Optimal Recharging of EVs for Peak Power Shaving and Valley Filling using EV-Aggregator model in a Micro-grid

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Abstract: This work presents an optimal recharging strategy for Electric vehicles (EVs) using Quadratic Programming (QP) to flatten the peak power demand on the utility. The increase in penetration of EVs in distribution systems causes a significant increase in peak power demand due to synchronization between the peak load hours and EV charging period. The optimization technique aims to assess the effects of optimal scheduling considering the initial State-of-charge (SOC) level, Demand Side Management (DSM) functionalities that meet both the grid and EV owners’ requirements. The feasibility of the scheme is verified with two case studies using different aggregator units and the effect on the system is analyzed by determining the load demands from local utilities and EVs. The aggregator units collect data from EV users with common interests such as EV battery specification, Battery SOC, recharging period and mediate with utility operators such as Transmission system operator (TSO), Distribution system operator (DSO). Further, other parameters such as peak power reduction, peak-to-average ratio (PAR), standard deviation, and peak-to-valley differences are also compared to test the effectiveness of the implemented optimization technique. The outcomes of the study show that using load demand profile and optimal rescheduling using aggregated EVs can flatten the load curve for the utility and lower the demand charges for the end-users.

Keywords: Electric Vehicles, EV Charging, Quadratic Programming, EV-Aggregator.

1. Introduction

In recent years, the Electrification of the Transportation system has emerged as the potential aid to reduce Greenhouse gas (GHG) emissions and fossil fuel depletion issues. Given the usage of large-scale incorporation of electric vehicles (EVs) to decarbonize both transport and power sectors, provided that the replacement of conventional means of transportation by EVs is associated with a significant need for additional electricity demand required for EV battery charging. EV charging level (Level 1-3) is mainly distinguished based on charging power limits and charger availability [1]. Simultaneous charging of EVs in an uncontrolled manner leads to increase in peak load in the utility’s service area due to the synchronization condition between two power peaks, EV charging power and Utility loads (lighting, and home appliances, etc.). The extent of impacts on distribution network depends upon factors such as
EV batteries capacity, charging strategy, and EV load characteristics. Further, EV load characteristics is very much dependent on factors like initial state-of-charge (SOC), EV type, and Level of charging.

Smartly charged EVs alleviates the additional stress on the local grid through optimal management of EV loads by using vehicle-to-grid (V2G) integration. V2G technology provides the means for services such as utility peak power shaving and valley filling [2]-[5]. In these studies, the objective is achieved by altering the charging-discharging pattern in a decentralized manner. In decentralized recharging control, each vehicle is provided with a computational load management system through which each vehicle performs its recharging decisions individually in a distributed manner. Recently, many papers have introduced the utilization of EV fleets as energy storage systems (ESS). The requirements of EV fleet managing entities such as an aggregator unit for network designing activities including Demand Side Management (DSM) and V2G is described in [6]. Demand Side Management (DSM) has become a prominent factor in most of the researches associated with micro-grid. The reason behind the existing hierarchy of energy markets. The energy price system can be taken into consideration when implementing a control strategy, which is widely known as ‘time-of-use’ recharging strategy. In [7], a day-ahead time-varying charge is used as an indirect scheme to coordinate an inclusive effect of demand filling. In [8], an Improved binary particle swarm optimization (IBPSO) technique along with a time-varying-price signal is used to frame the recharging process of EVs.

Previous studies related to EV aggregator recharging have not investigated the implementation of multiple control strategies in a centralized manner. In a centralized recharging approach, the intelligent entity or the aggregator aims to bring all active information from EVs sharing common interests and mediate with different system operators to schedule the recharging process for EVs. Also, most of the papers have analyzed the EV charging through aggregators at the local level only. Therefore, this paper develops the integration of a centralized smart recharging approach with a bi-level decision-making model that meets both grid and EV owners’ requirements. The recharging approach for EVs is scheduled with an objective to flatten the peak load demand and filling the valley of demand for the utility. Quadratic Programming (QP) optimization technique is used to handle the formulated minimization problem and is carried out within the MATLAB test environment. The role of the local and central aggregator is developed to achieve the objective for different cases.

The rest of this paper is structured as follows: The proposed Quadratic Programming (QP) optimization for EV management is discussed in Section 2. The implemented aggregator-based system for optimal management of EVs is briefly discussed in Section 3, and the outcomes of the study are explained in Section 4 for different case studies. Finally, Section 5 provides the conclusion to this article.

