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Reducing the Impacts of Electric Vehicle Charging on Power Distribution Transformers

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ABSTRACT This article investigates the effects of high penetration levels of Electric Vehicle (EV) charging on power distribution transformers and proposes a new solution to minimize its negative impacts. There has been growing concern over Greenhouse Gas (GHG) emissions within the transportation sector, which accounts for about 23% of total energy-related carbon-dioxide emissions. The main solution to this problem is the electrification of vehicles. However, large scale integration of EVs into existing grid systems poses some challenges. One major challenge is the accelerated aging of expensive grid assets such as transformers. In this article, a demand response mechanism based on the thermal loading of transformers, is proposed. The proposed solution is modeled as an optimization problem, where a new time of use (ToU) tariff is used to shift the EV load considering the thermal loading of transformers, thereby minimizing their accelerated aging. The simulation results show that the accelerated aging of transformers can be reduced without augmenting the existing grid.

INDEX TERMS Electric vehicles (EVs), time of use (ToU) tariff, loss of life (LoL), distribution transformer thermal aging.

Abbreviations

LoL Loss of life of transformer.
SOC State of charge.
SSE Sum of squared errors.

Parameters

β_t Spot electricity price in t^{th} hour.
 β_k Spot electricity price in k^{th} hour.
 $\Delta\theta_H$ Winding hot-spot temperature rise over top-oil temperature.
 $\Delta\theta_{TOR}$ Top-oil temperature rise over ambient temperature at rated load.
 $\Delta\theta_{TO}$ Top-oil temperature rise over ambient temperature of transformer.
 η Efficiency of the charger.
 λ_K^{SSE} Successive difference of SSE.
 μ Number of EVs per household.

ρ Exponent of loss function vs. top-oil temperature rise.
 τ_{TOR} Oil thermal time constant for rated load.
 τ_W Winding time constant at hot-spot location in hours.
 θ_A Ambient temperature.
 θ_{HR} Winding hot-spot temperature over top-oil at rated load.
 θ_H Winding hot spot temperature of transformer.
 A_k Incentive in k^{th} hour.
 A_t Incentive in t^{th} hour.
 d Daily mileage driven in km.
 e Energy consumption in kWh/km.
 E_{batt} Capacity of battery in kWh.
 E_{cons} Energy consumed by EV.
 E_{req} Energy required to charge EV.
 $E_{t,k}$ Cross elasticity in t^{th} hour.
 E_t Self elasticity in t^{th} hour.
 F_{AA} Accelerated aging factor of transformer.
 F_{EQA} Equivalent aging factor of transformer.

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F_{EQA}^{ToU}	Equivalent aging factor based on proposed method.
F_{EQA}^{Un}	Equivalent aging factor based on uncontrolled charging.
L_{EV}	EV load.
L_{normal}	Nameplate insulation life of transformer.
L_R	Residential load.
L_{t-1}	Ratio of initial load to the rated load.
L_T	Total load on transformer.
L_t	Ratio of ultimate load to the rated load.
$Life_{exp}^{ToU}$	Life expectancy of transformer based on proposed method.
$Life_{exp}^{Un}$	Life expectancy of transformer based on uncontrolled charging.
m	Exponent of load squared vs. winding gradient.
N	Number of EVs.
n	EV index.
N_{EVs}	Number of EVs.
N_{House}	Number of Household.
$P_t^{offpeak}$	Off-peak price at time t .
P_t^{peak}	Peak price at time t .
$P_t^{sdr_1}$	Threshold-1 price at time t .
$P_t^{sdr_2}$	Threshold-2 price at time t .
r	Ratio of load loss at rated load to no-load loss.
S_{nom}	Nominal apparent power of transformer.
S_t	Apparent power of transformer at t^{th} hour.
SOC_{ini}^n	Initial SOC of the n^{th} EV.
SOC_{min}	Minimum SOC of EV battery.
SOC_t^n	SOC of the n^{th} EV at time t .
T	Time horizon.
t	Time slot index.
th_{min}	Transformer's temperature to start off-peak price.
th_{peak}	Transformer's temperature to start peak price.
th_{sdr_1}	Transformer's temperature to start shoulder-1 price.
th_{sdr_2}	Transformer's temperature to start shoulder-2 price.
L_{EV}	EV load.
X_{pen}	Penetration level of EVs.

