Scheduling Electric Vehicle Charging for Grid Load Balancing

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***Abstract*—In recent years, electric vehicles (EVs) have been widely adopted because of their environmental benefits. However, the increasing volume of EVs poses capacity issues for grid operators as simultaneously charging many EVs may result in grid instabilities. Scheduling EV charging for grid load balancing has a potential to prevent load peaks caused by simultaneous EV charging and contribute to balance of supply and demand. This paper proposes a user-preference-based scheduling approach to minimize costs for the user while balancing grid loads. The EV owners benefit by charging when the electricity cost is lower, but still within the user-defined preferred charging periods. On the other hand, the approach reduces the pressure on the grid by balancing the grid load. Two methods, the greedy algorithm and nonlinear programming, are considered along with users' charging preferences and durations. For scheduling small numbers of charging activities, the nonlinear programming model achieves better load balancing than the greedy algorithm; however, for scheduling medium to large numbers of charging activities, the greedy algorithm has a clear advantage in terms of time complexity.**

***Index Terms*—Electric Vehicle, EV Charging, Optimization, Load Balancing.**

I. Introduction

Electric vehicles (EVs) have become increasingly important to society because of their environmentally friendly nature and because electricity is often more economical than gasoline. In 2011, more than sixteen thousand electric and plug-in hybrid vehicles were sold in the United States. By December 2020, that number had tripled to nearly 1.7 million [1]. By mid-2021, total sales of plug-in electric vehicles had exceeded 2 million. In 2020, there were over 200 million cars registered in the U.S. The U.S. grid has 1117.5 TW of utility power capacity [2]. If all these electric cars were charged at 7kw, they would require 2,000 TW or almost twice the grid's capacity.

As the number of EVs grows, the total grid electricity demand will substantially increase, and there is a possibility of grid overload becoming a common problem with critical consequences. Charging many EVs at the same time will result in high energy demand peaks, and if the peak is overly high, this may result in grid stability issues such as outages and even blackouts. Therefore, scheduling EV charging is the focal issue of this paper.

Load balancing aims to achieve a balance between demand and supply. With respect to EV charging, there are three main approaches to load balancing. The first approach is dynamic pricing, which impacts the number of EVs charging at certain hours by regulating the price so that EVs charging at peak times will be more costly. Therefore, fewer owners would be interested in charging their EVs during these peak hours. The second approach is vehicle-to-grid (V2G); in this model, EVs can sell energy back to the grid in peak hours to remedy the grid overload problem. The third approach is scheduling EV charging; the grid load would be balanced by arranging charge periods ahead of time.

Scheduling EV is a promising approach for grid balancing and it appears to be a more stable method than the other two [19]. Many studies [9] [11] [13] have provided ways to perform scheduling and good results have been achieved. However, these studies mainly take a single perspective, either that of the EV users or the grid owner/operator, and aim to minimize charging costs or reduce load peaks. The principal scheduling approaches are the deep learning model, multi-linear programming, and the greedy algorithm.

Nevertheless, a different scheduling approach is needed to benefit both perspectives, i.e., minimizing cost for the end electricity consumer and grid load balancing for the grid operator. This approach would give EV users a lower charging price within the user's preferred charging period and put less pressure on the grid by balancing the grid load. Consequently, this paper presents an approach that uses a greedy algorithm and nonlinear programming (NLP) for scheduling EV charging so that each user's preferences and lowest charging cost are satisfied with the grid load more evenly distributed. In this way, the proposed approach satisfies both perspectives: charging cost minimization for the end consumer and grid load balancing for the grid operator.

This paper is organized as follows: Section II describes related work for balancing grid load. Section III presents the simulator representing the real-life EV charging demands and the methods that balance the grid load. Section IV presents the evaluation with corresponding results. Finally, Section V concludes the paper.

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II. Related Work

The three standard techniques for grid load balancing with EVs are dynamic pricing, vehicle-to-grid (V2G), and scheduling [16]—this section first reviews related work in dynamic pricing and V2G. Then, the scheduling approaches are discussed.

A. Dynamic Pricing and V2G

Literature has studied various aspects of grid load balancing for EV charging: the focus here is on dynamic pricing and V2G.

