cost of the majority of vehicles (about 40.5%) is reduced by 40-60%. On the other hand, 41 EVs out of 264 have a charging cost increase (that only represents 15.5%).

In conclusion, the total charging cost reduction percentage of the whole system is 40.1% which is a satisfying percentage value. This cost reduction percentage could be increased by granting the priority of optimization to the charging cost of EVs by increasing its weighting factor $w_3$. 
FIGURE 13. Results of applying AR-CFC strategy for all feeders.

FIGURE 14. Simulation Results of applying AR-CFC strategy for 63% EVs penetration compared with the base case and the uncoordinated charging case (a) Power consumed, (b) Power losses, (c) Voltage magnitude.

FIGURE 15. Simulation Results of applying AR-IFC strategy for 63% EVs penetration compared with the base case and the uncoordinated charging case (a) Power consumed, (b) Power losses, (c) Voltage magnitude.
D. EXAMINING THE UNCERTAINTY IN EVs BEHAVIOR

A new scenario has been implemented to examine the effect of considering the uncertainty in EVs behavior as follows:

- The actual status of some EVs on two selected feeders had been changed randomly concerning the proposed optimized schedule.
- The ratio of EVs that have changed their actual status on each of the two selected feeders was 83.3% (10 EVs out of 12 EVs in each feeder) as shown in Table 6.
- That percentage equals 7.6% of the whole tested power system (20 EVs out of 264 EVs) which is considered a
It discusses the probability of the lack of commitment of some EVs owners’ by the charging time that is predetermined according to their entered data into aggregators. So, some of the EVs started charging late or early from the predetermined scheduled time (changing the starting time of charging: for example EVs No. 73, 83, 84, 97, 100, and 120).

2. Failure of the charging component:
The charger failure of one EV or more leads to charging the EV at another period (for example EVs No. 77, 81, 99, and 105).

3. Absence of EV:
The absence of an EV is due to many reasons such as the charger failure or it is already charged before (EV No. 104).

4. Other reasons such as changing the state of charge (the initial or the required state either by the increase or decrease, EVs No. 74, 76, 80, 103, and 106), or changing the charger type (EVs No. 75, 78, 98, 102, and 106). For these reasons, the charging duration will be changed.

The obtained results are summarized in Fig. 20 (the daily consumed power and the daily power loss) for the following two cases:

| TABLE 4. Cost reduction for AR-IFC strategy. |
|-----------------|-----------------|-----------------|
| Cost Reduction (%) | No. of EVs | EVs % From Total No. |
| > 60 & ≤ 80 | 59 | 22.35% |
| > 40 & ≤ 60 | 107 | 40.53% |
| > 20 & ≤ 40 | 31 | 11.74% |
| > 0 & ≤ 20 | 26 | 9.85% |
| Increase in Cost | 41 | 15.53% |
- Applying the proposed optimized strategy (AR-IFC) with 100% certainty of EVs behavior, and
- Applying the proposed optimized strategy (AR-IFC) considering the uncertainty in EVs behavior (the actual status of some EVs on Two selected feeders had been changed randomly with respect to the proposed optimized schedule).

It could be noticed that the difference between the two cases was inconsiderable. It ensures the effectiveness of applying the proposed optimized strategy (AR-IFC) even with the uncertainty in EVs behavior.

E. A COMPARATIVE STUDY OF AR-IFC RESULTS AGAINST SOME REPORTED STRATEGIES

Table 5 illustrates a comparison between the proposed strategy AR-IFC and other strategies in some research studies on the same tested system. These four studies in [26], [27], [32], and [33] have been chosen for a fair comparison as they are recent research that investigated the optimal charging of EVs without implementing any renewable resources. The studies applied different charging techniques, [27], [32], and [33] use fixed charging techniques, while [26] use variable charging techniques. Besides, the variety in their implemented objective functions, where [26] and [33] applied a single objective, but [27] and [32] implemented a double objective function. The results proved the effectiveness of the proposed strategy where both the peak consumed power and the peak power losses are the least among other researches, although they have implemented more advanced optimization techniques. In addition, [26], [27], and [33] did not discuss the charging cost reduction issue in their strategies which are considered a vital concern. In [32], the charging cost reduction has reached 22.4%, which is less than the proposed strategy by 17.7%.

VII. CONCLUSION

This research has implemented an optimal model for charging the EVs using the PSO algorithm. This model offers the appropriate time to schedule the charging of each EV without infringement on the user requirements, as each user enters its arrival and departure time, and the required state of charge according to his necessities. Four strategies are implemented: separated strategy with continuous fixed charging (S-CFC), accumulated strategy with continuous fixed charging (A-CFC), accumulated ranked strategy with continuous fixed charging (AR-CFC), and finally accumulated ranked strategy with interrupted fixed charging (AR-IFC). The advantages and disadvantages of each scheme are highlighted through tests applied to the modified IEEE 31 bus system with a 63% penetration level. All tests have been simulated using the combination of both OpenDSS and MATLAB m-file.

