Loading Pattern Study of Transformer Aging Utilizing Electric Vehicle Demand Flexibility

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***Abstract*— This study models the load demand management strategy of electrification with electric vehicles to mitigate distribution transformer thermal overloading and degradation. The approach focuses on the relationship between transformer aging and load profiles by suggesting the pattern indices. The analysis in this study examines how load patterns correlate with the aging process and different perspectives on the conventional load leveling concept. Therefore, we propose metrics for load mitigation strategies, not only peak reduction but also time duration for higher loads, and examine expected load shifting scenarios balancing with the load leveling and load magnitude aspects. The case study assesses inverse correlation with the shifting cost and load pattern indices. The result also finds that load leveling is generally favorable to the transformer loading condition in terms of minimizing load deviation and reducing peak loading.**

***Index Terms*—Electric vehicle charging, charging strategy, transformer aging, load profile patterns**

I. Introduction

The projection of electric vehicle (EV) load in power systems indicates the rapid growth of electrical demand. The growth for the EV penetration and charging demand increase will account for 10% of global electricity consumption by 2035 [1], challenges to the distribution grid are more direct in mitigating the impact of the concentrated timely charging patterns, line and transformer rating violations, and balancing the circuit. Transformers can temporarily handle loads up to 200% without major insulation issues. However, repeated overloading beyond 100%, especially above 125% to 150%, leads to increased degradation and failure [2]. The transformer thermal degradation model [3] provides an estimation of aging based on internal temperatures, aging factors, and loss of life, closely tied to the loading patterns of individual distribution transformers. A smart charging control concept for individual EV users is proposed in [4] to reduce grid impact by considering residential peak load and varying state of charge (SOC) levels. A customer feedback-based EV scheduling approach in [5] reduces peak load based on distribution transformer aging while considering maintenance and replacement. Regarding the loading pattern, load leveling is the controlled charging strategy where vehicle charging rates are scheduled and modulated over time in the ideal scenario. In recent works, the load profile patterns have been tested in terms of EV adaptation, charging, operation, and optimization. The proposed model in [6] is compared against a compromise optimization solution. The model uses optimized signals for load leveling to manage charging loads, factoring in control costs and transformer impacts. The study in [7] demonstrates that managing adoption rates can significantly cut transformer aging costs, allowing utilities to share upkeep savings with EV owners through incentives or bill credits. The optimal penetration of this model depends on cost incentives. The study explained the concept of cost and demand proportion together, although the optimal penetration highly depends on the cost incentives. A key challenge in load leveling is providing the right price signals and compensation for load shifting while considering transformer loading characteristics. Load leveling typically involves valley filling to flatten feeder loads, but costs must be accounted for controlled loads. This study explores load leveling benefits and goal-oriented shifting methods to address transformer aging, emphasizing the trade-offs in load shifting. Load pattern indices evaluate transformer efficiency, cost-effectiveness, and service life extension. The load profile, including additional EV charging, is assessed through a proposed scenario-based approach that considers various load patterns.

II. Transformer Aging with Load Profile Patterns

A. *Load Profile Patterns from Feeder Measurements*

Steady, flat loads are advantageous for system operators, while fluctuating loads can affect transformer thermal variation [8], [9]. We analyzed 3,285 daily load data samples from 9 feeder devices based on data from feeder measurement devices, revealing load patterns categorized by area (urban and rural), customer types, and power sources. In Fig. 1, 9 feeder-level daily load patterns for a year are sampled. Residential and commercial load profiles, particularly those with photovoltaic (PV) generation, demonstrate reduced loads

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during daylight, contributing to the "duck curve". Seasonal variations exhibit similar deviations, focusing on specific PV patterns showing reverse power flow effects on transformer loading. We selected 4 daily patterns among 14 types in Fig. 1 based on their shapes, energy fluctuations, and source characteristics for analyzing transformer aging. The selected patterns are shown in Fig. 2 as normalized load curves for profiles (LP1-LP4) and scaled to 0.5 per unit for generalization.

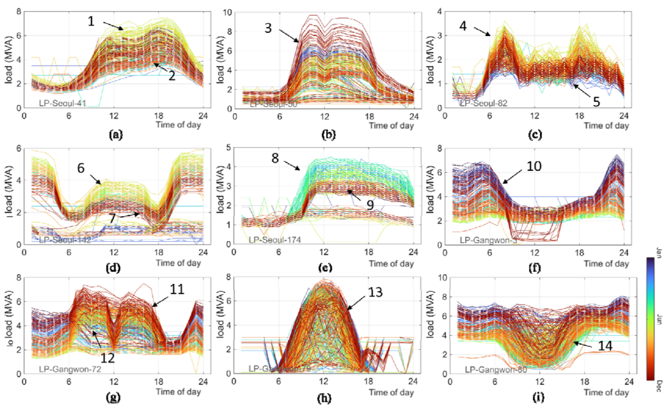

Fig. 1. Examples of daily load patterns sampled from field measurements of 9 feeders.