The studies discussed here addressed the problems of defining methodologies for dynamic pricing. Grid load prediction-based dynamic pricing models have been proposed [3] [4]. They use the energy consumption, time duration, start time, and end time of each EV to predict energy consumption patterns throughout the day and change the price accordingly based on an equation. The drawback is that EV owners have individual price preferences, and their behaviors are unpredictable and unknown to the grid owner. Two-stage models have also been explored [5]: the first stage minimizes the total cost of satisfying demands while the second stage considers dynamic prices for the current hour and the day ahead as estimates for future hours.

The following group of studies investigated the challenges of V2G technologies. Several studies [6]–[8] designed frameworks that effectively integrate aggregated EV batteries into the grid as distributed energy resources so that EVs can act as controllable loads and energy suppliers. Then, these controllable system can respond to demand during peak hours, thereby mitigating peak conditions in the grid. Also, in V2G, an EV can act like an electricity buyer or a seller and buy/sell electricity from/to the grid operator. A software-defined networking paradigm is included in the V2G model [8] to enable faster communication between vehicles and the grid.

Discussed studies [3]–[8] dealt with dynamic pricing and V2G models, whereas this work uses scheduling to do load balancing.

B. Scheduling EV Charging

There have been major advances in the area of EV scheduling in two directions: the first one include scheduling EV charging and the second one is planning EV routing and charging.

For the first direction, scheduling EV charging, several studies proposed different methodologies [9] [11] [13]. These works mainly discuss optimization problems concerning EV charging and scheduling. All EVs get their exact charging slots early in the day by allocating EV charging tasks with a schedule, and this advanced planning makes possible a well-balanced distribution of charging loads.

Similarities can be found in the work of Mallette et al. [9]; for those who intend to purchase an electric vehicle, the two incentive strategies should be considered to make them accept the scheduling method. EV sellers would either consider an upfront rebate for any individual who purchases an EV or a reduction in electricity prices per kWh when charging the EV. In their methodology [9], the authors provided incentives directly to the users and made them accept manually scheduled plans.

Several deep learning models [11] [13] have been proposed to address the optimization problem. EV charging/discharging scheduling problems have been formulated as a Constrained Markov Decision Process (CMDP) so that a scheduling strategy that minimizes charging cost and guarantees that the EVs can be fully charged can be achieved. To solve the CMDP problem, these researchers proposed a model-free approach based on safe deep reinforcement learning (SDRL). The SDRL approach generates the optimal charging/discharging scheduling through a deep neural network. Unlike existing reinforcement learning, it does not require manual design and adjustment of the penalty coefficients.

Wang et al. [12] proposed a new charging methodology based on joint admission and pricing (JoAP), scheduling, and admission control. This work minimizes the average waiting time for all EVs by scheduling, leading to lower costs and higher profit. They specifically used a tandem queueing network (TQN) model and characterized the best JoAP algorithm based on TQN.

For the second major direction, scheduling EVs for routing and charging, several studies proposed optimization methods. Organizing EVs to drive to the most convenient charging station results in less extra driving and lower costs.

Rigas et al. [14] proposed a solution for an EV hiring problem; their work dealt with EVs hired to drive from pickup points to drop-off points, using a mobility-on-demand framework to optimize the number of customers served or the total EV utilization. They used multi-linear programming (MLP) and greedy heuristic algorithms to solve the optimization problem. MLP was used for medium to significant demand problems, and the greedy heuristic algorithm was used for substantial-size problems.

Similarities can also be found in the public transportation scheduling. Sassi et al. [15] worked on scheduling and charging problems for electric vehicle transportation. In their paper, they proved that this problem is NP-hard. A mixed-integer linear program was formulated to solve small and medium instances. For large instances, sequential heuristics and a global heuristics methodology were proposed.

In two discussed papers [14] [15], the routing and charging problems were defined as NP-hard, and the authors split the cases according to their size. MLP was used for minor cases, and the greedy heuristics algorithm was used for more significant-sized cases. These papers laid the groundwork to support the greedy algorithm and multi-linear programming models to solve EV scheduling problems.

