Article

Novel PEV Charging Approaches for Extending Transformer Life

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Abstract: The study investigates how variable rate charging can affect PEV charging and identifies how this capability can be integrated into residential neighborhoods. The results show that creating PEV chargers that can deliver variable rates will enhance uncontrolled and controlled PEV charging. The integration is summarized into 4 phases. In phase 1, uncontrolled PEV chargers should be enabled to provide any rate to vehicles within 0 to 11.5 kW, which can reduce overloading by up to 28.34%. Phase 2 introduces smart chargers that use forecasted data to determine the optimal time intervals for PEVs to charge using a fixed rate of 4.8 kW, capable of reducing overloading by 42.69%. In Phase 3, a controlled smart charging strategy that can deliver any rate to a vehicle using SRVF’s approach is proposed, which will reduce overloading by up to 42.87%. Lastly, phase 4 recommends a smart charging control that can deliver any rate to a vehicle using RIVF’s approach, reducing overloading by up to 43.37%.

Keywords: energy usage; plug-in electric vehicle; valley filling; distribution transformer; electric vehicle charging; smart charging

1. Introduction

Plug-in electric vehicles (PEVs) are gaining popularity due to the depletion of natural resources, increased need for better energy efficiency, and policies aimed at decreasing greenhouse gas emissions [1]. Unlike traditional vehicles, which use gasoline and an internal combustion engine to power the vehicle, PEVs rely on an onboard battery that is fueled by electricity generated from external sources [2]. PEVs are able to operate more efficiently than traditional internal combustion engine vehicles due to the advancements in power generation from renewable energy and natural gas combined-cycle power plants [3]. The positive recognition has resulted in PEVs gaining large-scale acceptance and adoption [4]. Despite the positive impacts from increased PEV usage, numerous studies have indicated that increased PEV adoption can have a negative impact on electric demand, overload the current network, and damage residential distribution transformers [5–11].

Large-scale PEV adoption can cause residential transformer overloading because people generally arrive home and plug in their vehicles near the same time, producing large demand loads that exceed the limits that the current grid infrastructure was designed for [4]. Valley-filling techniques are used to mitigate damage from unregulated charging. Valley-filling is a charging protocol that strategically charges PEVs during low-demand periods, taking advantage of the “valleys” in the load curve.

Multiple PEV charging algorithms [12–17] have demonstrated promising results using valley-filling; however, these charging strategies are designed to solve a “global” valley-filling problem. Global solutions do not guarantee optimal results for localized distribution transformers, although Sanchez et al. show that by modifying the optimization constraints when there is not enough available power to charge all the PEVs connected to a system, global solvers can be effective [18]. Ramos Munoz et al. [19] expand the global grid valley-filling technique presented by Zhang et al. [17] by ensuring that the transformer limitations
from the IEEE C57.91 standard [20] are satisfied. This protocol could extend transformer life further if all transformer demands are optimized instead of focusing on transformers with demands that exceed operational limits.

Shao et al. [21] explore residential PEV charging under the use of demand load staggering and home load reduction. Staggering is a technique that enables residential PEV charging when a home’s demand load is lower than a preset threshold. Home load reduction techniques schedule large non-critical loads like washing machines around the time when PEVs charge. Using quadratic and dynamic programming, Clement et al. [22,23] employ stochastic programming to estimate household loads to resolve residential charging by optimizing the main grid load factor and reducing power losses. Limiting power losses is also used by Deilami et al. [24] to address uncontrolled charging. This algorithm is modified with maximum sensitivities selection (MSS) optimization for real-time functioning.

Met et al. [25] use iterative quadratic programming to reduce the difference between an optimal load and the baseload to determine the ideal charging profile. Gong et al. [26] produce a genetic algorithm that minimizes the loss of life factor of the distribution transformer. Han et al. [27] present an optimal scheduling algorithm for PEVs and assume that the maximum charging power can vary according to the current state of charge. Smith et al. [28] introduce a strategy that can adjust to significant unforeseen variations in the forecasted baseload and prove that its real-time capabilities outperform systems that apply optimization approaches on projected baseload data when the expected and actual baseload differ by more than 20%. In addition, many other studies in the literature [29–32] assume that the vehicles charge by using a continuous charging scheme. All the aforementioned methods demonstrate that they are effective, but they assume that the vehicles in the study accept any rate of charge between 0 kW and the vehicle’s maximum charging rate; however, most current commercial, residential plug-in electric vehicle chargers do not deliver variable charging rates to a vehicle and none take into account valley filling relative to transformers. Current commercial, residential charging technology is categorized into three charging levels and distributes a fixed-rate that exists between the bandwidth of that category.