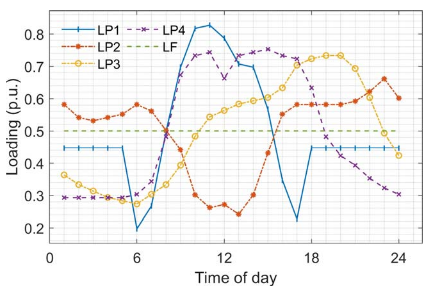

Fig. 2. Extracted general load patterns scaled to 0.5 per unit loading

B. *Transformer Thermal Aging by Loading Patterns*

The IEEE C57.91-2011 [3] loading guide outlines how internal temperature affects insulation degradation in transformers over time. It includes a model for life loss estimation that factors in temperature changes and time delays. We assess efficiency by applying this aging calculation to a specified transformer and load profile. The aging equation uses an acceleration factor to show that insulation degradation increases exponentially according to the Arrhenius relationship once temperatures exceed the winding hottest-spot limits.

C. *Load Pattern Index Consideration*

The load profile pattern is directly related to transformer efficiency and thermal aging. This relationship allows us to develop efficient criteria for selecting load patterns, enabling us to obtain more value from the same amount of energy the transformer consumes. The load leveling approach is typically used to identify the optimal load conditions that enhance transformer efficiency. The characteristics of these patterns, extracted from the load curves, are illustrated in Fig. 3. They explain concepts such as load deviation, maximum load, magnitude, and overloading metrics based on the measured loads. The load pattern indices to understand the correlation relationships between transformer aging and load shapes are utilized in this study for the load control calculation for EV demand. The suggested load pattern indices over a given period of a day $t \in T$ ($T = 24$) are calculated using the base load L_t^{b} and the EV charging load $\vec{L}_t^{\mathrm{c}}$ from the load profile patterns shown in Fig. 2 and EV loads calculated in the next section, 3. The hourly per unit loads of L_t^{b} and $\vec{L}_t^{\mathrm{c}}$ where $\vec{L}_t^{\mathrm{c}} = \sum_{i=1}^{d} L_i^{\mathrm{c}}$ by cumulating the charging load L_i^{c} for the charging duration of $i \in d$ where d represents the charging state.

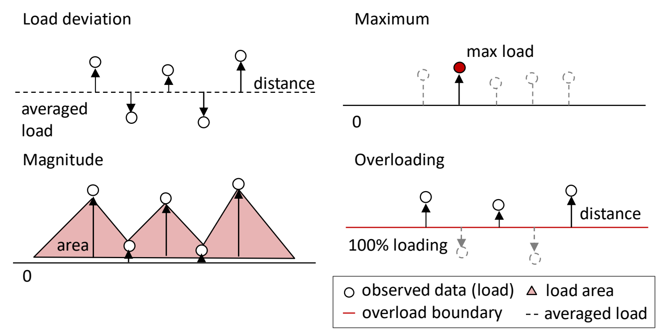

Fig 3. Load pattern index concepts for the transformer aging consideration

$$\rho_{\mathrm{T}}^{\mathrm{dev}} = \sqrt{\sum_{t=1}^{T}\left((L_t^{\mathrm{b}} + \vec{L}_t^{\mathrm{c}}) - \frac{1}{T}\sum_{t=1}^{T}(L_t^{\mathrm{b}} + \vec{L}_t^{\mathrm{c}}) \right)^2}\,, \tag{1}$$

$$\rho_{\mathrm{T}}^{\max} = \max(\mathrm{L}^{\mathrm{b}} + \vec{\mathrm{L}}^{\mathrm{c}})\,, \tag{2}$$

$$\rho_t^{\mathrm{mag}} = \left(L_t^{\mathrm{b}} + \vec{L}_t^{\mathrm{c}} \right)^{\beta}, \tag{3}$$

$$\rho_t^{\mathrm{over}} = \begin{cases} L_t^{\mathrm{b}} + \vec{L}_t^{\mathrm{c}} + 1, & \text{if, } L_t^{\mathrm{b}} + \vec{L}_t^{\mathrm{c}} > 1 \\ 1 & \text{otherwise} \end{cases}. \tag{4}$$