For the two directions mentioned above, many studies [9] [11] [13] have dealt with load balancing from the aspect of scheduling, mainly from the producer's point of view, by scheduling charging to make the final cost of electricity lower. They primarily used deep learning models [11] [13], linear programming models [14] [15], or greedy algorithms [14] [15] to solve the problem. These methods play an essential role in reducing the cost of charging for the user.

In contrast, we mainly used the greedy algorithm and the NLP model in this study to achieve grid load balancing. A specific penalty factor sensitive to the peak values was introduced to measure how much the grid load is balanced and to achieve the good grid balancing result by achieving the lowest value of the penalty factor. Moreover, we also consider the user's preference by considering the period when the user commonly charges; by arranging the charging activity within the preferred charging period.

III. Methodology

This section describes the methods to obtain an EV charging schedule. Two main methods are examined; the first one is based on the greedy algorithm, whereas the second takes advantage of nonlinear programming.

The greedy algorithm makes the best choice available at the current moment [17]. It does not consider if the decision in the current moment will lead to the overall global optimum and it does not revisit previous decisions; it only considers the local best choice. In some cases, even if the greedy algorithm does not obtain the overall optimal solution, the final result is a good approximation of the optimal solution. The time complexity of the greedy algorithm is low, requiring only $O(N)$ for the problem of EV charging schedules where the N refers to the number of charging activities.

Nonlinear programming is another effective method for determining the best solution [18]. When the optimization objective or constraint cannot be described as a linear function without giving up some fundamental nonlinear characteristics of the real-world system, nonlinear programming arises as a possible solution. The nonlinear programming algorithm typically creates a series of estimates for the decision variable vector x to determine the best value of x. In the case of EV charging optimization, the algorithm assigns a predetermined period to each user based on the user's available charging period and the required charging duration; as a result, this model produces a better grid load balancing outcome.

Both described approaches, greedy algorithm and nonlinear programming, were used with the dataset that simulates real-life charging demand behavior. A flowchart of the methodology is shown in Fig. 1, while the details are described in the following subsections.

A. Simulation

The state of the EV grid load per hour was determined based on the dataset collected from real-life charging activities. Two datasets were generated based on the collected charging activities. Dataset 1 simulated a scenario in which an electric vehicle always has the same charging duration of 1 hour while Dataset 2 simulated a scenario with varied charging durations within 24 hour period. Two terms are introduced here: the $timeslot$ refers to the duration of each charging activity and the $preferred-time-range$ refers to the user's preferred charging period. Dataset 1 contains three features: EV/ID as an EV identifier, period $start$ and end. In addition to those three features, Dataset 2 contains an additional feature, charging $duration$.

1) Dataset 1 Generation: Dataset 1 assumptions are:

- Customers can only have one $preferred-time-range$ throughout the day.
- Each $timeslot$ can only be one hour.

Data collected in real life were the bases for the dataset generation. Usually, the load distribution varies throughout the day; the average hourly grid load distribution for collected EV charging activities occurring on Mondays is shown in Fig. 2.

After the distribution is obtained for each day in the week, it is transformed into the percentage of EVs charged each hour throughout the day, as shown in Table I. Based on these percentages, a large number of charging activities were simulated.

To better simulate the user's preferred charging period, the 24-hour period was divided into seven ranges, which were taken as the seven options for the $preferred-time-range$ as shown in Table II. The seven ranges represent each user's work, school, and home schedules. As the actual schedule is not known, the preference is created based on historical data. For example 15% of users charged between 0 AM and 6 AM, therefore, as seen from Table II, in simulations, 15% of users are assumed to prefer this time period.

Based on the percentages of the $preferred-time-range$ in Table II, preferred charging start and end times were simulated. For instance, 15% of EVs had the $preferred-time-range$ from 0 AM to 6 AM; therefore, if 1000 charging activities are simulated, 150 charging activities will be assigned to the $preferred-time-range$ of "0-6". These simulated $preferred-time-range$ values then served as $start$ and end features for each vehicle in Dataset 1.

2) Dataset 2 Generation: Dataset 2 assumptions are:

- Customers can only select one $preferred-time-range$ throughout the day.
- The $timeslot$ identifies the duration of charging in multiples of 15 minutes, with the shortest $timeslot$ being 15 minutes and the longest $timeslot$ being 12 hours.

