Optimal Charging Scheduling for Electric Vehicles Based on a Moving Horizon Approach

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ABSTRACT

The rapid escalation in plug-in electric vehicles (PEVs) and their uncoordinated charging patterns pose several challenges in distribution system operation. Some of the undesirable effects include overloading of transformers, rapid voltage fluctuations, and over/under voltages. While this compromises the consumer power quality, it also puts on extra stress on the local voltage control devices. These challenges demand a well-coordinated and power network-aware charging approach for PEVs in a community. This paper formulates a real-time electric vehicle charging scheduling problem as a mixed-integer linear program (MILP). The problem is to be solved by an aggregator that provides charging service in a residential community. The proposed formulation maximizes the profit of the aggregator, enhancing the utilization of available infrastructure. With prior knowledge of load demand and hourly electricity prices, the algorithm uses a moving time horizon optimization approach, allowing an unknown number of arriving vehicles. In this realistic setting, the proposed framework ensures that power system constraints are satisfied and guarantees the desired PEV charging level within the stipulated time. Numerical tests on an IEEE 13-node feeder system demonstrate the computational and performance superiority of the proposed MILP technique.

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GENERAL AUDIENCE ABSTRACT

There is an enhanced rate of global warming due to emissions and increased usage of fossil fuels in the transportation sector. As a feasible solution, electrification of transportation has become a necessary step towards an environment-friendly future. The escalation in plug-in electric vehicles (PEVs) has increased the impact on loading and voltage fluctuations in the distribution grid due to uncoordinated charging. This puts on extra stress on the grid system and compromises the system performance. As a measure to control the vehicle charging in a residential setup, a real-time optimal charging scheduling algorithm is developed which is implemented at the neighborhood level. To increase the charging performance with the limited available resources, an aggregator is introduced. The charging profit is maximized as the PEV charging problem is solved optimally by the aggregator. This facilitates the reduction in night-time grid congestion and maximization of number of PEVs getting charged with limited dependency on communication to avoid long delays in charging control. The proposed technique guarantees the complete charging of the selected PEVs in the stipulated time while considering the power grid operational constraints. It also reduces the impact of peak load demand by flattening the base load demand curve. To demonstrate the efficiency of the proposed mixed integer linear programming optimization algorithm, numerical tests for an IEEE 13 node feeder are performed. The results are discussed to give an outlook on the balance between system and user requirements by meeting the demand of the PEV users.

Dedication

To my family

Acknowledgments

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Chapter 1

Introduction

Transportation electrification has become one of the leading-edge research areas in recent decades as its long-term benefits outweigh the present challenges. Electric vehicles are fast adopted and expected to be the future of on-road vehicle fleet as it aims to substitute the present widely used internal combustion engine (ICE) vehicles. Some of the primary advantages of EVs over ICE vehicles are the reduction in fuel consumption and greenhouse gas emissions, increase in clean energy usage, and enhancement of transportation energy efficiency. Although EV adoption is increasing, it is still limited due to requirements of the EV charging infrastructure and impact of EV load on the present distribution system. The existing grid was not primarily designed to take up a huge increase in the load caused by a sudden escalation of EV usage. This can be addressed by increasing the power generation, transmission and distribution infrastructure. Upgrading of these infrastructures is often capital intensive and has a long time-lag. However, a meticulously designed charging approach serves to minimize the infrastructure-upgrading requirements. Renewable energy resources are being widely incorporated to enhance the usage of clean sources on the generation side. On the transmission side, it can be increased by extending the physical infrastructure. Furthermore, to cater to the increased penetration of PEV on the distribution side, smart charging strategies are needed to optimize the utilization of circuit capacity.

1.1 Motivation

Besides increased load demand, important issues related to PEVs, including compromised power quality, grid reliability, and the longevity of transformers, can be mitigated by coordinated charging of PEVs. There have been studies about scheduling of the EV charging in a residential area, but the research is either oriented towards fulfilling utility's generation and circuit requirements or focused on prioritizing the customer's preference such as charging time and duration of charging. There are studies which include both aspects but in those cases circuit capacity constraints are not prioritized which may give rise to overvoltage operating conditions, making the distribution system prone to voltage and frequency fluctuations. Large scale deployment of EVs can be effectively supported by clean generation sources such as renewable energy. Much research has been conducted on the integration of renewable sources, e.g., photo-voltaics and wind turbines, and its impact on the grid. EV charging is considered on the distribution side in order to determine the need for an increased circuit capacity. The other issue concerning the use of electric vehicles as a battery source for supplying power provides a new platform of study. EVs as battery can provide energy to critical load on the grid during service restoration or peak load period.

Although EVs act as load or generation depending on the requirement, the basic concept of EV deployment lies in the large-scale usage of EV for transportation. This can be supported by accessible and convenient charging facilities. As developing the existing electrical infrastructure will not be at the same pace as that of EV penetration, various methods are implemented to improve the usage of available capacity.

The three major concerns related to PEV charging are:

(i) satisfying power system operation constraints;

(ii) meeting customers' PEV charging requirements with guarantees; and

(iii) catering to uncertainty in PEV arrivals over the operation period.

1.2 Literature Review

To examine the impact of PEVs on distribution systems, various charging strategies along with different PEV integration scenarios are considered in [1]. Similarly, to evaluate the effect of different levels of PEV penetration in the distribution system, charging strategies and energy losses are studied [2]. Reference [3] proposes an online coordinated charging decision algorithm to ensure that the EV are charged within the stipulated time, while minimizing the energy cost. The centralized controlled charging methods implemented in [4]-[6] focus on utility requirements to minimize the operational costs subject to grid constraints. Such approaches do not incorporate customer preferences and hence there is no guarantee that charging of PEVs will be completed within the available time.

Time-of-Use pricing with utilities having indirect control is adopted as a measure for co-ordinated charging to shift EV charging to off-peak hours [7]. Similarly, a decentralized counterpart for PEV charging technique is formulated to meet the power system limits using day-ahead prediction of the load profile; however, user preferences are not incorporated [8]. Charging scheduling approaches have been proposed that meet customer requirements without modeling of the distribution system. For instance, references [9] and [10] use the centralized charging scheduling approach in which customer's choice and charging profiles are included. Reference [11] proposes a centralized strategy with a complex communication network to implement the PEV charging schedule. A three-level hierarchical framework for decentralized control has been proposed in [12] to improve PEV charging and reduce the grid operational cost.