This work will create a practical dataset to reflect realistic charging demand and investigate how charging profiles are affected by variable rate charging to identify the benefit commercial residential charging technology could gain by implementing the capability of delivering a variable charging rate. Two procedures are developed and compared: Selected Rate Valley-Filling (SRVF) and Rate Interval Valley-Filling (RIVF). The purpose of this study is to contribute to creating a more sustainable future and discover the following:

1. How can vehicle charging be enhanced by creating chargers that can deliver variable rates?
2. If plug-in electric vehicle charging is enhanced by creating chargers that can deliver variable rates, is it limited to uncontrolled or controlled strategies?
3. Does the method that a smart charger utilizes deliver variable rates to a vehicle significantly affect how well the algorithm can reduce transformer overloading?
4. Can variable-rate uncontrolled PEV charging reduce transformer overloading better than fixed-rate controlled PEV charging?
5. If variable-rate controlled PEV charging does not perform significantly better than fixed-rate controlled PEV charging, what is an optimal fixed-rate that should be adopted?

2. Materials and Methods

2.1. Problem Formulation

The charging processes presented in this study are detailed in this section. Both systems create the final charge profile for a PEV by identifying the optimal charging intervals to lower the average load while charging and providing charging rates of 0 to 11.5 kW. SRVF evaluates several fixed-rate charging patterns and determines which rate increased the average load while charging the least. RIVF produces a charging profile for a vehicle by combining several rates through the total charging period. Although SRVF is
intrinsically more limited than RIVF, the findings are compared to see whether the greater charging rate variability in RIVF is useful.

The winding hot spot temperature (HST) rises when the transformer load factor (a ratio of the measured load to the stipulated limit) grows, according to Razeghi et al. [10]. The aging acceleration factor (AAF) is a metric for determining how much a changing load impacts transformer life. According to the IEEE C57.91 standard, the AAF is determined using Equation (1), which demonstrates that higher HST values increase the AAF [20].

\[
AAF = \exp \left( \frac{15,000}{383 - 15,000 \theta_{HST} + 273} \right)
\]  

(1)

Each time step’s AAF is calculated and utilized to calculate the equivalent aging factor, EAF, as shown in Equation (2).

\[
EAF = \frac{\sum_{i=1}^{N} AAF_i \Delta t_i}{\sum_{i=1}^{N} \Delta t_i}
\]  

(2)

The loss of life percentage (LOL%) is computed by multiplying the number of operating hours by EAF and dividing by the typical insulating life of 180,000 h.

\[
LOL\% = EAF \times \frac{\sum_{i=1}^{N} \Delta t_i \times 100}{180,000}
\]  

(3)

The purpose of this initiative is to reduce the percentage of transformers that fail by focusing on HST reduction. It will be done by decreasing the average transformer load during charging, as well as the observed load, load factor and, as a result, the HST.

In this study, it is assumed that the smart chargers that customers are using have the algorithms, highlighted in this work, embedded within them. The smart charger calculates when to charge the car based on the user’s inputs and the expected baseload. The smart charger is linked to a central distribution transformer and gets real-time baseload changes. The requested amount of energy, \( r_i \), current charge, \( c_i \), arrival time, \( a_i \), and dwell time, \( d_i \), are all inputs from the user, vehicle \( i \). The baseload, \( L \), is averaged into 0.25-h intervals for the period of \( d_i \), each time vehicle \( i \) plugs in, resulting in a localized baseload for vehicle \( i \), \( L_i \). The length of \( L_i \), creates \( k_i \), which represents the number of time periods in which vehicle \( i \) may charge.

2.2. Selected Rate Valley-Filling Methodology

SRVF assesses the available rates of charging for a PEV and calculates the optimal constant rate and charging intervals to minimally increase the demand load. Figure 1 is a graphical representation of SRVF, demonstrating how the algorithm operates. The rate vector, \( \overline{R}_i \), of length \( k_i \), is produced when vehicle \( i \) plugs in, as indicated in Equation (4). Each component of \( \overline{R}_i \) is a fraction, where \( r_i \) is divided by the row number, \( j \). These components indicate the different constant rates that the vehicle may use to charge to the kilowatt-hours that it has requested.

\[
\overline{R}_i = \begin{bmatrix} R_{i,1} \\ R_{i,2} \\ \vdots \\ R_{i,k_i} \end{bmatrix}, \text{ where } R_{ij} = \frac{r_i}{j} \text{ and } j = 1, 2, \ldots, k_i
\]  

(4)

The vector, \( S_i \), is created by sorting the localized baseload, \( L_i \), in ascending order. The provided charging rate (power) and the time intervals at which it is applied are the optimization variables in this method, which may be simplified to the row number, \( j \), inside
Equations (5) and (6) are the objective function, which decides which $R_{i,j}$ delivers the lowest average load during charging for vehicle $i$.

$$\min_{j} \frac{1}{j} \sum_{m=1}^{j} (S_i(m) + R_{i,j})$$ (5)

Subject to

$$R_{i,j} \leq 11.5$$ (6)

The variable, $j^*$, refers to the $j$ that fulfills Equations (5) and (6). Using Equation (7), $R_{i,j^*}$ is added to the timeslots in $L_i$, indexed by the corresponding indices of $S_i(1:j^*)$, to generate the charging profile for vehicle $i$, $CP_i$.

$$CP_i = L_i(S_i(1:j^*)) + R_{i,j^*}$$ (7)

2.3. Rate Interval Valley-Filling Methodology

RIVF analyses all conceivable rates a vehicle may get and determines the ideal rate a PEV should charge at every time interval to reduce the average transformer load while charging. Figure 2 is a visual representation of RIVF, demonstrating the algorithm's process flow. The program will use a notion from [25] to minimize the disparity between the actual and ideal load.