For the Dataset 2 generation, the EV/ID, $start$, and end features were the same as for Dataset 1 and the $duration$ feature was added. Again, the collected real-world data was used to determine the data generation. In the collected data, each row represented an independent charging activity. The

TABLE I
Percentage of EVs charged each hour

Percentage	Start	End
5.2%	0	1
4.6%	1	2
3.7%	2	3
...	...	...
8%	21	24

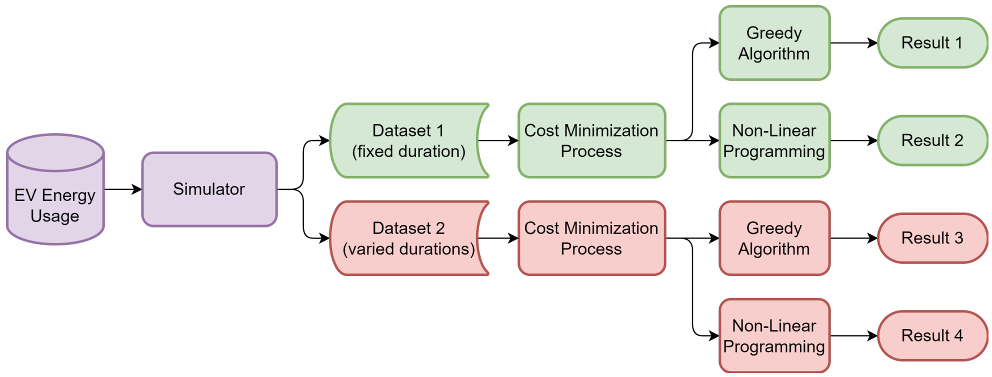

Fig. 1. Methodology flow chart

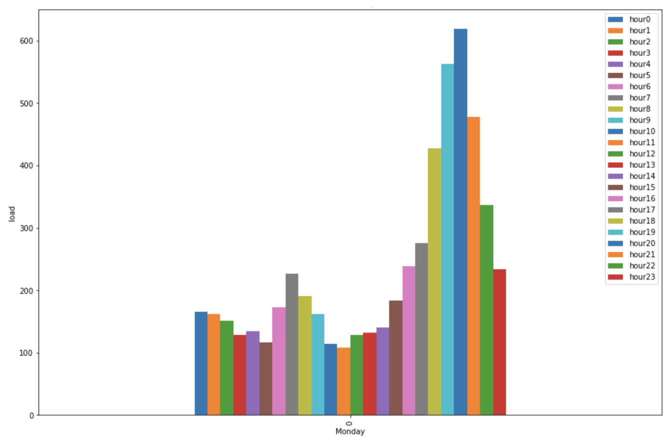

Fig. 2. Average load distribution for Monday

TABLE II
PERCENTAGE OF $preferred - time - range$

Percentage	Start	End
15%	0	6
9.5%	7	9
10%	9	12
6%	12	17
5.2%	17	19
10%	19	21
10%	21	24

consecutive charging activities of each EV were combined. For example, suppose an EV performs continuous charging in adjacent periods. First, the consecutive charging records for that vehicle were combined into one record with the *start* as the earliest charging start point, *end* as the latest charging point, and *duration* as the sum of the combined durations. This way, the distribution of charging throughout the day matching the collected data was maintained. Once the number of charging activities with their exact durations was known, the proportion of EVs charging for each possible charging duration (15 min to 24 hours, in increments of 15 min) was calculated.

EVs charging events of 15 minutes represented 25.5% of total cases, whereas EVs charging events of less than or equal to 12 hours represented 97% of total cases. Therefore, only cases with less than or equal to 12 hours of charging time were considered in the simulations. Because all times within 12 hours were included, each hour contained four cases of 15, 30, 45, and 60 minutes; therefore, there were 48 cases, indicating all the time lengths available. Finally, the percentages of events were found for the corresponding 48 duration cases.