In reference [13], a real-time scheduling (RTS) strategy is implemented using a fixed charging rate considering both circuit constraints and consumer's choice for frequency regulation. One-way broadcast communication by the utility is used along with randomized EV charging start times to develop EV charging control and avoid overload conditions [14]. Local optimal scheduling technique is used to reduce the total cost of operating EVs including the dynamic EV arrival rate [15]. These studies consider both circuit constraints and consumer's choice along with dynamic PEV arrival rate to reduce the charging cost for a fixed charging rate. A real-time load management control strategy for controlled and coordinated PEV charging is implemented using maximum sensitivities selection optimization [16]. In [17], the scheme for PEV charging management is based on a heuristic method using a genetic algorithm which takes into account the network constraints, charging requirements, and user driving behavior. Different optimization techniques are used to avoid overloading and over-voltage conditions in the distribution network. The study for topology identification uses MILP to find distribution network topology with smart meter data using inverter probing [18]. Also, distribution network reconfiguration is done by controlling all regulators and capacitor banks and local inverter control rules [19]. In [20], battery storage sizing is done using model predictive control (MPC, receding horizon control) to size storage in a distributionally robust framework. In this work, the effect of PEVs can be broadly visualised and a moving horizon approach is formulated to control PEV charging in a residential network to avoid overloading and over-voltage conditions.

1.3 Contribution

As it is difficult to expand the physical grid capacity, scheduling is needed for optimal use of the present available capacity without expanding the power system. In this research, a real-time EV charging scheduling algorithm is proposed considering both utility's circuit functional requirements and EV customer's charging preferences. Different priority-based modes for the charging algorithm is developed to accommodate maximum number of EVs charged and to avoid over-voltage or under-voltage operating conditions in the extended distribution circuit.

This work proposes a novel and computationally tractable algorithm for real-time PEV scheduling based on a moving time horizon setting. Charging schedules are generated and revised periodically based on the actual number of PEVs arriving in real-time.

The major contributions of the proposed formulation include:

1. The number of PEVs arriving in real-time is kept unknown, making the setup realistic.
2. Customers are offered different price choices that determine the time-of-return with required charging levels. Despite revisions to the charging schedules in every period, the time-of-return is satisfied for all customers under contract.
3. Power system operational constraints are incorporated in the proposed algorithm.

1.4 Thesis Organization

The remaining of this thesis is organized as: Chapter 2 describes the system model considered along with additional EV charging specifications related to the proposed study. Chapter 3 provides the charging scheduling problem formulation and the optimization algorithm. Numerical tests for the proposed method are shown in Chapter 4 along with the simulation results. Chapter 5 provides the conclusion and future work.

Chapter 2

System Model

2.1 Charging Model Setup

The PEV charging setup considered in this work comprises of an aggregator providing charging service to a residential community. The aggregator can be defined as an entity that controls the PEV charging to increase its profit, and guaranteeing the satisfaction of PEV power consumption in a stipulated time for the PEVs under contract. During the entire operating period, the aggregator is supposed to control the total real-time load of the station such that the power distribution system constraints for the entire feeder are satisfied. This arrangement minimizes the burden on utility for charging schedule and also reduces the dependency on high-end communication technology. It is assumed that the aggregator receives a day-ahead electricity prices, load forecast, and generation forecast for all buses. At every time instant, the aggregator receives the real-time arrival data of registered PEVs and depends on PEV owner's input for the charging requirements and time of availability. A deterministic model is considered for simplicity. However, it is assumed that the aggregator is not aware of the number of PEV's arriving at different times across the day. Hence, a moving horizon based scheduling algorithm is developed that periodically updates the schedule based on real-time arrival of PEVs at the charging station.

The novelty of the proposed algorithm is that if a PEV arrives at the charging station and a contract is established, the scheduling process guarantees that the charging commitments are met despite of uncertain future schedule revisions. The charging commitments comprise of two components:

(i) time of return after charging; and

(ii) final charging level of PEV on return.

While the final charging level is determined by customers' needs, the time of return is determined as described next. When a PEV arrives with a charging request, the aggregator gives the PEV owner the flexibility of choosing a charging cost option. For every cost option, the charging time required by the aggregator for charging the PEV to its required level will be provided. Based on this information, the PEV owner decides the charging cost. The charging time limit is decided by dividing the required charging power with an average charging rate for each cost option. In this setup, two charging cost options are given to the PEV owner.

Table 2.1: Charging Costs

Charging Cost	**Characteristic**	
	Cost type	***Decided by***
C_1	Fixed cost	Aggregator
C_2	Fixed cost	Aggregator
C_{elec}	Time-of-use cost	Utility

Two charging prices C_1 (\$/kWh) and C_2 (\$/kWh) are considered here as shown in the Table 2.1. This can be scaled for a greater number of charging options. Here, C_1 is greater than C_2. So, the costumers choosing C_1 as charging cost have higher priority than that of C_2. The reason for a customer opting for C_1 is less charging time guaranteed by the aggregator. The PEVs selecting the cost option C_1 are grouped as one category and PEVs selecting C_2 are grouped as another. The aggregator solves the optimization problem of maximizing its charging profit by generating optimal charging schedule at the beginning of each 1 hour time interval.

C_{elec} is the hourly electricity pricing per kWh at which the aggregator is purchasing power for total EV charging at that time instant.

With new PEVs requesting charging, the aggregator can revise the previous charging schedule facilitating maximal PEV charging at all times, the aggregator can alter the previous charging schedule, based on the number of new PEVs requesting charging. Depending on the available charging capacity, power system load levels, and existing charging commitments from previous hours, the aggregator selects the PEVs from the two groups for providing the charging power.

After solving the optimization problem at the beginning of the t^{th} time interval, it provides a charging schedule from t^{th} interval to the end of the remaining period for the selected PEVs. The charging schedule for t^{th} time interval is implemented and the remaining schedule is discarded. At the next $(t+1)^{th}$ time interval, the aggregator solves the problem again for the already selected PEVs at t^{th} time and the new incoming PEVs present in two cost groups. Again the charging schedule for $(t+1)^{th}$ time is implemented and rest discarded. This process continues for next time intervals.

In this setup, PEVs arriving for charging between two intervals are assumed available for charging from the next time step. Also, the charging for PEV is not necessarily continuous, i.e., a PEV might sometimes remain idle. The schematic diagram of the scheduling arrangement is summarized in Figure 2.1.