2. QP for Management of EV’s
In this section, a centralized recharging approach is introduced as a reference methodology to manage the available fleet of EVs. This approach uses a quadratic optimization technique, to search for an optimal recharging period to flatten the peak load demand by discharging stored energy in EV batteries while simultaneously filling the valley of demand by recharging itself during hours of low peak demand. The objective is achieved by considering objective function (by minimizing the grid peak power) while taking into account the technical constraints (EV and grid constraints). During the scheduling process, the aggregator trades off each EV’s charging and discharging requests with the system operators to find a globally optimal solution to satisfy the minimization problem.

2.1. Problem Formulation
The problem of optimal charging scheduling rises due to the increase engrossment of larger numbers of EVs into the present utility network. In this study, the problem is formulated based on minimizing the peak power on the utility. The problem can be mathematically expressed as follows,

\[
\text{Minimize}, (G_{\text{power}}^2) \quad (1)
\]

\[
G_{\text{power}} = P_D + P_{\text{C}_{i,t}} \quad (2)
\]
Where, $G_{\text{power}}$ is the total grid demand power, $P_D$ is the daily demand power without EVs, and $P_{C_{i,t}}$ signifies the recharging power of each EV $i$ at time $t$. Therefore, the objective function can be formulated as,

\[
\text{Minimize, } \sum_{i=1}^{M} \sum_{t=1}^{T} (P_D + P_{C_{i,t}})^2
\]  

Subject to following constraints, $M$ represents the maximum available EVs and $t$ is the total time steps in the scheduling period.

During the recharging scheduling period, the objective function is minimized subject to certain constraints.

### 2.2. Constraints

Current limitations for charging and discharging of EVs are defined with inequality constraint given as,

\[
I_{i,\text{min}} \leq I_{C_{i,t}} \leq I_{i,\text{max}}
\]

Where, $I_{i,\text{max}}$ denotes the maximum current limit and $I_{i,\text{min}}$ is the minimum charging limit or maximum discharging limit.

The state of charge (SOC) of battery which represents the remaining amount of energy is set within limits. $SOC_{i,\text{min}}$ has a value of 0.2 (20%) below which the EV battery cannot be drained, while $SOC_{i,\text{max}}$ has a value of 0.9, which means the EV battery is not allowed to charge beyond 90%.

\[
SOC_{i,\text{min}} \leq SOC_{i,t} \leq SOC_{i,\text{max}}
\]

Subject to

\[
SOC_{i,t} = SOC_{i,t-1} + b_i I_{C_{i,t-1}}
\]

Where, $SOC_{i,t-1}$ is the SOC at a previous time interval $(t-1)$, $b_i$ is the battery capacity of $i$th EV and $I_{C_{i,t-1}}$ is the charging current of EV $i$ at previous time step $t-1$.

Subject to,

\[
\text{Desired SOC} = SOC_{\text{desired}}
\]

Where, $SOC_{\text{desired}}$ is the desired SOC level at time $t$ as per EV owner’s requirement.

As the (dis)charging power is transferred between the utility and the vehicle energy storage system, therefore power associated with EV $i$ is set within limits as,

\[
P_{i,\text{min}} \leq P_{C_{i,t}} \leq P_{i,\text{max}}
\]

Where, $P_{i,\text{max}}$ is the maximum allowed charging power and $P_{i,\text{min}}$ is the minimum allowed charging power or maximum allowed discharging power.

Finally, the total grid power is kept within limits to make sure average power remains constant and is given as,

\[
0 \leq G_{\text{power}} \leq P_D + \sum_i P_{i,\text{max}}
\]

### 2.3. QP Solver

The objective function outlined in Eq. (1) becomes a quadratic programming problem. Quadprog function solves this problem which can be rearranged into a standard form as,

\[
\min \frac{1}{2} x^T H x + f^T x
\]
Such that,

\[ A \cdot x \leq b \]
\[ A_{eq} \cdot x = b_{eq} \]
\[ lb \leq x \leq ub \]  \hspace{1cm} (11)

Authors in [9],[10] and [11], have implemented the matrices \((H,A,and Ae\)q\), and vectors \((f,b,beq,lb,ub,x)\) for a Plug-in Hybrid Electric Vehicle (PHEV) and Plug-in Electric Vehicle (PEV) model respectively. In this study, the same has been modified for the EV model.

3. Aggregator for Management of EV’s

Based on the need for a bi-level control strategy and the large-scale requirements of Demand Side Management (DSM), a centralized EV-Aggregator based approach is attempted in this paper. The centralized Aggregator based system is an intelligent computational technology for managing large fleet of EVs. In literature, the requirements for the aggregator-based system for micro-grid planning and operation activities including DSM and V2G is described in [5]. In this section, the proposed aggregator system architecture is discussed, and the coordination strategies used by the aggregators and system operators for managing EVs to adapt to change in demand load is explained.