Table III shows a segment of the obtained cumulative charging distribution. This list, in the pseudo-code referred to as CP, is then used for the generation of charging duration as described in Algorithm 1. The process first generates a random number between 0 and 1. Then, the algorithm iterates (Line 3) over the list of charging durations from Table III. When the generated random number is greater than the cumulative percentage CP for the considered timeslot (Line 4), the current timeslot is returned. The process indicated by Algorithm 1 is repeated for each of the generated charging activities. This way, the distribution of charging durations in the generated data remains the same as the distribution in the collected real-world data. Finally, the generated data in Dataset 2 contain EV/ID, $start$ and end of the preferred charging time, and $duration$ feature specifying the needed charging duration.

TABLE III
PERCENTAGE FOR CHARGING DURATION

Time Range	Cumulative Percentage (CP)
15 minutes	0.255
30 minutes	0.45
45 minutes	0.52
1 hour	0.59
1 hour 15 minutes	0.611
...	...
12 hours	1

Algorithm 1 Timeslot Generation Process

procedure GETTIMESLOT
  $m \leftarrow rand[0-1]$ //m is the random variable that ranges from 0 to 1.
  for $i \leftarrow 1, n$ **do** //Iterate through durations in Table III
    if $m \geq CP[i]$ **then**
      //If m is greater than the cumulative percentage
      //at index i, return that index.
      return i
    end if
  end for
end procedure

B. Cost Minimization Process

The scheduling algorithm must take into consideration local energy prices; for example, with the time-of-use pricing, the cost of energy changes for different times of the day, and the algorithm must select charging time slots that will result in the lowest cost for the EV owner. The greedy approach is used for each charging activity to find the time slots with the lowest cost based on the price plan, which in our experiments is the Ontario Energy Board time-of-use pricing at the time when experiments were conducted. Next, two approaches for scheduling were engaged: with fixed and with varied durations.

C. Scheduling with Fixed Duration

Scheduling with fixed duration uses Dataset 1 to generate the charging schedule. Two models are considered, the greedy algorithm and the nonlinear programming.

For the **greedy algorithm model**, the EVs are first sorted in ascending order according to the length of the $preferred-time-range$ and then assigned to the time slot with the lowest total load within the preferred charging time. In each iteration, for each EV from the sorted list, the greedy algorithm chooses the hour that has the minimum currently assigned load. As charging activities are sorted from shortest to longest $preferred-time-range$, EVs with less flexibility in charging times are assigned first, followed by those with more time flexibility.

Using a **nonlinear programming approach** to solve this problem, an objective function and appropriate constraints must be defined. The objective function establishes a penalty term for each hourly load. Then, the hourly penalty terms are summed up and the objective is to minimize this sum. Consider a binary variable G_{ij} representing whether EV i is charged at timeslot j. With respect to the grid, the objective is to have small variations of the concurrently charging EVs. Therefore, two penalty terms, square and cubic penalty, are considered for the scheduling. The objective functions can be written as follows:

$$\text{minimize}\sum_{j=0}^{n}(\sum_{i=1}^{m} G_{ij})^2 \ or\ \text{minimize}\sum_{j=0}^{n}(\sum_{i=1}^{m} G_{ij})^3 \quad (1)$$

where n is the number of time slots and m is the number of records in the generated dataset.

Finally, the $start$ times resulting in a minimum penalty sum under constraints are chosen for each charging activity. In the case of fixed charging time, the assumption is that all EV charging activities have timeslots of one hour. With Ei_{start} as the start time and Ei_{end} as the end time of the $preferred-time-range$ for the EV i, this constraint can be written as:

$$\text{for every i:} \sum_{j=Ei_{start}}^{Ei_{end}} G_{ij} = 1 \quad (2)$$

In our implementation, the optimization problem defined with objective function from Equation 1 under constraints defined with Equation 2 was solved using nonlinear programming, specifically the Python Pyomo library.

D. Scheduling with Varied Durations

Scheduling with varied durations uses Dataset 2. Again, two models are considered, the greedy algorithm and the nonlinear programming.

For the **greedy algorithm model**, the EVs are sorted by duration and length of $preferred-time-range$ in ascending order. Before scheduling, the greedy algorithm needs a list of 24 to record the current hourly grid load. The objective is to find the $timeslot$ that will cause the minimum value of the penalty term expressed as follows:

$$\text{minimize} \sum_{j=0}^{23} H_j^2 \quad (3)$$

where H_j is the current grid load for hour j. Iterating over the sorted list of vehicles, the start time that gives the minimum penalty is selected. As only local decisions are considered, this can lead to a sub-optimal solution.