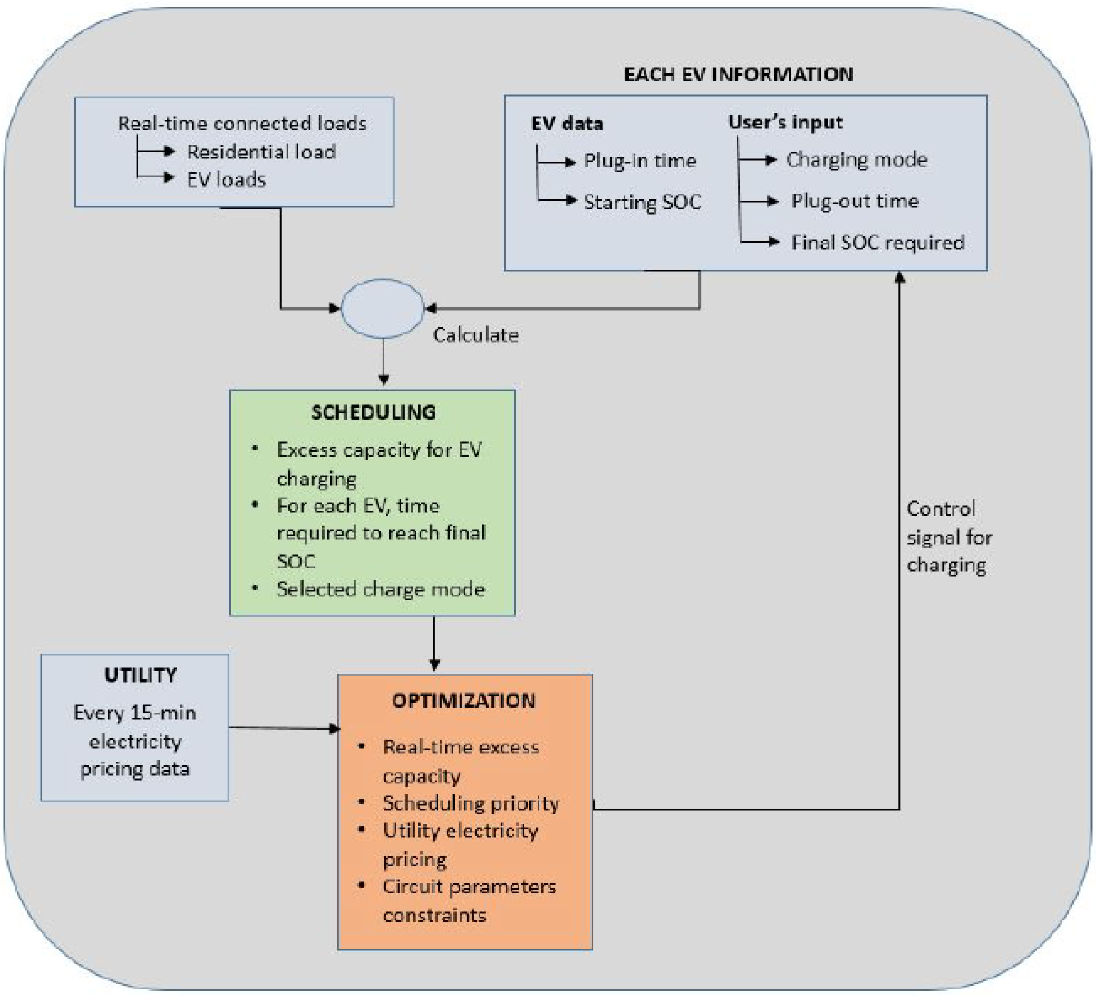

Figure 2.1: Aggregator's Algorithm Setup

2.2 Residential Load Profile

In a residential area, peak load hours are assumed to fall within 5 pm-10 pm. During a weekday evening, residents come home from work and basic residential loads are in use, along with which PEV load is plugged in under uncoordinated charging. This practice leads to higher loading conditions. The off-peak hours in a residential setup is from 8 am- 2 pm. So, the primary idea behind scheduling the PEV charging is to spread out the charging start times causing less steep peaking. The residential basic load profile curve follows the trend shown in Figure 2.2.

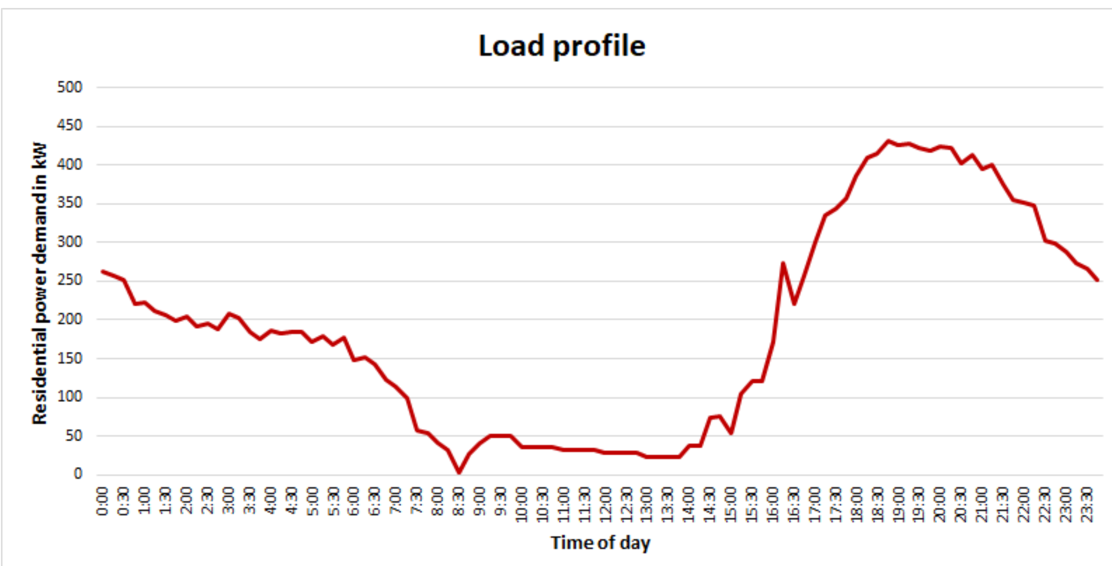

Figure 2.2: Residential load profile

2.3 Electric Vehicles Charger Specifications

There are 3 different widely used charging setups presently available which is specified in Table 2.2:

Table 2.2: Charging Types

Charging type	Voltage	Power	Charging duration
Level 1	120 V AC	1.8 kW	6-8 hour
Level 2	240 V AC	7.2 kW	3-5 hours
DC charging	480 V DC	50 kW	20-30 min

DC charging is the fastest mode yet least used due to its high infrastructure cost. Level 1 charger does not require any additional charging infrastructure but takes long time to charge depending on the PEV battery size. The trade-off between longest charging time and higher cost is smoothed out by Level 2 charger.

Here, Level 2 charging is considered that uses a 240V AC setup and can be configured for variable charging power of 3.3- 19.2 kW. The variable charging power is due to the controllable current in the charging setup. This characteristic gives scope to optimally schedule PEV charging at different time interval based on the available power.

2.4 Electric Vehicle Battery Capacity

Depending on the make and model of EV, distance range and affordability, PEVs can have varying range of battery capacities between 15 kWh and 90 kWh. To ensure longevity of battery operating margin, the minimum SOC (i.e. SOC_{min}) level is assumed to be 20% and maximum SOC (i.e. SOC_{max}) is to be limited at 90% provided that the user has not specified requirement. With an increase in usage and losses incurred by the charging setup, the battery charged is less than the input grid energy. The charging efficiency (η) is assumed to be 90%.

2.5 Electric Vehicle Charging Availability Profile

The PEV arrival and departure times in a residential setup follows a Gaussian probability distribution [21] which is shown in Figure 2.3 and it closely follows the basic load demand profile. The mean in the probability distribution for arrival time occurs at around 6:00 PM and for departure is around 8:00 AM.