When vehicle $i$ plugs in, Equation (8) calculates $A_i$, the average baseload value over vehicle $i$'s dwell duration. Dividing $r_i$ by $k_i$, as given in Equation (9), the fixed-charger load, $F_i$, is calculated.

$$A_i = \frac{1}{k_i} \sum_{m=1}^{k_i} L_i(m)$$ (8)

$$F_i = \frac{r_i}{k_i}$$ (9)

Equation (10) generates a row vector of zeros the length of $k_i$, initializing $CP_i$ for each vehicle $i$.

$$CP_i = \text{zeros} \ (1 \times \ # \ of \ available \ charging \ intervals)$$ (10)

In Equation (11), $A_i$ and $F_i$ are combined to generate the optimum load, $O_i$.

$$O_i = F_i + A_i$$ (11)
In Equation (12), \( C_i \), the charging intervals is computed, subtracting the localized baseload, \( L_i \), from \( O_i \). The corresponding intervals in \( C_i \) are positive when \( O_i \) are greater than \( L_i \) indicating where PEV charging should be scheduled. If one of the elements in \( C_i \) are negative, it is limited to zero.

\[
C_i = O_i - L_i
\]  

(12)

In Equation (13), the charging rates in \( CP_i \) are incrementally increased by 0.1 kW using a while loop. The index of \( C_i \)'s greatest value is identified, and 0.1 kW is added to the corresponding indexed interval in \( CP_i \) and \( L_i \). The procedure is continued until \( CP_i \) satisfies \( r_i \).

\[
\text{While } \sum (CP_i \times 0.025 \text{ h}) \leq r_i \\
\quad t = \text{index}(\max(C_i)) \\
\quad CP_i(t) = 0.1 + CP_i \\
\quad L_i(t) = 0.1 + L_i
\]

(13)

Figure 2. RIVF flow chart.

2.4. Transformer Data

This study’s transformer data was collected on 25 September 2014, from a 75 kW house transformer in Irvine, California, and will be used to simulate expected demand. The lowest and highest temperatures for the day were 22.2 °C (72.0 °F) and 31.1 °C (88.0 °F), respectively. The demand before any PEV charging demand is applied is the transformer’s baseload. This study’s transformer supplies electricity to 20 residences with surface areas ranging from 176.5 to 269.4 m² (1900 to 2900 ft²). Electric car charging was not included in the transformer baseload in this study, and data was collected every 5 min.

The demand curve utilized in this research was recorded from midnight to midnight. The load profile is extended from 24 to 48 h, with the middle 24-h (hours 12 through 36) serving as the baseload, resulting in an overnight period spanning from noon to noon, as illustrated in Figure 3. From hereon, this baseload will be referred to as the forecasted baseload.

2.5. Transformer Data

The PEV data presented in this study is generated to emulate realistic driving patterns and energy needs in the present day. The PEV dataset used includes details that reflect current:

- Commute distances
- Commute times
Vehicle charging needs
• Travel time distribution
• Vehicle model type distribution

50,000 driver patterns were assumed. Each driver is placed within a category of 5 different work schedules, using ratios found in the Job Flexibilities and Work Schedules Summary published by the U.S. Bureau of Labor Statistics [33]. The drivers within each work schedule have a mean start time shown in Table 1. The actual time when each driver in each category arrives to work is determined using a normal gaussian distribution with a 30-min standard deviation. For example, all of the workers in the day-schedule arrive to work between 6:00 a.m. and 9:00 a.m., following normal gaussian distribution with a mean value of 7:30 a.m.

Figure 3. Transformer baseload on 25 September 2014.

