Optimal Coordinated Plug-In Vehicle Charging

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ABSTRACT

The widespread adoption of Plug-in Electric Vehicles (PEVs) at even moderate levels may negatively impact the electrical distribution infrastructure through uncoordinated charging. We propose developing an optimized plug-in electric vehicle (PEV) charging tool to lower the impact of PEV adoption on the local power infrastructure by coordinating and distributing PEV charging demand through the use of an extensive database of residential and PEV power demand profiles. A dashboard-based optimization tool allows a user to explore the impacts of coordinating PEV charging on metrics relevant to local electrical distribution transformer life, such as severity index ($\alpha 1.5$), standard deviation (σ), and peak power demand. Significant decreases in all 3 metrics are achieved using the proposed coordinated charging optimization compared to uncoordinated charging on 10 test cases.

1 INTRODUCTION

Growing recognition of the contribution of internal combustion engines to global warming, the desire to reduce reliance on foreign oil, and volatility of the cost of fuels such as gasoline and diesel have been accelerating the adoption of PEVs [18]. However, this poses significant challenges for the existing power infrastructure, which is not designed for the severe short-term overloads that uncoordinated PEV charging tends to produce. As a result, the existing infrastructure will require significant costly upgrades, limiting the rate of PEV adoption and increasing costs to both utilities and customers.

Although many optimization methods are proposed in the literature, none focus on lowering the impact on the electrical distribution infrastructure. Additionally, the proposed methods use simplified statistical assumptions or small and under resolved datasets to develop their methods.

We propose an optimal coordinated charging tool that will lower the negative impacts of PEV adoption on local power grid transformers by reducing power demand variation, significantly increasing transformer life. We will create an interactive user dashboard that will allow users to choose different temporal and PEV market share scenarios and evaluate the resulting optimization's effect on different local transformer networks using various visualizations of power consumption and relevant metrics. The dashboard will interface with a database of highly resolved residential and PEV charging data.

This project is both unique and innovative for the following reasons:

1. We use a highly resolved year-long database of residential and PEV charging data
2. We optimize the PEV charging schedule in order to reduce the impact on local power infrastructure
3. We provide a dashboard to allow a user to explore the effects of the optimization on different date and PEV market shares across an electrical network consisting of 200 houses and 33 transformers with real-time calculations

Problem Statement: Uncoordinated charging of PEV vehicles can cause severe short-term overloading of local electrical distribution transformers, which will require costly infrastructure upgrades if left unmanaged.

2 LITERATURE REVIEW

The rapid expansion of PEVs' market share has the potential to impact the electric infrastructure of the U.S [7]. The growth is related to regulatory changes that have been adopted to reduce harmful emissions. The particulate matter emitted by vehicles with internal combustion engines is one of the leading causes of pollution in large urban centers [20], and the health and climate benefits of reducing household greenhouse gas emissions have been well-documented [23]. However, most of the existing U.S electrical system is old and not designed to handle the rapid increase in electricity demand from PEVs and will require significant investments to improve reliability [8]. The increase of power demand caused by electric vehicles can overload the system during peak hours, specifically when considering a scenario where most people return to their homes from work and start charging their cars which can take several hours [11]. This study will help power distribution companies manage increasing demand, reduce costs to customers, and accelerate PEV adoption [17].

Many previous studies relied on assumptions, simulations, or averaged statistics to generate low fidelity charging profiles that are generally not publicly available [3, 4, 16]. The data used in this study consists of three separate data sets, which contain electrical demand profiles of residential households, level 1, and level 2 PEV vehicles taken at 10-minute intervals over an entire year. The residential household data set represents the electricity demand of 200 random households selected from RECS survey data [13] and is calculated based on the model provided by Muratori et al. [14]. The level 1 data set represents 348 PEVs charging at 1920 W, and the level 2 PEV data represent 348 PEVs charging at 6600 W [15]. All three data sets are available to the public [12].

In this study, we aim to minimize the impact of PEV charging on local residential distribution transformers. Various studies identify the factors that contribute to the usable life of an electrical transformer. Studies have identified cyclic heat loads as a critical contributor to transformer life [4, 9, 10, 24]. These studies show transformer life decreases exponentially with the amount of time and magnitude that the transformer operates above the mean operating power. However, actual data and models related to thermal loading effects of PEVs on local transformers are limited, so the use of cyclic power demand has been used as a proxy [5]. In this study, we will use the standard deviation of power demand and a load severity index $\alpha(1.5)$, defined in [13], as metrics to optimize and evaluate PEV charging. Both metrics quantify the daily variation of power demand, which will allow us to optimize charging to increase transformer life. It is noted that transformers are designed to withstand short-term overloads, and therefore this project will focus on aggregated 1-hour time intervals [2].