When **non-linear programming method** is used to solve this problem, the objective functions remain the same as for scheduling with fixed duration as defined in Equation 1.

The $start$ time for each charging activity is selected to achieve the minimum penalty sum. For scheduling with varied durations, Ei_{start} is the $start$ time and Ei_{end} is the end time of the $preferred-time-range$, and $Ei_{duration}$ is the duration of the $timeslot$ for the EV i. For each EV, only a $timeslot$ from the $preferred-time-range$ can be selected, with the $timeslot$ being represented by $Ei_{duration}$. For example, if the $timeslot$ is 45 minutes, then $Ei_{duration}$ is three units. Because the minimum charging length is 15 minutes, three units of $Ei_{duration}$ represent 45 minutes. The constraint that ensures that the three units are selected can be written as follows:

$$\text{for every i:} \sum_{j=Ei_{start}}^{Ei_{end}} G_{ij} = Ei_{duration} \quad (4)$$

As in scheduling with fiexed duration, the optimization problem is solved with nonlinear programming, specifically the Python Pyomo library.

IV. Evaluation

This section first introduces the dataset and provides implementation specifics for cost minimization and simulation process. Next, evaluation metrics are introduced and scheduling results presented.

A. Dataset

Real-world EV charging data was used for the evaluation of the presented scheduling approaches. Data collected by the London Hydro research group tracked the EV charging behavior from 2020/01/29 to 2021/02/23. The data set contained 400,192 rows and four columns representing features: the EV ID represents the distinct EV identity, the $start$ represents the start time of the charging activity, the end represents the end time of the charging activity, and the consumption feature represents energy consumption during the charging activity. There is one entry for each 15 min interval; therefore, when the charging time is several hours, it is recorded as several consecutive rows.

B. Cost minimization Process

As the evaluation is conducted using data from London, Ontario, Canada, the time-of-use pricing from the Ontario Energy Board shown in Table IV is considered. According to this pricing scheme, three phases are considered: off-peak, mid-peak, and on-peak.

Both datasets, Dataset 1 and Dataset 2, go through the greedy algorithm that finds the lowest cost intersection between the preferred charging activity and the Ontario Energy Board prices. Specifically, each charging activity is processed by the charging algorithm following the order: off-peak, med-peak, and on-peak. After this, the charging time will be narrowed down to the minimum-cost time slots.

C. Simulation Process

As very limited data were available, the 1000 charging activities were simulated for Dataset 1 and Dataset 2 as described in Subsection III-A. Each of the simulated activities contained the charging start time, the charging end time, and in Dataset 2, the time needed for charging. For both datasets, the collected data from actual EV owners were used to simulate the charging behavior of additional EV owners as realistically as possible by following the same daily distributions and charging duration distributions.

TABLE IV
ONTARIO ENERGY BOARD TIME-OF-USE PRICES AT THE TIME EXPERIMENTS WERE CONDUCTED

	Time Range	Price
Off-peak	0am-7am 7pm-12am	8.2 cent/kWh
Mid-peak	11 am-5pm	11.3 cent/kWh
On-peak	7am-11am 5pm-7pm	17 cent/kWh

D. Evaluation Metrics

To evaluate the results produced by these methods, two evaluation metrics were used:

$$E1 = \sum_{i=0}^{n} H_i^2 \tag{5}$$

$$E2 = \sum_{i=0}^{n} H_i^3 \tag{6}$$

The interpretation of both $E1$ and $E2$ is similar: the larger their value, the more imbalanced the grid load, and the smaller their values, the more balanced the grid load. The difference between these metrics is that E1 is more accommodating to peaks, whereas E2 penalizes the peaks more.

E. Scheduling Results

As the goal is to carry out the load balancing while considering charging preferences and providing minimum cost for EV owners, this section compares the two presented approaches, greedy algorithm and nonlinear programming, in terms of grid balancing with the two described datasets.