Table 1. User workplace scheduling patterns.

| Schedule    | Percentage | Mean Start Time | Time Duration |
|-------------|------------|-----------------|---------------|
| Day         | 84%        | 7:30 a.m.       | 8 h           |
| Evening     | 6%         | 3:30 p.m.       | 8 h           |
| Night       | 4%         | 11:30 p.m.      | 8 h           |
| Day Shift   | 3%         | 5:00 a.m.       | 12 h          |
| Night Shift | 3%         | 5:00 p.m.       | 12 h          |

The Bureau of Transportation Statistics (BTS) Omnibus Household Survey is used to obtain the commute time and distance for each driver from home to the workplace [33]. This document was published in 2003; however, a study from The Washington Post shows that commute times have increased 6.27% since 2003 [34]. We multiplied each commute time and distance listed in the (BTS) Omnibus Household Survey by 6.27% to transform the data measured in the 2003 study to reflect 2019 driving patterns. Figure 4 below shows the final distribution of commute distance, plot (A), and time for each driver, plot (B), in this study.
Table 2 shows five common activities that are randomly added to the end-of-day shift workers. The table shows the percentage of the day-shift population that engages in each activity and how much the activity increased their commute home in terms of distance and time.

Table 2. Common activities people engage in after work.

| Activity              | Engaged Population | Added Time to Commute | Added Distance to Commute |
|-----------------------|--------------------|------------------------|---------------------------|
| Caring for and helping household members | 14.6%  | 30 min | 3 miles |
| Leisure and sports   | 28.7%  | 1 h     | 3 miles |
| Purchasing goods and services | 40.8%  | 1 h     | 3 miles |
| Eating and drinking  | 19.5%  | 1 h     | 3 miles |
| Personal care         | 3.4%   | 1 h     | 3 miles |

The total size of the data set is 50,000 vehicles. This study will implement a penetration assumption from Zhang et al. [17] and Ramos Munoz et al. [19] that 9 out of 20 vehicles per residential block are electric. This assumption translates to randomly extracting 22,500 vehicles from this set and assuming they are electric. Finally, this study assumes that the vehicle types of the 22,500 electric vehicles are distributed in the same ratio as reported in Forbes America’s Best-Selling Electric Cars in 2020 [36]. Figure 5 depicts the distribution of the vehicle types.
Each vehicle’s individual kWh per mile ratio is referenced using the U.S Department of Energy’s Fuel Economy website [37] and is shown in Table 3.

Table 3. Plug-in vehicle fuel economy.

| Vehicle Model  | kWh/100 miles |
|----------------|---------------|
| Tesla Model 3  | 26            |
| Tesla Model Y  | 28            |
| Tesla Model X  | 33            |
| Chevy Bolt     | 29            |
| Tesla Model S  | 31            |
| Nissan Leaf    | 30            |
| Audi e-tron    | 44            |
| Porsche Taycan | 49            |

The information regarding each user’s electric vehicle model and fuel economy is used to determine each driver’s kWh need once they return home. For example, if a driver from the day-shift has a 20-mile commute to work from home, goes to a gym to exercise and a supermarket to buy groceries after work (adding 6 miles total), and drives a Tesla Model 3 (which needs 26 kWh per 100 miles driven), then they would drive 46 miles total and need 11.96 kWh when they return home.

3. Results and Discussion

Without smart charging protocols, vehicles begin charging immediately when they are plugged in, despite the time or current demand load, which is referred to as uncontrolled charging. In this study, seven cases are created to simulate seven different rates that are used in uncontrolled charging. Cases 1 through 6 use 1.9, 3.3, 4.8, 7.2, 9.6 and 11.5 kW, respectively. Case 7 uses a variable-rate that ranges between 0 and 11.5 kW. Case 7’s rate is determined by dividing a vehicle’s requested charge by its dwell time. If this rate exceeds 11.5 kW, it is saturated to this value.

The graphical results for cases 1–7 of uncontrolled charging applied to the baseload are shown in Figure 6. Each subplot represents a different rate at which the PEVs are charged. The red curve in these figures represents the baseload. Each one of the 2500 green curves reflects the total load seen by a single transformer. The transformers’ rated limit, 75 kW, is shown in blue.

Table 4 shows the results from the seven simulated uncontrolled charging cases. Focusing on the six cases that use a fixed-rate to charge the PEVs, case 1 produces the smallest overload, and case 6 produces the largest overload. In case 1, each car requires 1.9 kW to charge, and the absolute maximum peak power attained across all transformers, the average maximum peak power reached by each transformer, and the average load generated while charging are, respectively, 98.33 kW, 90.92 kW, and 59.02 kW. In case 6, the absolute maximum peak power attained across all transformers, the average maximum peak power reached by each transformer, and the average load during charging are 153.14 kW, 109.11 kW, and 77.73 kW, respectively. In case 7, which uses any rate between 0 and 11.5 kW, and the absolute maximum peak power attained across all transformers, the average maximum peak power reached by each transformer, and the average load during charging produced are 95.84 kW, 88.95 kW, and 55.70 kW, respectively. Case 7 demonstrates that overloading from uncontrolled charging can be reduced without smart charging. Current chargers, which do not rely on forecasted data, can be enhanced by creating chargers that can deliver variable rates.