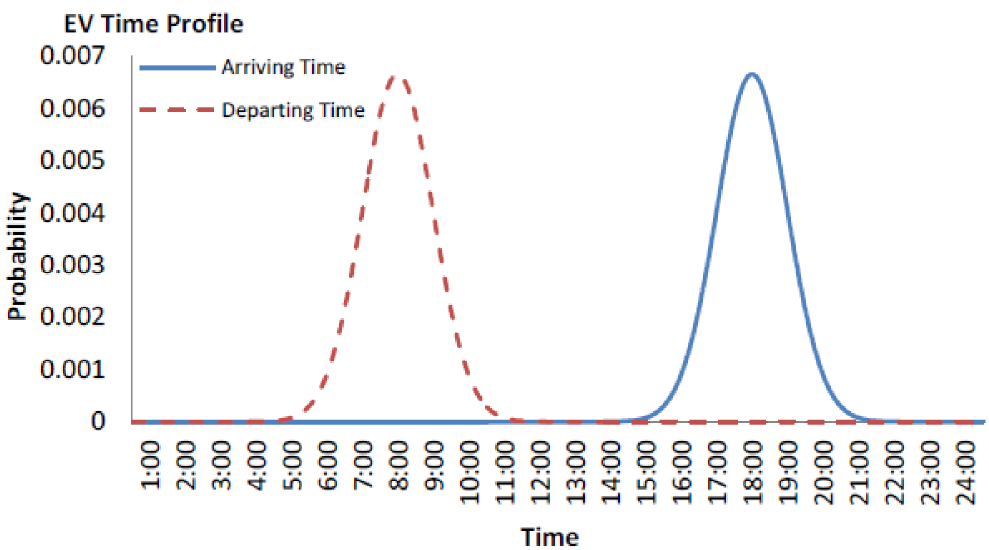

Figure 2.3: Arrival and Departure Time Profile for the PEV [21]

Chapter 3

Problem Formulation

In this section, a MILP is formulated that the aggregator solves at the beginning of every time interval and generates a charging schedule for the remaining time intervals. A single-phase radial power distribution system is considered for clarity of the formulation. The developed approach however can be conveniently extended to multi-phase unbalanced systems.

3.1 Power System Constraints

Consider a single-phase radial distribution system with N nodes. Let $p_{i,t}$ and $q_{i,t}$ represent the net active and reactive power injection at node i during time t. It is assumed that the active and reactive power generations $(p^g_{i,t}, q^g_{i,t})$, and loads $(p^\ell_{i,t}, q^\ell_{i,t})$ are known a priori. The nodes hosting the aggregator charging facility will have additional active power load $p^{EV}_{i,t}$. Thus, the power balance for any network node i entails

$$p_{i,t} = p^g_{i,t} - p^\ell_{i,t} - p^{EV}_{i,t}, \ \forall t \tag{3.1a}$$

$$q_{i,t} = q^g_{i,t} - q^\ell_{i,t}, \ \forall t. \tag{3.1b}$$

Oftentimes there are maximum apparent power limits $\bar{s}_i$ based on the feeder rating, transformer rating or contracted capacity. These constraints are quadratic in general. However, with known reactive power, the quadratic constraints $p^2_{i,t} + q^2_{i,t} \leq \bar{s}^2_i$ can be written as linear constraints

$$|p_{i,t}| \leq \sqrt{\overline{s}_i^2 - q_{i,t}^2}. \tag{3.2}$$

Given the nodal power injections, the voltages may be determined using the power flow equations. In this formulation the linearized distribution flow (LDF) model is employed for computational tractability [22]. Let $v_{i,t}$ be the squared voltage at node i at time t, and $\mathbf{v}_t$ be the $N-1$-length vector collecting all nodal squared voltages other than the substation node voltage v_0 for time t. Similarly, let $\mathbf{p}_t$ and $\mathbf{q}_t$ be the collection of active and reactive power injections at non-substation nodes, respectively. Then, the linear power flow model dictates

$$\mathbf{v}_T = v_0\mathbf{1} + \mathbf{R}\mathbf{p}_t + \mathbf{X}\mathbf{q}_t \tag{3.3}$$

where $\mathbf{R}$ and $\mathbf{X}$ are derived from the network topology and impedances as detailed in [22]. Next, any stipulated limits on power injections and voltages may be imposed as

$$\underline{p}\mathbf{1} \leq \mathbf{p}_t \leq \overline{p}\mathbf{1}, \ \forall\ t \tag{3.4a}$$

$$\underline{q}\mathbf{1} \leq \mathbf{q}_t \leq \overline{q}\mathbf{1}, \ \forall\ t \tag{3.4b}$$

$$\underline{v}\mathbf{1} \leq \mathbf{v}_t \leq \overline{v}\mathbf{1}, \ \forall\ t. \tag{3.4c}$$

where $(\underline{p},\ \underline{q})$ and $(\overline{p},\ \overline{q})$ are the limits on active and reactive power respectively. The voltage limits $\underline{v}$ and $\overline{v}$ are the minimum and maximum permissible squared voltages of the distribution system. As a voltage deviation between a distribution transformer and the service voltage is expected, the voltages at the distribution transformers level is maintained within $\pm 3\%$ pu, resulting in the squared voltage limits as $[0.97^2\ 1.03^2]$.

3.2 PEV Scheduling Constraints

For a given day, the entire time horizon may be divided into intervals of length Δt, say $\Delta t = 1$ hr. Let us index the intervals as $t = 1, 2, \cdots, T$. Let M_k denote the number of PEVs that have entered a charging contract by the k-th interval and have not yet reached the desired charging level. Denote the number of new PEVs requesting charging at the beginning of k-th interval as n_k. Thus, at the beginning of k-th interval, the aggregator would try to prepare a charging schedule for $N_k := M_{k-1} + n_k$ over the remaining $T_k = (T - k + 1)$ intervals $t = k, k+1, \cdots, T$. An optimal schedule shall first ensure that the charging requirements for the previously contracted M_{k-1} PEVs are fulfilled in the remaining T_k intervals. Next, a subset of the new n_k PEVs shall be selected to enter a charging contract such that the optimal schedule can successfully fulfill their charging requirements. Indexing the N_k PEVs by $n = 1, \ldots, N_k$, let the binary variable u_n denote whether a contract is established with PEV n ($u_n = 1$); or otherwise ($u_n = 0$). Since the first M_{k-1} PEVs are already contracted from previous binary instances, we have

$$u_n = 1, \quad \forall n = 1, \ldots, M_{k-1} \tag{3.5a}$$

$$u_n \in \{0, 1\}, \quad \forall n = M_{k-1}, \ldots, N_k. \tag{3.5b}$$

Note that while M_k and n_k are problem parameters, the decision for establishing a contract u_n is an optimization variable.