The deviation index $\rho_{\mathrm{T}}^{\mathrm{dev}}$ in (1) is used as the diversity factor of the daily load profile. This assumption suggests that load variability causes inefficiencies, serving as a direct metric for load leveling. The maximum index in (2), denoted as $\rho_{\mathrm{T}}^{\max}$ captures the maximum load recorded during the day that coincides with the highest transformer temperature over time. The magnitude index ρ_t^{mag}, which forms a vector $\rho_{\mathrm{T}}^{\mathrm{mag}}$, directly indicates the load level by substituting the load values with the magnitude index. The load weight β modifies the index to adjust the gap between magnitude values while keeping the same deviation, typically set between 0.1 and 0.5 which reduces dependence on per unit loading. The study uses the 0.5 weight to scale the magnitude index level as the other 3 indices. The overloading index ρ_t^{over} sets a vector ρ^{over} to identify loads exceeding the transformer rating capacity of 1.0 per unit after accounting for additional EV charging demands. Overloading contributes to transformer aging, highlighting thermally unstable conditions in the daily load pattern. The correlation graph in Fig. 4, derived from 288 daily load samples across 9 feeders, illustrates the relationship between the transformer aging factor and pattern indices. It depicts the equivalent aging (FEQA), calculated from normalized average loading patterns, indicating cumulated thermal aging. With original data ranging from 0.2 to 0.7 average loading and lacking overload conditions, no correlation was found at low loading levels. By scaling the data to 75% of the average load to account for overload scenarios, the graph reveals a non-linear exponential trend, indicating that higher indices correlate with accelerated aging.

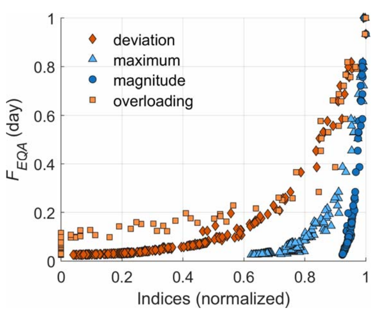

Fig. 4. Transformer thermal aging FEQA according to the pattern indices for the load profile dataset

III. EV LOAD MANAGEMENT FOR TRANSFORMERS

A. *Demand Shift for Transformer Aging Consideration*

When developing a load control strategy for EV charging, the focus should be on load leveling, but transformer load patterns are essential to prevent overloading. Solely relying on load leveling may increase costs and reduce transformer lifespan. A practical approach involves selectively controlling loads to minimize transformer stress and aging. We can effectively manage overloading by identifying optimal shifting locations while integrating additional EV charging demand to enhance the overall base load profile.

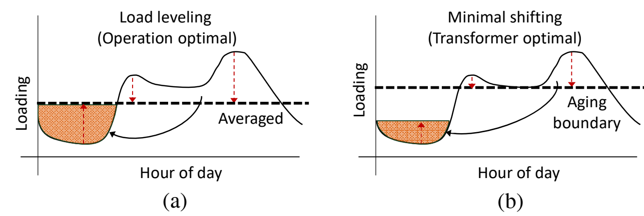

Fig. 5. The demand shift concept example for aging consideration

B. *Charging Load Control and Load Shifting Strategy*

Preliminary analysis shows that specific load indices are interdependent. We propose a new load control criterion, recognizing that transformer cases exhibit different curve patterns. When uncontrolled charging reflects concentrated demand within a specific timeframe, load leveling control minimizes variation and optimizes operations to reduce peak loading. The aging shifting concept manages additional EV charging demand while considering aging effects. The weight-based optimization solver calculates both aspects, and the load pattern for leveling is derived accordingly.

$$\omega_{t,i} = \frac{L^{\mathrm{b}}_{t} + \vec{L}^{\mathrm{c}}_{t,i}}{\sum_{t=1}^{\mathrm{T}} L^{\mathrm{b}}_{t,i}}, \qquad \forall t, i. , \tag{5}$$

where the charging load, denoted as $\vec{L}^{\mathrm{c}}_{t,i}$ is calculated until i. The cumulative charging load is derived by merging the values into a single value as $\vec{L}^{\mathrm{c}}_{t,i} = \sum_{j=1}^{i-1} L^{\mathrm{c}}_{t,j}$ where $i, j > 0$. The charging load $L^{\mathrm{c}}_{t,i}$ is determined using the objective functions (7) and (8) during the i-th step where the weight is updated in each iteration in $\forall j \in i$. Therefore, the previous value $L^{\mathrm{c}}_{t,i-1}$ is combined with the next weight value. Additionally, the load pattern weight for the aging shift suggests integrating the weight with the index values to consider loading characteristics:

$$\omega^{\rho}_{t,i} = \omega_{t,i} \cdot \rho_{\mathrm{T}}^{\mathrm{dev}} \cdot \rho_{\mathrm{T}}^{\max} \cdot \rho_t^{\mathrm{mag}} \cdot \rho_t^{\mathrm{over}} . \tag{6}$$