Unlike uncontrolled charging, smart charging protocols do not immediately begin charging vehicles when they are plugged in. The algorithm will analyze the forecasted load, a vehicle’s energy needs, and how long a vehicle is connected to the grid to determine the optimal time intervals that vehicle should charge to minimize the demand load. In this study, eight cases are created to simulate eight different rates being used in controlled charging. Cases 1 through 6 use 1.9, 3.3, 4.8, 7.2, 9.6 and 11.5 kW, respectively. The controlled
charging protocols used in these cases function similarly to the strategies outlined in Anh et al. [14] and Zhang et al. [17]. Fixed-rate controlled charging will be implemented in this study by modifying SRVF to only have one rate in the rate vector it uses to select the optimal rate. Cases 7 and 8 use a variable-rate that ranges between 0 and 11.5 kW. Case 7 uses SRVF to determine what rate PEVs receive, and case 8 utilizes RIVF.

Figure 6. Charging profiles created from (a) 1.9 kW, (b) 3.3 kW, (c) 4.8 kW, (d) 7.2 kW, (e) 9.6 kW, (f) 11.5 kW, and (g) 0–11.5 kW uncontrolled charging.
Table 4. Demand from each uncontrolled case.

| Case # | Case Type      | Absolute Maximum Peak (kW) | Average Maximum Peak (kW) | Average Load during Charging (kW) |
|--------|----------------|-----------------------------|---------------------------|----------------------------------|
| 1      | Uncontrolled 1.9 kW | 98.33                      | 90.92                     | 59.02                            |
| 2      | Uncontrolled 3.3 kW | 106.23                     | 92.17                     | 65.91                            |
| 3      | Uncontrolled 4.8 kW | 113.48                     | 94.34                     | 69.79                            |
| 4      | Uncontrolled 7.2 kW | 123.18                     | 99.33                     | 73.03                            |
| 5      | Uncontrolled 9.6 kW | 139.33                     | 104.93                    | 75.67                            |
| 6      | Uncontrolled 11.5 kW | 153.14                     | 109.11                    | 77.73                            |
| 7      | Uncontrolled 0–11.5 kW | 95.84                      | 88.95                     | 55.70                            |

Figure 7 demonstrates the outcomes when regulated charging is applied to the baseload, same as Figure 6. The curves in each subplot correspond to the same parameters as those in Figure 6. Each subplot in Figure 7 has 2500 green curves, each of which represents the whole load observed by one transformer. Figure 6 shows vehicles charging without a scheduling system (uncontrolled charging), which means they begin charging as soon as they get home. This results in a lot of fluctuation between the 2500 green curves, resulting in little overlap between the curves and giving the impression that there is a lot of charging going on due to the visible green shading. Vehicles in Figure 7, on the other hand, are charged under valley-filling methods. Regardless of when each car arrives at its perspective home, most of the vehicles in Figure 7 start charging at roughly the same time. Because there is a limited amount of apparent green shading, there is very little variance between the 2500 green curves, resulting in a substantial overlap between the curves and giving the impression that very little charging is taking place.

Table 5 shows the results from the 8 simulated controlled charging scenarios, cases 8–15. Focusing on the six cases that use a fix rate to charge the PEVs, case 13 produces the smallest overload and case 8 produces the largest overload. In case 13, each vehicle uses 11.5 kW to charge, and the absolute maximum peak power reached amongst all transformers, the average maximum peak power reached by each transformer, and the average load during charging produced are 86.58 kW, 86.58 kW, and 46.77 kW, respectively. In case 8, each vehicle receives 1.9 kW to charge, the absolute maximum peak power attained across all transformers, the average maximum peak power reached by each transformer, and the average load during charging produced are 90.73 kW, 87.73 kW, and 49.15 kW, respectively.

Table 5. Demand from each controlled case.

| Case # | Case Type      | Absolute Maximum Peak (kW) | Average Maximum Peak (kW) | Average Load during Charging (kW) |
|--------|----------------|-----------------------------|---------------------------|----------------------------------|
| 8      | Controlled 1.9 kW | 90.73                      | 87.73                     | 49.15                            |
| 9      | Controlled 3.3 kW | 89.88                      | 86.60                     | 45.11                            |
| 10     | Controlled 4.8 kW | 87.93                      | 86.58                     | 44.55                            |
| 11     | Controlled 7.2 kW | 86.58                      | 86.58                     | 44.99                            |
| 12     | Controlled 9.6 kW | 86.58                      | 86.58                     | 45.85                            |
| 13     | Controlled 11.5 kW | 86.58                     | 86.58                     | 46.77                            |
| 14     | SRVF            | 86.58                      | 86.58                     | 44.41                            |
| 15     | RIVF            | 86.58                      | 86.58                     | 44.02                            |