Define matrices $\mathbf{D}^{(k)} \in \{0,1\}^{N_k \times T_k}$, and $\mathbf{P}^{(k)} \in \mathbb{R}^{N_k \times T_k}$ to represent the overall schedule prepared at the beginning of k-th interval, as detailed next. The binary entry $D_{nt} = 1$ represents that PEV n is scheduled to receive a charging power P_{nt} during the t-th time interval. Otherwise, entry $D_{nt} = 0$ implies PEV n remains idle during interval t, and receives no charging. Since only the PEVs entering a contract shall participate in the schedule, the following constraints hold

$$D_{nt} \leq u_n, \quad \forall n,\ t \tag{3.6a}$$

$$\underline{p}^{EV}\mathbf{D}^{(k)} \leq \mathbf{P}^{(k)} \leq \overline{p}^{EV}\mathbf{D}^{(k)} \tag{3.6b}$$

where $[\underline{p}^{EV},\ \overline{p}^{EV}]$ represent the limits on charging power of PEVs. The assumption of common limits $[\underline{p}^{EV},\ \overline{p}^{EV}]$ is made without loss of generality.

Let a_n^k denote the number of time intervals starting from the k-th interval within which PEV n must receive s_n^k units of energy. The values for parameters a_n^k and s_n^k are derived based on the contract established between the aggregator and PEV owner, and is updated after every time interval as detailed in Section 3.4. The following constraints impose the requirements for charging times and total charge needed

$$D_{nt}^{(k)} = 0, \quad \forall t > a_n^{(k)},\ \forall n \tag{3.7a}$$

$$\mathbf{P}^{(k)}\mathbf{1} = \mathbf{u} \odot \mathbf{s}^{(k)} \tag{3.7b}$$

where $\mathbf{u}$ and $\mathbf{s}^{(k)}$ collect the contract statuses u_n's and charging requirement s_n^k's for the N_k PEVs, and $\odot$ represents the entry-wise product of the two vectors. Constraint (3.7a) ensures that in the prepared schedule at the beginning of interval k, PEV n receives no charging power after time a_n^k. Constraint (3.7b) ensures that the row-sum of $\mathbf{P}^k$, representing the total charge received by PEV n, considering $\Delta t = 1$, matches with the needed charge s_n^k.

The total power consumed by the PEVs getting charged at time interval t appears in the power flow equations of the distribution network as $p_{i,t}^{EV}$ where i is the power system node hosting the aggregator EV charging facility. The aforementioned coupling is captured by

$$p_{i,t}^{EV} = \sum_{n=1}^{N_k} P_{n,t}^{(k)}, \ \forall t. \tag{3.8}$$

Additionally, the maximum number of PEVs getting charged at a time interval is limited by the maximum number of available charging spots $\overline{\mathsf{N}}$

$$\mathbf{1}^\top \mathbf{D}^{(k)} \leq \overline{\mathsf{N}}\mathbf{1}^\top \tag{3.9}$$

3.3 Objective Function

At the beginning of k-th interval, the aggregator would try to prepare a schedule over the next T_k intervals that maximizes the profit. Let $\mathcal{N}_1^k$ and $\mathcal{N}_2^k$ be the set of PEV owners willing to pay the charging prices C_1 (\$/kWh) and C_2 (\$/kWh) respectively. Thus, the total number of new PEVs is $n_k = |\mathcal{N}_1^k \cup \mathcal{N}_2^k|$. Based on the prepared schedule, the aggregator would have to pay the electricity prices to the utility. With $\mathbf{c}_e \in \mathbb{R}^{T_k \times 1}$ representing the electricity prices for the next T_k instances, the anticipated electricity cost is given by $\mathbf{1}^\top \mathbf{P}^{(k)} \mathbf{c}_e$. Therefore, the scheduling problem solved by the aggregator at the start of k-th time interval can be formulated as a MILP

$$\begin{aligned} \min_{\mathbf{D}^{(k)},\mathbf{p}^{(k)},\mathbf{u}} \ & \mathbf{1}^\top \mathbf{P}^{(k)} \mathbf{c}_e - \sum_{n \in \mathcal{N}_1^k} C_1 u_n s_n^k - \sum_{n \in \mathcal{N}_2^k} C_2 u_n s_n^k \\ \text{s.to} \ & (3.1) - (3.9) \end{aligned} \tag{P1}$$

Problem (P1), if feasible, yields a possible schedule such that the PEVs selected for establishing a charging contract ($u_n = 1$) receive their requested charging s_n^k within the agreed time a_n^k. The proposed algorithm solves (P1) periodically on a moving horizon basis while ensuring feasibility and profitability.

3.4 Moving Time Horizon Updates

In a realistic setup for local aggregators, the number of PEVs n_k, arriving at time k is not known a priori. Therefore, an optimal schedule cannot be generated at the start of the day. Rather, based on the initial n_1, an initial candidate schedule may be prepared, which is subsequently updated. In detail, at the start of any interval k, the aggregator shall solve (P1) and obtain a schedule for the next T_k intervals; implement the schedule for k-th interval; discard the remaining schedule and solve (P1) again at the beginning of $k+1$-th interval.

The proposed framework guarantees that the charging commitments (s_n, a_n) are fulfilled for PEVs with contract ($u_n = 1$). To see this, note that for the first instance $t = 1$, contracts are established for PEVs for which there exists a feasible schedule $\mathbf{P}^{(1)}$ over the next T intervals. Thus, after implementing the first interval, the remaining $T-1$ columns of $\mathbf{P}^{(1)}$ are still a candidate solution to (P1) for $t = 2$ with no new contracts established; hence guaranteeing the feasibility of (P1). Similarly, since the truncated schedule from $\mathbf{P}^{(1)}$ is still feasible, any new schedule generated as $\mathbf{P}^{(2)}$ must yield a higher profit by optimality. Continuing the argument for all intervals, it is evident that the novel approach of enforcing (3.5) and (3.7) in a moving horizon basis guarantees fulfillment of commitment towards PEV owners while maximizing profit.