3.1. Proposed EV-Aggregator System

The proposed system consists of 3 different Areas each having different base power, EV Charging Station, Local Aggregators (EV management at the local level), Central Aggregator (EV management at central level), Grid Agent (TSO and DSO) represents the system operators. A schematic overview of the attempted aggregator model is shown in Figure 1. The goal of Local Aggregators, Central Aggregator, TSO, and DSO are independent of one another, but they are not independent in terms of coordination. To achieve the system’s objective these operators, need to coordinately function within themselves through communication network.

![Figure 1. Schematic Overview of the EV-Aggregator System.](image-url)
3.2. Control Strategies
Since EVs are providing the required power back to the utility, they need significant power to recharge themselves. The aggregator is responsible for scheduling the required energy for the EVs and therefore the aggregator units require forecasted data. Figure 2 shows how EVs send their (dis)charging requests through aggregators. The coordination strategies at the central level include:

- The Local Aggregator collects information regarding EV status and shares it with the Central Aggregator. The message signal contains EV’s SOC level, required charging/discharging power, desired level of SOC. This process is applicable to all the 3 localities available in the system.
- A request is sent by the Central Aggregator for charging or discharging to the system operator (TSO).
- The Central Aggregator and TSO collectively arrange a scheduling scenario considering grid and EV constraints. The preferred scenario is in context to Grid congestion avoidance. The allowed charging/discharging power is then sent back to the respective Local Aggregator via Central Aggregator.
- The local aggregator then announces the mutually agreed recharging or discharging power for the EV.

3.3. Case Studies Formulation
The validity of the implemented optimization model is verified with two case studies with different scenarios of baseload, load demand curve, and EV parameter. The first case study is conducted for one day in each locality individually. In this study, the role of Local Aggregator is utilized for peak power shaving and valley filling for the local utilities. During the second case study, the role of Central Aggregator is utilized for peak power shaving over the entire grid. During this case study, optimization is performed over the demand curve which is the summation of demand load from all three localities. Parameters used during the simulation process are given in Table 1. It can be observed that the desired SOC level at 16:00 hours is 0.55 (55%) for Area 1 and 0.60 (60%) for Area – 2 & 3. As fast charging method is taken into consideration, it is assumed that the SOC level must reach 0.80 (80%) by midnight hour. Further, to implement the optimization technique a much higher capacity is chosen as a collective of all the EV batteries available in each locality. The uncontrolled and controlled load curves are

![Figure 2. Operation of an Aggregator based system for scheduling recharging process of EVs](image-url)
compared to verify the efficiency of the proposed system. Comparison is mainly done based on Peak power demand, Average power, Peak-to-average ratio (PAR), Standard deviation, and Peak-to-valley difference.

**Table 1. Area wise Parameter values used during the simulation.**

| Parameter                  | Area-1 | Area-2 | Area-3 |
|----------------------------|--------|--------|--------|
| Max. discharging current   | -125 A | -125 A | -150 A |
| Max. charging current      | 125 A  | 125 A  | 150 A  |
| Min. SOC level             | 0.2 (20%) | 0.2 (20%) | 0.2 (20%) |
| Max. SOC level             | 0.9 (90%) | 0.9 (90%) | 0.9 (90%) |
| Desired SOC                | 0.55 & 0.80 | 0.60 & 0.80 | 0.60 & 0.80 |
| Desired time               | 16:00 & 24:00 | 16:00 & 24:00 | 16:00 & 24:00 |
| Max. discharging power     | -75 kW | -87.5 kW | -80 kW |
| Max. charging power        | 75 kW  | 87.5 kW | 80 kW  |
| Utility base power         | 6 MW   | 5 MW   | 4 MW   |

4. Simulation Results

4.1. Case Study I: Scheduling using Local Aggregator
Preliminary simulation studies for optimal management of EV scheduling using Local Aggregators are presented in this subsection. Load demand from each Area (considered individually) and EVs are optimized for peak power shaving and filling of valley. Figure 3, 4, and 5 describes the effect of optimal recharging strategy for Area 1, 2 and 3 respectively. From these figures, it can be observed that most of the EV’s recharging process is altered from peak load hours to low peak hours that are mostly during night hours or dawn hours.