1) Scheduling with Fixed Durations: Example results of the scheduling with fixed duration for the greedy algorithm are shown in Fig. 3. Comparing this figure with Fig. 1 showing the load distribution before scheduling, it can be observed that before the scheduling, there was a large peak around 8 pm (Fig. 1) while after scheduling, a much more balanced load is achieved (Fig. 3) as the consecutive hourly grid loads are very similar. From the perspective of the two models, the performance of both algorithms is fairly similar.

Table V compares the greedy algorithm and nonlinear programming in terms of the two described metrics, $E1$ and

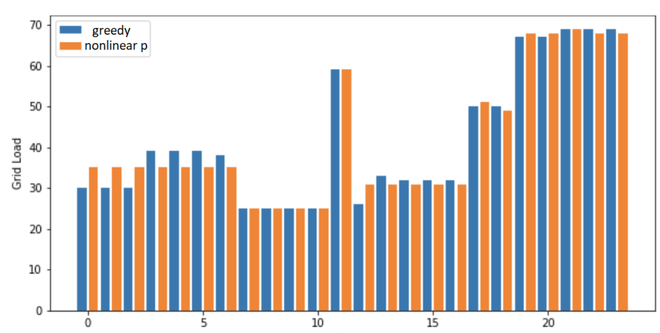

Fig. 3. An example of scheduling with fixed durations: grid load distribution

TABLE V
RESULTS FOR SCHEDULING WITH FIXED DURATIONS

	Greedy Algorithm	NLP
E1	47,786	47,660
E2	2,570,578	2,553,834

$E2$. In terms of both metrics, the nonlinear programming approach achieved better balance. Furthermore, when computing the nonlinear programming algorithm, the cubic objective function achieved slightly lower $E1$ and $E2$ than the square optimization function while also converging faster.

2) Scheduling with Varied Durations: The charging activities were scheduled to entail the lowest charging cost and to balance the grid load while considering EV owner preferences. The example results of greedy algorithm scheduling with varied durations are shown in Fig. 4. It can be observed that they follow a fairly similar pattern to that achieved with fixed durations shown in Fig. 3.

The greedy algorithm completed the computational procedure and produced good results in a relatively short time. For nonlinear programming, the time complexity of planning charging activities of different durations is very large; no polynomial time solution exists. After reducing the number of charging activities and allowing extensive time for the nonlinear programming model to perform the computations, results were still not obtained. This means that the time complexity of the problem is too expensive to apply this kind of computation. Nonlinear programming is, therefore, not practical for scheduling charging activities of varied durations.

V. Conclusion

This paper schedules EV charging with the objective of load balance for the grid operator and minimum cost for the EV owner while considering EV owner charging preferences. Two different techniques were used, the greedy algorithm and the nonlinear programming model, and two scenarios, fixed and varied durations, were considered. The scenario with varied durations is more realistic, but fixed durations are included for comparison. The greedy algorithm achieved a good result while also having quite low time complexity. On the other hand, the nonlinear programming algorithm obtained the best result, but its time complexity is high. Therefore, in the future, when dealing with scheduling problems, the model selection will depend on the total number of charging activities. The nonlinear programming model could be used for a small number of charging activities to obtain the best result. The greedy algorithm model could be used for medium to large numbers of charging activities. With the greedy algorithm model, a good result can be generated within a small amount of time.

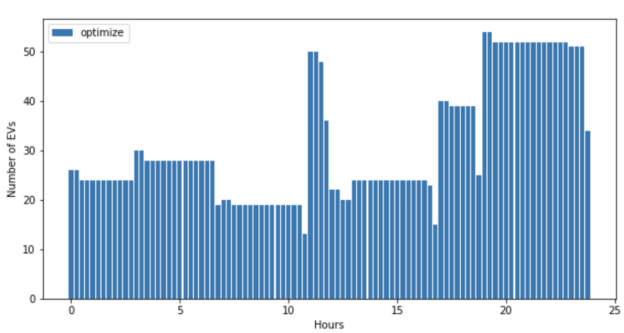

Fig. 4. Example of scheduling with varied durations for the greedy algorithm: grid load distribution

Future research will examine the behavior of the models on a large dataset and in presence of diverse loads. Moreover, incorporating incentives for for load shifting will also be considered.

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