The initialization and updating of parameters s_n^k's and a_n^k's are explained next. When a new

PEV arrives, its charging energy requirement is computed as

$$s_n = \frac{(\mathsf{SOC_{plugout}} - \mathsf{SOC_{plugin}}) \times \mathsf{Bcap_n}}{\eta \times \Delta t}$$

where $\mathsf{SOC_{plugout}}$ is the final SOC of an PEV to be reached and $\mathsf{SOC_{plugin}}$ is the SOC at the PEV's time of arrival. $\mathsf{Bcap_n}$ is the battery capacity of n^{th} PEV. Once the total energy requirement s_n is computed, the guaranteed *time of return* a_n may be computed based on the price option C_1 or C_2 opted by the PEV owner. In detail, let P_{C_1} and P_{C_2} be the average charging power for the two cost options with $P_{C_1} > P_{C_2}$ for $C_1 > C_2$. Then the time of return is given by the ceiling value of the following expression:

$$a_n^k = \frac{s_n}{P_{C_j}}, \ \forall \ n \in \mathcal{N}_j^k.$$

Once the optimal schedule is obtained for k^{th} time, the charging power requirement and time availability of the selected M_k PEVs are updated for the $(k+1)^{th}$ time interval.

$$\begin{aligned} s_n &= s_n^{(k)} - P^{(k)}(n,1), && \forall n \text{ with } u_n^{(k)} = 1 \\ a_n &= a_n^{(k)} - 1, && \forall n \text{ with } u_n^{(k)} = 1 \\ c_n &= c_n^{(k)}, && \forall n \text{ with } u_n^{(k)} = 1 \end{aligned} \tag{3.10}$$

Chapter 4

Numerical Tests

The proposed approach is tested on a single-phase IEEE 13-node feeder with nominal voltage of 4.16 kV which is further stepped down to serve residential loads. Figure 4.1 below illustrates the distribution system setup in which the residential structure at node 645 (or node 5) is magnified (denoted by green dashed line) to better illustrate the configuration of the area. The primary feeder in the setup consists of 13 kV overhead lines connecting the substation to heavy power industrial and commercial loads and is a medium voltage radial distribution system. The medium voltage lines are stepped down through distribution transformers to provide power to the local residential systems. So in this setup, one aggregator is assumed to be present at node 5 which is responsible for the charging decision of PEVs present in Feeder 1- Feeder n. This is done in contrast to having individual uncoordinated charging at every customer in the residential arrangement which leads to high peak demands. The aggregator receives hourly electricity pricing update from the utility based on which it selects the number of PEVs to guarantee charging.

To obtain a load curve for a 24 hr period, real-world residential demands from Pecan street Data is used [23]. In detail, 15-min based data for 300 houses was taken from Pecan Street; summed and normalized to obtain an hourly demand profile. Since the Pecan Street data set does not provide reactive power demands, a power factor of 0.9 lagging is considered to generate normalized reactive power demands. Next, the normalized profile is scaled by the spot-load data form the 13-node feeder. The PEV charging station is assumed to be located

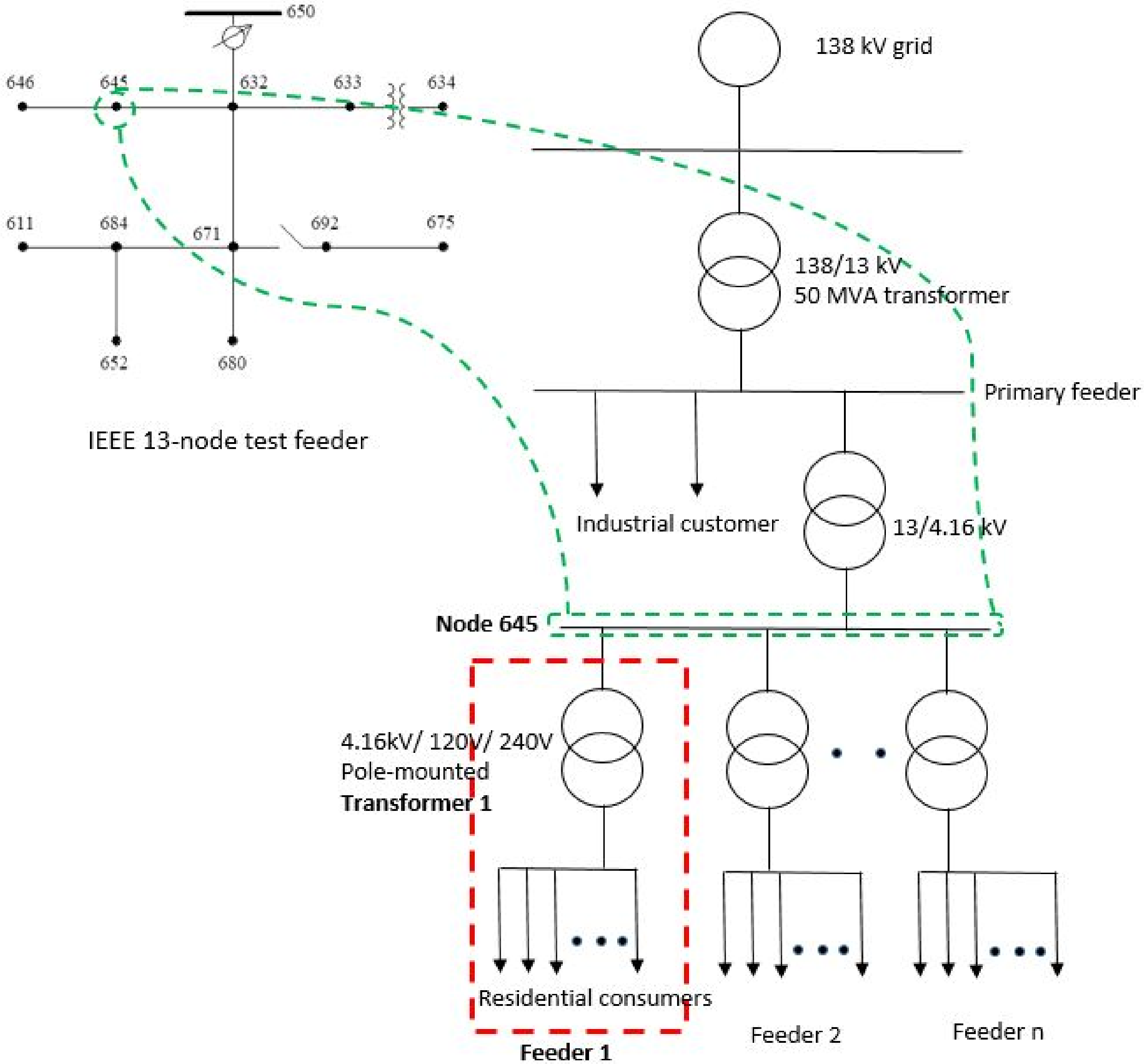

Figure 4.1: Distribution System Setup

at node 5 of the feeder. Problem (P1) is solved using YALMIP and Gurobi, on a 2.7 GHz Intel Core i5 computer with 8GB RAM [24], [25].

For a random arrival of PEVs opting the two price options C_1 and C_2, Figure 4.2 shows the PEV selection process over 24 hours (12 AM- 11:59 PM) for a single day. It can be observed that, in the initial off-peak hours, the aggregator selects number of PEVs for charging along with already existing vehicles from previous time instants. Moreover, almost all the PEVs are being selected to be charged within the committed time during off-peak hours. However, that is not the case during evening peak hours as the base load increases and possible time remaining for charging decreases (as it is solved for 24 hours). As it is a moving time horizon approach, the aggregator chooses a subset of arriving PEVs for evening peak demand hours. It can be observed that for last hours in the day i.e. off-peak hour, the aggregator ensures complete charging of available PEVs along with selection of limited number of PEVs due to limited grid power availability at that time instant.