Case 14 uses SRVF to deliver any rate between 0 and 11.5 kW to vehicles. The maximum peak power from the baseload, the absolute maximum peak power attained across all transformers, and the average maximum peak power achieved across all transformers are 86.58 kW, 86.58 kW, and 46.77 kW, respectively, according to this technique. The absolute maximum peak power attained across all transformers, the average maximum peak power reached by each transformer, and the average load during charging generated by Case 15 are 86.58 kW, 86.58 kW, and 46.77 kW, respectively, when using RIVF to determine what rate a car receives.
Table 5 shows the results from the 8 simulated controlled charging scenarios, cases 8–15. Focusing on the six cases that use a fixed rate to charge the PEVs, case 13 produces the smallest overload and case 8 produces the largest overload. In case 13, each vehicle uses 11.5 kW to charge, and the absolute maximum peak power reached amongst all transformers, the average maximum peak power reached by each transformer, and the average load during charging produced are 86.58 kW, 86.58 kW, and 46.77 kW, respectively. In

Figure 7. Charging profiles created from (a) 1.9 kW, (b) 3.3 kW, (c) 4.8 kW, (d) 7.2 kW, (e) 9.6 kW, (f) 11.5 kW, and (g) SRVF and (h) RIVF controlled charging.

Table 6 shows the final state of each vehicle’s battery after they have finished charging. Rates less than 4.8 kW, regardless of being used in control or uncontrolled charging, may lead to customer dissatisfaction because they do not provide enough energy to charge all vehicles above 90% during the vehicles’ dwelling period.
Table 6. Number of vehicles charged in each case.

| Case # | Case Type  | <50% | 50–59.9% | 60–69.9% | 70–79.9% | 80–89.9% | >90% |
|--------|------------|------|----------|----------|----------|----------|------|
| 1      | Uncontrolled 1.9 kW | 8    | 33       | 93       | 129      | 237      | 21,989 |
| 2      | Uncontrolled 3.3 kW | 0    | 0        | 2        | 4        | 3        | 22,491 |
| 3      | Uncontrolled 4.8 kW | 0    | 0        | 0        | 0        | 0        | 22,500 |
| 4      | Uncontrolled 7.2 kW | 0    | 0        | 0        | 0        | 0        | 22,500 |
| 5      | Uncontrolled 9.6 kW | 0    | 0        | 0        | 0        | 0        | 22,500 |
| 6      | Uncontrolled 11.5 kW | 0   | 0        | 0        | 0        | 0        | 22,500 |
| 7      | Uncontrolled 0–11.5 kW | 0  | 0        | 0        | 0        | 0        | 22,500 |
| 8      | Controlled 1.9 kW | 8    | 33       | 93       | 129      | 237      | 21,989 |
| 9      | Controlled 3.3 kW | 0    | 0        | 2        | 4        | 3        | 22,491 |
| 10     | Controlled 4.8 kW | 0    | 0        | 0        | 0        | 0        | 22,500 |
| 11     | Controlled 7.2 kW | 0    | 0        | 0        | 0        | 0        | 22,500 |
| 12     | Controlled 9.6 kW | 0    | 0        | 0        | 0        | 0        | 22,500 |
| 13     | Controlled 11.5 kW | 0   | 0        | 0        | 0        | 0        | 22,500 |
| 14     | SRVF        | 0    | 0        | 0        | 0        | 0        | 22,490 |
| 15     | RIVF        | 0    | 0        | 0        | 0        | 0        | 22,490 |

Table 7 depicts how much each charging strategy tested in this study reduces uncontrolled charging. All fixed-rate charging strategies that use rates below 4.8 kW are disregarded because they do not successfully charge all vehicles above 90% of the total amount of energy that the vehicle requested. The results show that using variable-rate uncontrolled charging can reduce overload from fixed-rate uncontrolled charging by to 28.34%. In addition, the results show that any fixed-rate controlled charging can reduce overloading better than variable-rate uncontrolled charging. SRVF and RIVF perform better than all fixed-rate controlled charging evaluated, proving plug-in electric vehicle charging can be enhanced by creating chargers that can deliver variable-rates. RIVF does perform better than SRVF but only marginally, suggesting that the additional freedom of selecting any charging rate is not a significant advantage. Most of the effectiveness of these algorithms is derived from the ability to select the single best charging rate for a vehicle. Lastly, the results show that fixed-rate controlled PEV charging using 4.8 kW produces similar results to SRVF; however this is under the demand simulated in this study, and as vehicles needs increase, the fixed-rate needed will increase as well.