Many previous studies optimize electric vehicle charging for various reasons. [19, 21, 22] optimize PEV charging and discharging to integrate them as energy storage devices used to stabilize grids. [16] proposes strategies for optimizing PEV charging schedules in order to reduce electricity costs. However, none of these studies attempt to reduce the effects on local infrastructure. [6] proposes an optimization model which shaves the peaks and fills the valleys of power consumption at a university building by leveraging electric vehicles charging at a local parking lot as storage devices to reduce peak power consumption. Our project will use similar techniques and algorithms but focus on reducing standard deviation and $\alpha(1.5)$, resulting in less stress on a local transformer and increased transformer life..

3 METHODOLOGY

3.1 Data

The raw data for the electrical demand profiles of residential households, level 1, and level 2 PEV vehicles are available as multiple .xlsx files available on a public repository at the National Renewable Energy Lab website [12]. For this work, the data is collected, processed, transformed, and stored in SQLite 3 database as shown in Figure 1.

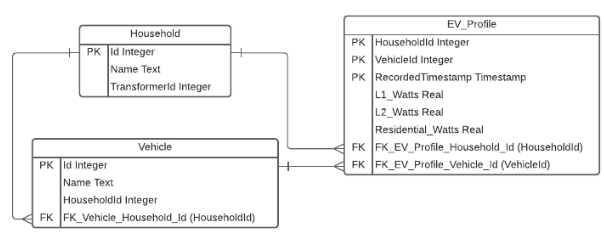

Figure 1: SQLite 3 - Entity Relationship Diagram

Table 2 provides further insights into database metrics such as size and number of rows.

Data exploration reveals that vehicles typically charge over continuous multi-hour periods. Therefore, we have decided to optimize aggregated 1-hour intervals in our model. SQL queries are used in real-time to extract, process, aggregate, and return the correct data for the optimization giving the user-defined variables in the

Table 1: Database Metrics

Metric	Value
Total Size	2.20 GB
Total Households Count	200 rows
Total Vehicles Count	348 rows
Total Transformers Count	33 rows
Total EV Profiles Count	18,290,532 rows

dashboard. Descriptions of a sample of relevant SQL queries are given below:

1. **all_households_list**: returns list of all households
2. **household_list**: returns list of households connected to a given transformer.
3. **household_hourly_usage**: returns power usage across all houses connected to a given transformer on a specified date in 1-hour intervals.
4. **pev_1_hourly_usage**: returns power usage across n random PEV Level 1 vehicles connected to a given transformer on a specified date in 1-hour intervals.
5. **pev_2_hourly_usage**: returns power usage across n random PEV Level 2 vehicles connected to a given transformer on a specified date in 1-hour intervals

3.2 Metrics

The goal of this work is to decrease the damage to transformers caused by un-coordinated vehicle charging. As mentioned in the literature review, transformer life decreases exponentially with the amount of time and magnitude that the transformer operates above the mean operating power. Our optimization aims to flatten the power demand curve representing the daily power distribution on a single transformer, resulting in increased transformer life. The metrics used to evaluate our optimization's performance are standard deviation (σ), severity index ($\alpha(1.5)$), and peak power demand. Equations formally describing σ and $\alpha(1.5)$ can be seen in Equations 1 and 2, respectively.

$$\sigma = \sqrt{\frac{1}{N} \times \sum (x - \mu)^2} \tag{1}$$

$$\alpha(1.5) = \frac{100 * \sum (TPH > (\alpha \times \overline{TPH}))}{24} \tag{2}$$

Where:

TPH: Total Hourly Power Demand

$\alpha(1.5)$ is a metric developed explicitly in [13] to quantify a power demand's effect on transformer life and represents the % time a transformer spends above 1.5 times the mean power demand. We note that peak power and $\alpha(1.5)$ demand may be only an effect of residential power demand and un-affected by the vehicle charging optimization in some cases.

3.3 Optimization Algorithm

The optimization problem posed in this project is a discrete combinatorial optimization problem. Given a fixed residential power demand for each hour of the day, arrange the fixed discrete hourly vehicle power demand to minimize the difference between the maximum and minimum hourly power demand, which in turn should lower standard deviation, severity index, and possibly peak power demand. An optimization problem of this nature is NP-complete and can therefore be solved using brute force. However, this is not feasible in the time frames desired for this project to allow real-time optimization within the dashboard. We have chosen to solve this problem using a customized implementation of a multi-knapsack dynamic programming solver library in R named adagio [1].