![Figure 3. Peak Shaving and Valley filling using optimal recharging in Area-1.](image-url)
The parameters obtained before and after the implementation of the optimization technique are compared and given in Table 1. The average load demands from each area and EVs remains the same in each case, however, the peak power is reduced by 8.33% in Area-1, 10.20% in Area-2, and 18.75% in Area-3. As the peak power is reduced and the average value remains the same it can be estimated that the demand charges for the utility also get reduced. The peak-to-average ratio (PAR) is reduced by 10.4%, 9%, and 4.44% in Area-1, 2 and 3 respectively. PAR value holds a key factor for the utilities, not the EV owners. It is preferably used during network designing objectives as it decides the net required generation capacity for an area. Further, peak-to-valley difference power also gets reduced by 20.8% in Area-1, 13.6% in Area-2, and 20.10% in Area-3. This indicates the objective of peak power shaving and valley filling is achieved quite effectively.
### Table 2. Results from Local Aggregators.

| Parameter                           | Area-1 Before | Area-1 After | Area-2 Before | Area-2 After | Area-3 Before | Area-3 After |
|-------------------------------------|---------------|--------------|---------------|--------------|---------------|--------------|
| Peak Power [MW]                     | 6.00          | 5.50         | 4.90          | 4.40         | 4.00          | 3.25         |
| Average Power [MW]                  | 3.12          | 3.12         | 2.40          | 2.42         | 1.40          | 1.38         |
| Peak-to-average ratio [PAR]         | 1.92          | 1.76         | 2.00          | 1.82         | 1.80          | 1.72         |
| Standard Deviation                  | 1.34          | 1.22         | 1.89          | 1.63         | 1.42          | 1.72         |
| Peak-to-valley difference [MW]      | 4.65          | 3.68         | 4.40          | 3.81         | 3.88          | 3.10         |

#### 4.2. Case Study II: Scheduling using Central Aggregator

The simulation study for optimal recharging of EVs considering Local Aggregators, DSO, Central Aggregators, and TSO is presented in this subsection. This bi-level control architecture shifts EVs charging/discharging power demands throughout a day to reduce the peak load curve and fill the demand valley. In this study, load profile considering all three areas and power demands from EVs is optimized to achieve the objective considering both EV and grid constraints. The optimized load curve is shown in Figure 6.

![Figure 6. Peak Shaving and Valley filling using Central Aggregator.](image)

The penetration of EVs depends upon the availability of EVs in each area during the recharging process. Figure 7, describes the frequency of EVs charging or discharging during the simulation period. It can be observed most of the EVs are recharged during low peak hours or night hours. During peak load hours as most of the EVs are parked idle therefore they participate in V2G mode to provide energy back to the grid to reduce the additional stress on the utility.

Further, Table 3 provides a comparison between the actual utility load before optimal charging and after optimal charging. From the data available, it shows that the peak power is reduced by 11.69%. As the average power on the utility remains constant the PAR is reduced by 11.36%. 14.28% reduction in peak-to-valley difference power indicates that the implemented optimization technique had achieved the objective of peak power minimization quite efficiently.
Figure 7. Area wise EVs participation during V2G

Table 3. Results from Central Aggregator.

| Parameter                        | Before Optimization | After Optimization |
|----------------------------------|---------------------|--------------------|
| Peak Power [MW]                  | 13                  | 11.48              |
| Average Power [MW]               | 7.38                | 7.35               |
| Peak-to-average Ratio [PAR]      | 1.76                | 1.56               |
| Standard Deviation               | 4.11                | 3.66               |
| Peak-to-valley Difference [MW]   | 11.06               | 9.48               |

5. Conclusion
This article presents a centralized aggregator-based approach for efficient management of EV recharging process in a micro-grid. To verify the effectiveness of the proposed model two different scenarios are considered. The results are compared based on peak power, average power, peak-to-average ratio, standard deviation, and peak-to-valley differences power. In the case of scheduling through local aggregators, the maximum peak power reduction occurs in Area-3 by 18.75%. The percentage of power reduction depends upon the utility peak load, and number of available EVs in idle condition. During each optimization case, the average power more or less remains the same. Further, the reduction in PAR value and the peak-to-valley difference indicates the effectiveness of the proposed system. In the second case study during scheduling through the central aggregator, the average power on the utility remains the same, however, there is a reduction in peak power by 11.69% after implementing the optimization technique. Moreover, the reduction in PAR and peak-to-valley difference power by 11.36% and 14.28% respectively, indicates that the demand charges on the utility also gets reduced. However, for large-scale integration of EVs, there has always been a compromise between the recharging costs and peak power consumption. Furthermore, this study can also be extended with different EV penetration levels and different charging levels.
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