Table 7. Uncontrolled vs-controlled average load during charging percent difference.

| Case          | Uncontrolled 4.8 kW | Uncontrolled 7.2 kW | Uncontrolled 9.6 kW | Uncontrolled 11.5 kW | Uncontrolled 0–11.5 kW |
|---------------|---------------------|---------------------|---------------------|----------------------|------------------------|
| Uncontrolled 0–11.5 kW | 20.19%             | 23.73%             | 26.39%             | 28.34%               | -                      |
| Controlled 4.8 kW       | 36.17%             | 39.00%             | 41.13%             | 42.69%               | 20.08%                 |
| Controlled 7.2 kW       | 35.54%             | 38.40%             | 40.54%             | 42.12%               | 19.29%                 |
| Controlled 9.6 kW       | 34.30%             | 37.22%             | 39.41%             | 41.01%               | 17.74%                 |
| Controlled 11.5 kW      | 32.98%             | 35.96%             | 38.19%             | 39.83%               | 16.09%                 |
| SRVF                     | 36.37%             | 39.19%             | 41.31%             | 42.87%               | 20.30%                 |
| RIVF                     | 36.93%             | 39.72%             | 41.83%             | 43.37%               | 21.03%                 |

By forecasting the winding hottest-spot temperature, \( \theta_{HST} \), and transformer loss of life, the classic thermal model in IEEE C57.91 [20] will be used to compare the techniques in this study. Equation (14) is used to compute the temperature of the winding hot spot.

\[
\theta_{HST} = \theta_{AMB} + \Delta \theta_{Oil} + \Delta \theta_{HST} \tag{14}
\]

For each time period, Equations (15)–(17) are utilized to compute the temperature increase of the oil above ambient, \( \Delta \theta_{Oil} \).

\[
\Delta \theta_{Oil} = (\Delta \theta_{Oil,i} - \Delta \theta_{Oil,j}) \left(1 - \exp \left(-\frac{t}{\tau_{Oil}}\right)\right) + \Delta \theta_{Oil,j} \tag{15}
\]
\[ \Delta \theta_{\text{Oil},i} = (\Delta \theta_{\text{Oil},R}) \times \left( \frac{K_i^2 R + 1}{R + 1} \right)^n \]  
\[ \Delta \theta_{\text{Oil},U} = (\Delta \theta_{\text{Oil},R}) \times \left( \frac{K_U^2 R + 1}{R + 1} \right)^n \] 

Equations (18)–(20) may be used to calculate the hot spot temperature increase over the oil, \( \Delta \theta_{\text{HST}} \), at each time period.

\[ \Delta \theta_{\text{HST},i} = (\Delta \theta_{\text{HST},R}) \times K_i^2 \left( \frac{1}{R + 1} \right) + \Delta \theta_{\text{HST},i} \] 

When the operation’s length is evaluated in minute intervals, Chun-Yao Lee et al. [38] demonstrate that the load difference between the starting and final states may be ignored, represented by Equation (21).

\[ K = K_i = K_U \] 

This assumption reduces Equations (18)–(20) into Equation (22), which may be used to compute winding hot temperatures.

\[ \theta_{\text{HST}} = \theta_{\text{AMB}} + \Delta \theta_{\text{TO},R} \times \left( \frac{K^2 R + 1}{R + 1} \right)^n + \Delta \theta_{\text{H},R} \times K^2 \] 

Table 8. Recommended limits of temperature and loading for a distribution transformer.

| Figure Limit                                | Limit  |
|---------------------------------------------|--------|
| Oil temperature                            | 120 °C |
| Winding hot spot temperature               | 200 °C |
| Short time loading (30 min or less)        | 300%  |

Table 8 depicts the spiraling hot spot temperature that results from each day’s baseload. The findings reveal that the baseloads do not exceed the 200 °C limit. Furthermore, the baseload does not exceed temperatures beyond 140 °C, which is critical. Operating at 140 °C is within the acceptable range but gassing in the solid insulation and oil pose a danger to the transformer’s integrity [20].

Table 9 shows the number of transformers that surpass 140 °C, which may cause gassing, and exceed the winding hot spot limit of 200 °C. Cases 1–6, which are the uncontrolled strategies that use 1.9, 3.3, 4.8, 7.2, 9.6 and 11.5 kW, respectively, to charge resulted in 14, 162, 500, 1409, 2016, and 2201 transformers of the 2500 surpassing the 140 °C. Cases 5 and 6 surpass the working temperature limit of 200 °C.

For a 24-h period, the HST is used to determine the aging acceleration factor (AAF), equivalent aging factor (EAF), and loss of life percent. Table 10 shows the EAF and LOL percent outcomes for each scenario. Distribution and power transformer model tests indicate that the normal life expectancy is 20.55 years, equating to a loss of life percentage of 1.333 × 10^{-2} per day. The results show that uncontrolled 7.2, 9.6, and 11.5 kW charging produce a LOL% of 1.727 × 10^{-2}, 1.384 × 10^{-1}, and 6.168 × 10^{-1}, respectively. The maximum LOL% produced by these three cases translates to a transformer reaching its
100% life expectancy in 15.86, 1.98, and 0.443 years, respectively. This shows that if we continue charging PEVs using uncontrolled charging methods and increasing the rates customers can use to charge a vehicle at home, the existing infrastructure will not withstand the increased load from the demand of the vehicles. In contrast, the results also show that all controlled charging methods (SRVF, RIVF, and each fixed-rate method), the uncontrolled 4.8 kW, and the uncontrolled 0–11.5 kW achieve a LOL% less than $1.33 \times 10^{-2}$ for every profile they were tested on.