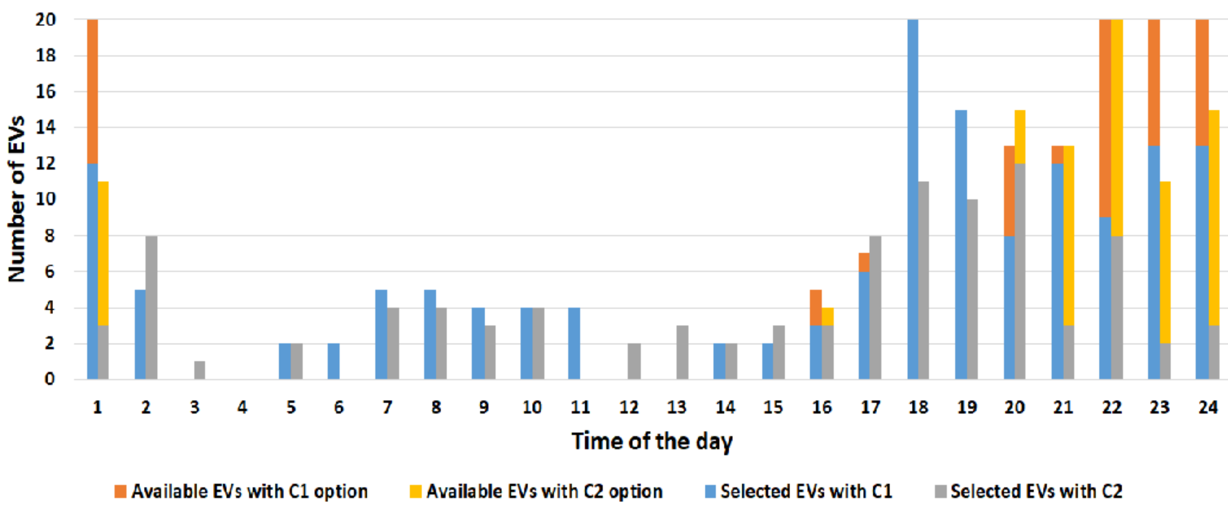

Figure 4.2: Number of Available and Selected PEVs over 24 Hours

The novelty of the algorithm is the guarantee the aggregator provides in terms of charging time. The charging power provided by the aggreagator in terms of the percentage of respective charging power required by the selected PEVs are shown in Figure 4.3. The PEV charging power distribution for a subset of PEVs over 10-time steps is depicted for clear understanding. The colored area for each PEV depicts its availability for charging before the time of return and the percentage of charging completed in every time step is mentioned. All selected PEVs are shown to receive 100% of their charging requirement. Further, it can be observed that the charging rate is non-uniform and charging is discontinuous during the available period of PEV, as anticipated. The value of percentage charge given here depends on the battery capacity and charge requirement for each PEV as it is randomly generated over its available period.

Timesteps

EV IDs	1	2	3	4	5	6	7	8	9	10
1	40%		28%	14.50%	17.49%					
2		43%		24.57%	32.40%					
3			22%		49%			29%		
4					12%	63%	25%			
5							7.50%	15.93%	32.67%	43.91%

Figure 4.3: PEV charging power allocation

Next the variation of active power load of the EV charging station in response to price and power system load variations is shown in Figure 4.4. All quantities are normalized for clarity, wherein the EV charging load is normalized with the transformer rating at node 5. It may be observed that, the charging station demand diminishes at high price period to minimize cost, while it complements the network-load to alleviate over/under voltages. PEV charging pattern follows the normal load demand curve in a residential setup as PEVs return home for charging in normal weekdays, it can also be observed from the figure that during peak loading, the PEV charging power is shifted from peak hours to non-peak hours. This results in a smoothly distributed power demand curve with a valley-filling technique for the same.

Finally, to analyze scalability, 100 instances of (P1) were solved for random arrival of PEVs

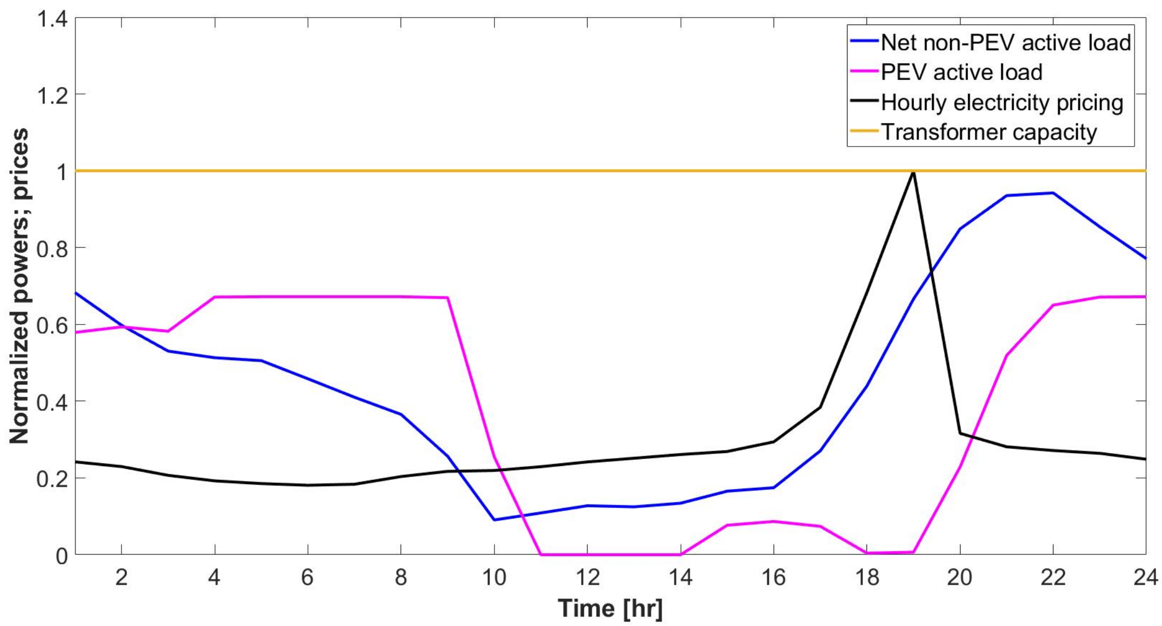

Figure 4.4: Intraday Profile of Power System Load in Response to EV Station Load and Electricity Prices

over a 24 hr period in Figure 4.5. The total time for solving (P1) was found to be in the range [11, 25.6] sec with median at 15.4 sec.

Figure 4.6 shows that at peak hours, the optimized scheduling algorithm provides EV charging power within the maximum capacity limits for safe operation without any over-voltage condition. At the same time, the total power requirement with uncoordinated (or uncontrolled charging) exceeds maximum transformer capacity set at 1 p.u.