The results of these strategies proved the effectiveness of the A-CFC and AR-CFC strategies for minimizing both the peak power consumed on the network (peak demand).

| Strategy | Charging Technique | Objective Function | Constraints | Optimization Tool | Peak Power Consumed | Peak Power Loss | Weakest Bus Voltage | Cost Reduction | Novelty/Contribution |
|----------|-------------------|--------------------|-------------|-------------------|--------------------|----------------|--------------------|----------------|---------------------|
| [26]     | Variable          | Single Objective (Customer Satisfaction) | Voltage and Consumption | Coordinated Aggregated FSO | 0.84 MW | 31 kW | 0.9 pu | Not mentioned | - It takes into account the grid constraints without deviating from customer satisfaction. |
| [27]     | Fixed             | Double Objective (Losses & Voltage drop) | Consumption | Binary PSO | 0.84 MW | 29 kW | 0.925 pu | Not mentioned | - It proposes a fixed charge rate PEV charging coordination while considering the optimal dispatch of switching capacitors and TC to minimize the power losses and voltage deviation. |
| [32]     | Fixed (as inferred by authors) | Double Objective (Losses & Cost) | Voltage and Consumption | Binary Evolutionary Programming & analytic hierarchy process | 0.84 MW | 28 kW | 0.9 pu | 22.4% | - It minimizes power loss and the charging cost of PEVs. |
| [33]     | Fixed             | Single Objective (Losses) | Voltage and Consumption | Binary Evolutionary Programming | 0.84 MW | 33 kW | 0.9 pu | Not mentioned | - It offers the flexibility to the EV customers to charge their vehicle into their desired periods while maximizing network performance. |
| Proposed AR-IFC | Interrupted Fixed | Multi-Objective (Consumption, Losses & Cost) | Voltage, State of Charge, and time | PSO | 0.8383 MW | 27.85 kW | 0.9 pu | 40.1% | - It divides the distribution network with high EVs penetration into a subgroup of feeders to get more accurate optimization results, where the number of variables decreased from 264 to 12 variables. Thus, it can be applied to any large system to get the best-optimized results. |

- The gradient in the proposed strategies until reaching the proposed optimal strategy (AR-IFC) is extensively validated. The proposed strategy depends on ranking the feeders, and the diversity between continuous and interrupted fixed charging.
- It applies a multi-objective optimization (the reduction of power loss, the power consumed, and the charging cost), with adequate normalization for the three terms of the equation.
and the peak power loss. The results also show that the AR-IFC scheme gives the highest reductions, as the peak power consumed reached 0.8383 MW less than the SCL. Furthermore, the voltage drop has been kept within a predetermined 10% range via using capacitors and a substation transformer tap changer. Most importantly, the maximum power consumed is 149 MW.

It is worth highlighting that implementing the AR-IFC proposed strategy may be done in future work by more advanced metaheuristic techniques rather than the PSO algorithm to achieve better optimization results.

REFERENCES

[1] S. Habib, M. M. Khan, F. Abbas, L. Sang, M. U. Shahid, and H. Tang, “A comprehensive study of implemented international standards, technical challenges, impacts and prospects for electric vehicles,” IEEE Access, vol. 6, pp. 13866–13890, 2018, doi: 10.1109/ACCESS.2018.2812303.

[2] Y. Tao, M. Huang, Y. Chen, and L. Yang, “Ordering charging strategy of battery electric vehicle driven by real-world driving data,” Energy, vol. 193, Feb. 2020, Art. no. 116806, doi: 10.1016/j.energy.2019.116806.

[3] A. Bilh, K. Naik, and R. El-Shattat, “A novel online charging algorithm for electric vehicles under stochastic network load,” IEEE Trans. Smart Grid, vol. 9, no. 3, pp. 1787–1799, May 2018, doi: 10.1109/TSG.2016.2598189.

[4] C. Cruzier, T. Mostyn, and M. McCluloch, “The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems,” Appl. Energy, vol. 268, Jun. 2020, Art. no. 114973, doi: 10.1016/j.apenergy.2020.114973.

[5] J. Quiros-Tortós, L. F. Ochoa, S. W. Alnaser, and T. Butler, “Control of EV charging points for thermal and voltage management of LV networks,” IEEE Trans. Power Syst., vol. 31, no. 4, pp. 3028–3039, Jul. 2016, doi: 10.1109/TPWRS.2015.248602.

[6] H. Suyono, M. T. Rahman, H. Mokhls, M. Othman, H. A. Illias, and H. Mohamad, “Optimal scheduling of plug-in electric vehicle charging including time-of-use tariff to minimize cost and system stress,” Energies, vol. 12, no. 8, pp. 17–21, 2019, doi: 10.3390/en12081500.

[7] V. Torres-Sanz, J. A. Sanguesa, F. F. Martinez, P. Garrido, and J. M. Márquez-Barragán, “Enabling the charging process of electric vehicles at residential homes,” IEEE Access, vol. 6, pp. 22875–22888, 2018, doi: 10.1109/ACCESS.2018.2829158.

[8] A. Shahkamranii, H. Askarain-Abanehe, H. Nafisi, and M. Marzbani, “A framework for day-ahead optimal charging scheduling of electric vehicles providing route mapping: Kowloon case study,” J. Cleaner Prod., vol. 307, Jul. 2021, Art. no. 127297, doi: 10.1016/j.jclepro.2021.127297.