The load control objective function uses weights for suggested charging scenarios calculated using solvers. Each duration step individually calculates the objective functions, which alters the constraints. Therefore, the function is iteratively calculated by stacking load profile values while solving during the designated charging duration d. In the load leveling case, the weight $\omega_{t,i}$ is set to focus on the load aspect during the solving process. The weight in the objective function (7) prioritizes each time slot based on the average load weighting, guiding the solver to flatten the load throughout the calculation. The proposed objective function in (8) addresses the proportional problem, prioritizing load selection.

$$\min_{r_{t,i}} \sum\nolimits_{t=1}^{\mathrm{T}} \omega_{t,i} \cdot L^{\mathrm{c}}_{t,i}\,, \tag{7}$$

$$\min_{r_{t,i}} \sum\nolimits_{t=1}^{\mathrm{T}} (\omega^{\rho}_{t,i})^{\alpha} \cdot p_{t,i}^{(1-\alpha)\cdot\gamma} \cdot L^{\mathrm{c}}_{t,i}\,, \tag{8}$$

$$\text{s.t.} \sum\nolimits_{t=1}^{\mathrm{T}} r_{t,i} = 1/d, \quad \forall t\,. \tag{9}$$

In function (8), the weights represent the load and price aspects. This setup aims to find a compromise that balances load leveling by magnitude with the shifting load price. The scale parameter α is set based on the average system load or the transformer load level to scale the load profile magnitude. The parameter helps narrow the gap in the optimal load shift searching process. The mismatch between load shift costs and the amount of shifted load is adjusted by cost exponential γ. This helps minimize costs and mitigate overloads due to charging load. The vehicle availability constraint at the charger is considered in (9) accounting for grouped charging demands based on the estimated number of vehicles connected to chargers as estimated. Although the cumulative proportions $r_{t,i}$ indicate total charging availability as 1.0, the constraint is divided by the charging duration d, where $r_{t,i}$ is used for $L^{\mathrm{c}}_{t,i}$ calculation.

IV. Case Study

The case study configuration was based on vehicle and charging patterns, focusing on household charging loads. It involved approximately 9% of EVs with a nominal charging of 3kW, ranging from 1kW to 7.4kW for level 1-2 chargers. The amount of vehicles was 1,753 EVs for a 10MW feeder and 87 vehicles per 500kVA transformer [10]. EV proportions varied with loading conditions, such as 16% at 0.5 per unit, 11.14% at 0.75, and 8.35% at 1.0, maintaining a constant electrification factor. The average daily distance was 35-37 miles, leading to a daily charging demand of 13.29kWh and an average charging duration of 4.43 hours [11]. The cases had four load patterns through three scenarios, which were unmanaged charging, load leveling control, and aging shifting. The loading level ranged from 0.2 to 1.0 per unit to analyze, particularly how the aging shift model selects optimal solutions based on different loading patterns and aging acceleration points. The load profiles in Fig. 6 display simulation results using base load patterns (LP2), which exhibit a duck curve with low noon demand and a typical urban load pattern. EV charging loads ranged from D1-D4 (1h) to D5 (0.43h) added to the base. Both unmanaged and load leveling calculations yielded similar charging patterns; unmanaged cases showed a general pattern, while load leveling utilized controlled strategies with load weights. On the other hand, the aging shift relied on load profile characteristics, resulting in varied control strategies, as seen in Fig. 6 (c) and (d). Despite concentrated charging loads during uncontrolled times, loads were evened out during overload conditions to prevent transformer aging.

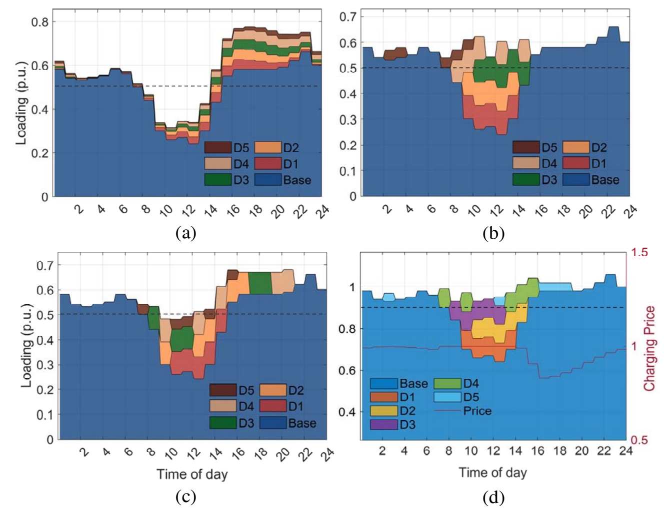

Fig. 6. EV loading scenario case (LP 2) results. (a) unmanaged, (b) load leveling, (c) aging shift with 50% averaged loading, and (d) aging-based strategy with 90% averaged loading for overloading conditions