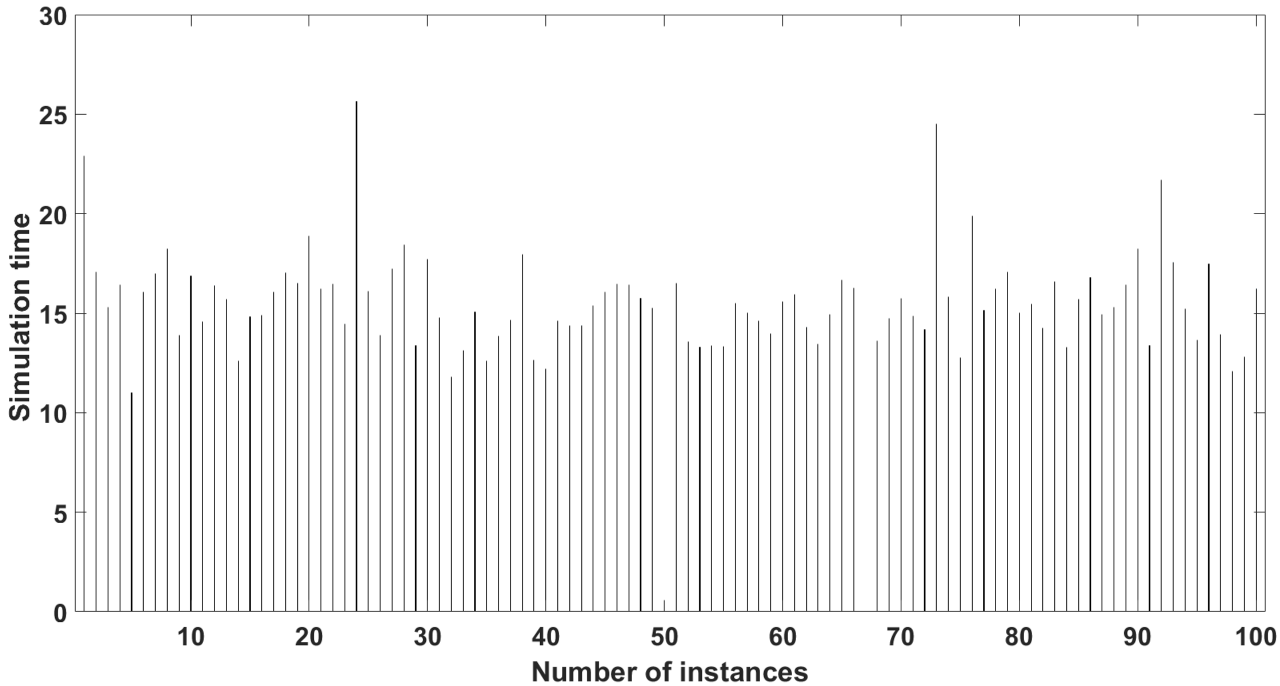

Figure 4.5: Time Taken to Solve for Each Instance for Random Arrival of PEVs over a 24 hr Period

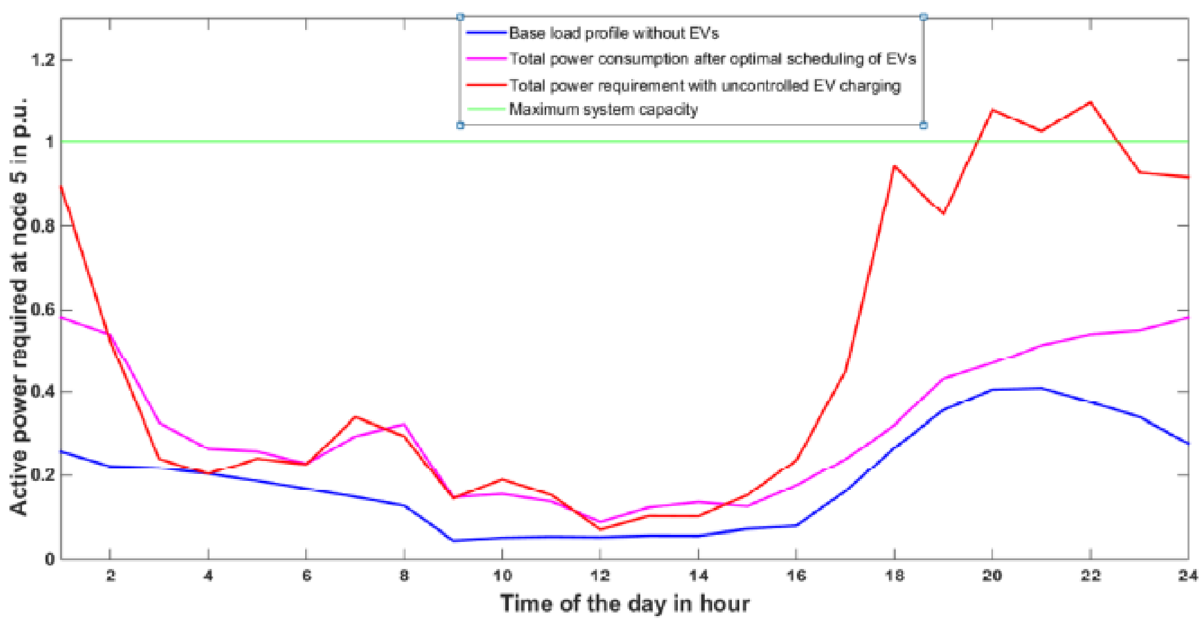

Figure 4.6: Active Power Demand at Node 5 over 24 Hours

Chapter 5

Conclusions

The proposed formulation gives the optimal charging scheduling of incoming PEVs, considers system constraints and maximizes the number of PEVs charged at a real-time scenario. The simulation results validate the proposed MILP formulation for a moving time horizon. It can be scaled down to smaller time intervals for detailed system framework. Also, it can be extended for multiple aggregator charging decisions in a medium-sized power system network with higher PEV penetration. Although simulation did not involve distributed energy resources such as solar PV or battery storage, it is seen in the problem formulation that it can be accommodated in the design. The primary goal of the proposed framework is achieved as it maximizes the number of PEVs getting charged with the limited available infrastructure and cater to customer satisfaction by guaranteeing complete charging within the stipulated time.

Chapter 6

Future work

As part of future work, this model is supposed to be improvised to allow bidirectional PEV power flow, i.e., the vehicle to grid power injection at peak hours along with capacity market constraints to delve deeper into the economic side of the PEV charging market. As the present work only involved one aggregator, the scope of the work can be extended to accommodate a greater number of aggregators in the system. This improvement will require communication technology to be considered and a more complex coordinated charging approach to be implemented to operate the whole system within grid capacity and flow constraints while maximizing their own profit. For different percentages of PEV penetration in the system, a comparative analysis of the formulation can be implemented to obtain a quantitative measure of the efficiency of the approach.

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