The multi-knapsack solver attempts to maximize the profit of a discrete number of items with weight (w) and price (p) by arranging the items in *n* knapsacks (m), each with a given maximum capacity of (k). For this problem, each 24 hour period of a day is a knapsack with a capacity inversely proportional to the residential demand for that hour. Each item is an hour bin with a weight equal to the total aggregate vehicle demand for that hour, and all items are assigned the same price. To solve our actual objective, we implement a loop that solves the multi-knapsack solver as described above, with each loop equally decreasing knapsack capacities until all items can no longer fit into the backpacks. The final arrangement is an approximate solution to our objective. Algorithm 1 gives a formal description of the implementation.

3.4 Dashboard

R Shiny is used to create the interactive dashboard for this work. Shiny is an open-source R package that facilitates interactive web applications and visualizations directly from R. Shiny also allows for R, CSS, HTML,

Algorithm 1: Customized Optimization

Set price of each item = 1;
Set knapsack capacity inversely proportional to residential demand;
Run knapsack solver once to get initial knapsack item assignments;
while *All items fit in at least* 1 *knapsack* **do**
  Decrease all knapsack capacity by some amount n;
  Run dynamic program knapsack solver to maximize profit;
end
Result: Optimized Vehicle charging demand

and D3.js integration and provides web-hosting capabilities. The dashboard will allow a user to explore the optimization tools' effect on various date, transformer, and PEV level 1 and 2 market share scenarios.

The dashboard provides functionality for the user to choose a date, PEV market share scenarios, and a specific transformer at the selected variable values to optimize via various user input controls on the left side of the dashboard. Once chosen, the user can click on an "apply" button to run the optimization algorithm on the selected inputs.

After the optimization algorithm is complete, 3 fields in the main window of the dashboard are updated with the following information. A heatmap is created displaying all 33 transformers. The heatmap is colored using a relative scale based on the calculated σ for each transformer given the selected inputs. The heatmap is used for selecting specific transformers that would benefit from optimization. The second field contains a bar plot showing the hourly electricity demand for residential and PEVs for the selected inputs and transformer before and after optimization. The third field displays a table with the calculated values of σ, $\alpha(1.5)$, and peak power for the selected inputs and transformer before and after optimization. Additional interactive capabilities such as zoom, data tips will be implemented for the plots. An example of the dashboard after optimization can be seen in figure 2.

4 EXPERIMENTS

Experiments designed to evaluate the efficiency, effectiveness, and stability of the optimization tool for a wide range of scenarios are listed below in Table 2. A total of 10 test cases were chosen with random values selected for the input variables transformer number $(1-33)$, date (any date in the year 2010), and level 1 and 2 Market share (0.1 - 0.5). Note that the ranges for market share are limited such that the combined value of the PEV market share can not exceed 1.0, which would indicate that all vehicles driven by the residences are electric.

Table 2: Experiments for Testing Tool

Exp.	Trans. #	Date	% L1 Share	% L2 Share
1	5	05/22/2010	50	50
2	21	09/27/2010	20	40
3	13	01/06/2010	40	40
4	32	07/17/2010	10	50
5	2	03/11/2010	30	30
6	33	11/04/2010	50	20
7	17	04/30/2010	40	50
8	29	08/15/2010	10	10
9	14	03/03/2010	30	40
10	2	10/28/2010	30	50

The experiment results showing the unoptimized and optimized $\alpha(1.5)$ are presented in table 3. $\alpha(1.5)$ decreased more than 30% in 7 of the 10 experiments. 2 experiment cases resulted in severity index decreasing to 0. The optimizations for cases $2, 6, and 8$ result in no decrease in severity index. These results indicate that $\alpha(1.5)$ for those specific test cases are driven primarily by residential power demand, not PEV charging.

Table 3: Severity Index (-) For Experiments

Exp.	Unoptimized	Optimized	% Change
1	17	8	-53
2	4	4	-0
3	8	0	-100
4	33	21	-36
5	4	0	-100
6	4	4	-0
7	17	4	-76
8	17	17	-0
9	12	4	-67
10	12	8	-100
Average	13	6	-53

Figure 2: Interactive dashboard displaying transformer heatmap, stacked bar plot of electrical demand before and after optimization, and evaluated metrics before and after optimization

The experiment results showing the unoptimized and optimized σ are presented in table 4. σ decreased 29% or more in all experiments. These results indicate that the σ of electrical charging demand can be reduced in significant amounts even in cases with low overall PEV adoption rates.