![Figure 10. Path tracking response of the straight line: spatial representation (a) and its contour error (b).](image)

Table 8. Hot spot temperature for the baseload.

Table 9. Number of transformers exceeding the HST limit.

| Case # | Case Type       | Number of Transformers Exceeding HST of 140 °C | Number of Transformers Exceeding HST of 200 °C |
|--------|-----------------|-----------------------------------------------|-----------------------------------------------|
| 1      | Uncontrolled 1.9 kW | 14                                            | 0                                              |
| 2      | Uncontrolled 3.3 kW | 162                                           | 0                                              |
| 3      | Uncontrolled 4.8 kW | 500                                           | 0                                              |
| 4      | Uncontrolled 7.2 kW | 1409                                          | 0                                              |
| 5      | Uncontrolled 9.6 kW | 2016                                          | 27                                             |
| 6      | Uncontrolled 11.5 kW | 2201                                         | 120                                           |
| 7      | Uncontrolled 0–11.5 kW | 0                                          | 0                                              |
| 8      | Controlled 1.9 kW       | 0                                            | 0                                              |
| 9      | Controlled 3.3 kW       | 0                                            | 0                                              |
| 10     | Controlled 4.8 kW       | 0                                            | 0                                              |
| 11     | Controlled 7.2 kW       | 0                                            | 0                                              |
| 12     | Controlled 9.6 kW       | 0                                            | 0                                              |
| 13     | Controlled 11.5 kW      | 0                                            | 0                                              |
| 14     | SRVF                     | 0                                            | 0                                              |
| 15     | RIVF                      | 0                                            | 0                                              |
4. Conclusions

Selected Rate Valley-Filling (SRVF) and Rate and Interval Valley-Filling (RIVF) are two algorithms that have been designed and tested as strategic ways for reducing overload on distribution transformers caused by uncontrolled PEV charging. Both techniques are computationally quick, scalable, and real-time, and they optimize nonlinear systems. Both algorithms are compared to fixed-rate uncontrolled, variable-rate uncontrolled, and fixed-rate controlled charging.

This study showed that: (1) Uncontrolled and controlled PEV charging can be enhanced by creating chargers that can deliver variable rates. (2) Rates less than 4.8 kW, regardless of being used in controlled or uncontrolled charging, may lead to customer dissatisfaction because they do not provide enough energy to charge all vehicles above 90% during the vehicles’ dwelling period. (3) Using variable-rate uncontrolled charging can reduce overload from fixed rate uncontrolled charging by up to 28.34%. (4) Any fixed rate-controlled charging can reduce overloading better than variable-rate uncontrolled charging. (5) Fixed-rate controlled charging using 4.8 kW produces similar results to SRVF; however, this is under the demand simulated in this study. As vehicles’ needs increase, demand will as well, making 4.8 kW less effective and proving to be a temporary solution. (6) The additional freedom of selecting any charging rate that RIVF has over SRVF is not a significant advantage. Most of the effectiveness of these algorithms is derived from the ability to select the single best charging rate for a vehicle. (7) If no control algorithm is used, rates above 7.2 kW can begin to reduce transformer life below the expected lifespan.

Based on the results discovered in this study, mitigating overloading from uncontrolled charging can be approached in four phases: Phase 1, enabling PEV chargers to provide any rate to vehicles within 0 to 11.5 kW, reducing overloading by up to 28.34%. Phase 2, introducing a smart charger that uses forecasted data to determine the optimal time intervals for a PEV to charge using a fixed-rate of 4.8 kW, capable of reducing overloading by 42.69%. Phase 3, presenting a controlled smart charger that can deliver any rate to a vehicle using SRVF’s approach, reducing overloading by up to 42.87%. Even though the results show that fixed-rate controlled smart charging using 4.8 kW produces similar results to SRVF, this is not a robust solution. As technology evolves, the number of devices connecting to the grid, and their power demand, will continue to increase. A charger that can vary the rate it can administer to a vehicle will scale with demand, while a charger that provides a fixed-rate will not, indicating why phase 2 is a temporary solution. Lastly, phase 4 releasing controlled smart chargers that can deliver any rate to a vehicle using RIVF’s approach, reducing overloading by up to 43.37%. This phase is not critical because
RIVF only performs marginally better than SRVF; however, it is still included as a final phase because it produces the best results in the study.

The algorithms provided in this research depict how expanding the rates supplied to PEVs extends transformer life. To install controllers and properly apply regulated charging methods, a hardware update at the distribution level is required. In addition, technology such as cloud battery management systems as described by Yang et al. [39] can be used to enhance the implementation of these algorithms. The efficacy of this work illustrates the value of what can be accomplished if the infrastructure to support these types of ideas is built.

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