The charging scenarios for four base load profiles depict different strategies in Fig. 7. The unmanaged charging loads were added to the base loads, resulting in varied outcomes for deviation and overloading. In the load leveling case, charging loads were allocated to leveling time slots without considering the amount of load shifting. In contrast, the aging shift scenario aimed to minimize overloading while allowing charging loads to remain, distributing a few charging loads to fill valleys and reduce peak loads and duration, ultimately minimizing thermal degradation. The case focused on minimizing shifts by matching base load patterns and charging loads. The aging-considered charging results of LP3 in Fig. 6(c) and (d) showed that charging loads shifted to different time intervals based on load indices and pricing. The method balanced these factors, as shown in Fig. 8, where the shifting price $p^{\mathrm{s}}_{t,i}$ increased from 0.1 to 1.0 per unit during the LP3 study. The differentiated EV load shift $\dot{L}^{\mathrm{c}}_{t,i}$ influenced the shifting price and subsequent duration calculations.

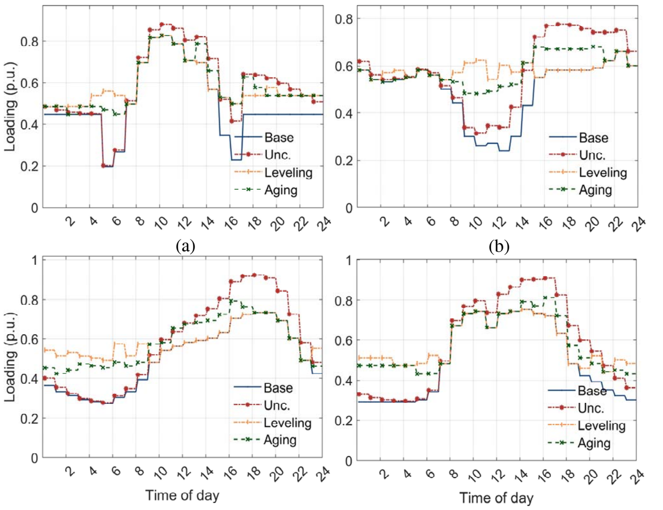

Fig. 7. EV charging load scenario results in 4 load profile patterns with 50% average loading.

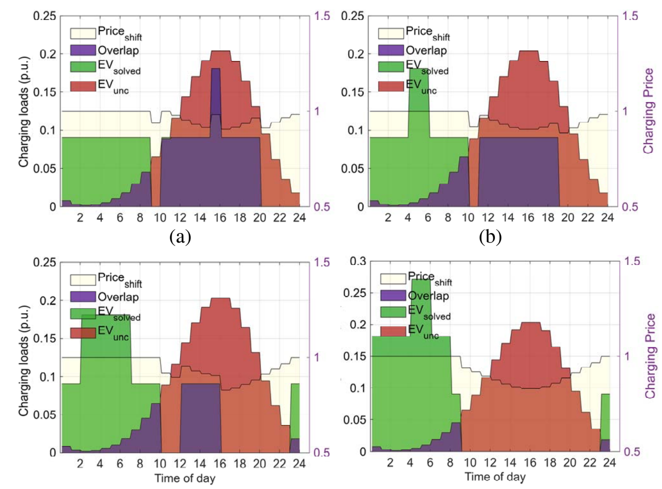

Fig. 8. The load shift selection of the load comparison between the uncontrolled and controlled loads with the overlapped area and the shifting price (LP 3). (a) 0.1, (b) 0.3, (c) 0.6, and (d) 1.0 loading levels

V. CONCLUSION

The relationship between load leveling and transformer aging patterns was analyzed by examining various load profiles that affect transformer degradation. The analysis revealed that specific load profile patterns can accelerate transformer aging, even when the loading conditions are the same. Among the patterns studied, the load profile featuring a photovoltaic generation feeder showed particularly negative characteristics for transformer loading, especially at higher loading levels.

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