The experiment results showing the unoptimized and optimized peak power demand are presented in table 4. Peak power demand decreased an average of 17% over the 10 experiments. Experiment case 6 showed no decrease in peak power. This is because the hour containing the peak value has no vehicles charging for this particular scenario.

Table 4: Standard Deviation (kW) For Experiments

Exp.	Unoptimized	Optimized	% Change
1	35	14	-60
2	44	18	-59
3	19	10	-47
4	59	48	-19
5	43	22	-49
6	27	17	-37
7	24	14	-42
8	24	17	-29
9	28	13	-53
10	47	17	-64
Average	35	19	-46

Table 5: Peak Power Demand (kW) For Experiments

Exp.	Unoptimized	Optimized	% Change
1	144	100	-31
2	231	186	-20
3	95	74	-22
4	196	183	-7
5	218	182	-16.5
6	146	146	0
7	108	100	7.4
8	106	78	26.4
9	124	99	20.2
10	229	173	25
Average	160	132	-17

A stacked bar plot showing the hourly power demand for unoptimized and optimized case 10 can be seen in Figure 3.This plot demonstrates the optimization algorithm's objective of flattening out the daily power demand by re-distributing the PEV electric charging bins.

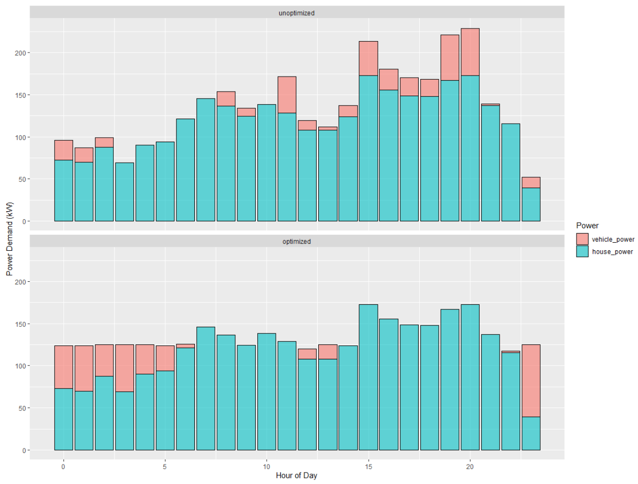

Figure 3: Stacked bar plot showing hourly power demand before and after optimization for case 10.

Although not directly relatable, the observed reduction of all 3 metrics in this work is comparable and often better compared to models based on simplified inputs and data in the literature [10].

The dashboard generally runs efficiently enough to allow for real-time optimization. Initial loading of the optimized metrics for each transformer on a specific date takes approximately 1 minute. The actual optimization algorithm and plot update process for a specific transformer and market share scenario generally runs in less than 10 seconds. However, a small number of cases took significantly longer. One of these cases required approximately 5 minutes to optimize, and another ran for approximately 1 hour before manually stopping it. However, this accounted for only a tiny sample of the tested scenarios. All cases were tested on a desktop home computer with 128 GB ram and an Intel i9 processor @ 3.70GHz.

5 CONCLUSIONS

The push to increase the adoption of PEVs has raised concerns over the suitability of the existing electricity distribution system. Uncoordinated PEV charging at even modest market shares has been shown to greatly increase local transformer energy demand variation, contributing to decreased useable life and the necessity for costly infrastructure upgrades. We propose a coordinated PEV charging tool that optimizes charging to minimize the effects on local distribution transformers. The dashboard-based tool uses a high-fidelity database of historical residential and PEV charging profiles to allow a user to explore the effect of the algorithm on different PEV charging scenarios.

The algorithms and dashboard were developed using the R programming language and interface with an SQLite database. The efficiency, effectiveness, and stability of the coordinated charging tool are evaluated on 10 test cases. The 3 metrics of interest showed significant improvements on average with σ, $\alpha(1.5)$, and peak power values decreasing by 46, 53, and 17% respectively. However, certain combinations outside of the 10 test cases did result in long optimization run times.

The future scope of this work is to extend the capabilities of this tool to ultimately operate as an automated optimization tool deployed in-situ in the electrical infrastructure using real-time data. Immediate next steps in this development may include increasing the scalability of the optimization algorithm, using machine learning to determine windows of charging availability given the history of a residence's power usage, and developing or incorporating existing models to enable PEVs usage as an alternative energy storage devices.

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