[9] A. Mehrabi, M. Stekkinen, A. Vla-Iaasik, and G. Aggarwal, “Mobile edge computing assisted green scheduling of on-movie electric vehicles,” IEEE Syst. J., vol. 16, no. 1, pp. 1661–1672, Mar. 2022, doi: 10.1109/SYSTJ.2021.3084746.

[10] A. Mehrabí, H. S. V. S. K. Nuna, A. Daldani, S. Moon, and K. Kim, “Decentralized greedy-based algorithm for smart energy management in plug-in electric vehicle energy distribution systems,” IEEE Access, vol. 8, pp. 75666–75681, 2020, doi: 10.1109/ACCESS.2020.2987970.

[11] A. Y. S. Lam, J. J. Q. Yu, Y. Hou, and V. O. K. Li, “Coordinated autonomous vehicle parking for vehicle-to-grid services,” in Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm), Sydney, NSW, Australia, Nov. 2016, pp. 6–9, doi: 10.1109/SmartGridComm.2016.778775.

[12] M. Saffie-Khah, E. Heydarian-Forushani, and G. J. Osorio, “Optimal behavior of electric vehicle parking lots as demand response aggregation agents,” IEEE Trans. Smart Grid, vol. 7, no. 6, pp. 2654–2665, Nov. 2016, doi: 10.1109/TSG.2015.2496796.

[13] M. Zare Osokouei, B. Mohammadi-Ivatloo, M. Abapour, A. Anvari-Moghadam, and H. Mehrjerdi, “Practical implementation of residential load management system by considering vehicle-for-power transfer,” Sustain. Cities Soc., vol. 60, Sep. 2020, Art. no. 102144, doi: 10.1016/j.scs.2020.102144.

[14] M. Jawad, M. B. Qureshi, S. M. Ali, N. Shabbir, M. U. S. Khan, and R. Nawaz, “A cost-effective electric vehicle intelligent charge scheduling method for commercial smart parking lots using a simplified convex relaxation technique,” Sensors, vol. 20, no. 17, pp. 1–19, Aug. 2020, doi: 10.3390/s201747842.

[15] A. Y. S. Lam, J. J. Q. Yu, Y. Hou, and V. O. K. Li, “Coordinated autonomous vehicle parking for vehicle-to-grid services: Formulation and distributed algorithm,” IEEE Trans. Smart Grid, vol. 9, no. 5, pp. 4356–4366, Sep. 2018, doi: 10.1109/TSG.2017.2655299.

[16] A. Ito, A. Kawashima, T. Suzuki, S. Inagaki, T. Yamaguchi, and Z. Zhou, “Model predictive charging control of in-vehicle batteries for home energy management based on vehicle state prediction,” IEEE Trans. Control Syst. Technol., vol. 26, no. 1, pp. 51–64, Jan. 2018, doi: 10.1109/TCST.2017.2664727.

[17] S. Golshannavaz, “Cooperation of electric vehicle and energy storage in reactive power compensation: An optimal home energy management system considering PV presence,” Sustain. Cities Soc., vol. 39, pp. 317–325, May 2018, doi: 10.1016/j.scs.2018.02.018.

[18] J.-H. Ahn and B. K. Lee, “High-efficiency adaptive-current charging strategy for electric vehicles considering variation of internal resistance of lithium-ion battery,” IEEE Trans. Power Electron., vol. 34, no. 4, pp. 3041–3052, Apr. 2019, doi: 10.1109/TPEL.2018.2848850.

[19] E. Nandakumar and S. Shobana, “Analysis and modeling a cost-effective and range assurance hybrid energy storage system for electric vehicle,” Int. J. Sci. Res. Rev., vol. 8, no. 2, pp. 3101–3115, Jun. 2019.

[20] S. U. Ieon, J. W. Park, B. K. Kang, and H.-I. Lee, “Study on battery charging strategy of electric vehicles considering battery capacity,” IEEE Access, vol. 9, pp. 89757–89767, 2021, doi: 10.1109/ACCESS.2021.3090763.

[21] W. Tushar, C. Yuen, S. Huang, D. B. Smith, and H. V. Poor, “Cost minimization of charging stations with photovoltaics: An approach with EV classification,” IEEE Trans. Intell. Transp. Syst., vol. 17, no. 1, pp. 156–169, Jan. 2016, doi: 10.1109/TITS.2015.2462824.

[22] K. Chaudhuri, A. Ukel, K. N. Kumar, U. Manandhar, and S. K. Kollimalla, “Hybrid optimization for economic deployment of ESS in PV-integrated EV charging stations,” IEEE Trans. Ind. Informat., vol. 14, no. 1, pp. 106–116, Jan. 2018, doi: 10.1109/TII.2017.2713481.

[23] S. Limmer and T. Rodemann, “Peak load reduction through dynamic pricing for electric vehicle charging,” Int. J. Electr. Power Energy Syst., vol. 113, pp. 117–128, Dec. 2019, doi: 10.1016/j.ijepes.2019.05.031.
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