I. INTRODUCTION

Electric Vehicles (EVs) are becoming increasingly popular due to growing concerns about global warming and greenhouse gas emission [1], [2]. EVs produce significantly less carbon emissions compared to internal combustion engine (ICE) vehicles, even when the source of electricity is from non-renewable resources. It has been predicted that penetration levels of EVs will substantially increase in coming decades, where it has been forecasted that by 2040, about 30% of the global passenger fleet will be electric [3].

Most of the research and work related to EV focuses on their integration into the transport system from the user's viewpoint and means of mitigating the associated problems. Whereas, it is also equally important to reduce the impact of

the inevitable integration of EV from the perspective of the utility (e.g., transformer aging, line overloading, etc). One of the biggest obstacles to successful integration of EVs into current transportation systems is their negative impacts on power distribution system [4]–[6]. Authors in [4] and [5] have concluded that simultaneous charging of EV and peak load periods will overload the distribution system. Furthermore, augmentation investment cost can rise to 15%, and energy losses can reach 40% with EV penetration level of 60% [6]. Therefore, determination of the hosting capacity of the distribution system is vital. Reference [7] looks into determining the maximum hosting capacity based on voltage constrained method and proposes a controlled charging as a facilitator for EV integration. Marginal hosting capacity calculation is proposed in [8] based on linear power flow model, and it can be used to identify nodes that are more impactful in using the network capacity. In [9], the concept of EV chargeable region optimization model is proposed without violating the technical constrain of the network. As most of the charging load of EVs takes place on the low voltage side of the grid, negative impacts will be more pronounced. The power demand of typical EV chargers at AC level 2 is about 19.2 kW [10], which is almost twenty times the power demand of a typical household appliance [11]. This can lead to an unstable system with real-time power mismatch leading to voltage and frequency deviations. The distribution system grid should accommodate the additional EV load without jeopardizing the stability of the network, as augmentation of the grid usually takes decades due to grid assets' long service life [12]. Therefore, the effect of aggregated uncoordinated charging will have a catastrophic effect on a power system, especially its transformers. Transformers are considered to be the most critical and expensive element of an electric network, where replacing them will be very costly. When they fail, critical infrastructure such as hospitals and industries, to name a few, will suffer [13], [14].

Therefore, this article investigates the negative impacts on distribution assets, particularly accelerated aging of distribution transformers, due to integration of EVs. Loading transformers beyond their nameplate rating increases temperature of mineral insulating oil and winding, which subsequently deteriorates the insulating papers wrapped around the winding, thereby reducing the nominal life of transformers [15].

The integration of EV into power distribution systems is inevitable, where charging EVs without jeopardizing the network is of paramount importance. To address the aforementioned problem, this article proposes a solution for charging EVs based on the temperature of the transformer, where the demand response is determined by a time of use tariff. Compared to current research, the key contributions to this article are as follows.

- 1) In this article, we introduce a demand response mechanism to minimize the accelerated aging of transformers by implementing a new time of use (ToU) price signal based on the thermal loading of transformers. We consider the impact of EV loads and ambient temperature,

and model the research challenge as an optimisation problem.

- 2) To validate the proposed solution, we used multiple case studies and conducted comprehensive analysis. We observed promising results for the proposed solution, which are presented in this article.

The rest of this article is structured as follows. Section II introduces previous work on the impacts of EV on distribution transformers. Proposed solution to reduce the impact of integration of EV is defined in Section III, presenting a system model and proposed method for solving the problem of LoL minimization of the distribution transformer. Section IV introduces the findings of the simulation and discusses the introduced case studies followed by a conclusion.

II. RELATED WORK

High penetration levels of EVs, Photovoltaics (PVs), and Energy Storage Systems (ESSs) modifies the shape of load curves seen by distribution transformers. In particular, the natural coincidence of conventional peak load and likely EV demand will cause significant overload at the distribution level [16]–[18]. It has also been pointed out in [19] and [20] that the effect of the EV will be dramatic, as the diversity of load is relatively lower in the distribution level than in the transmission level.

A comprehensive literature review on the effects of various loads and other factors on power distribution transformers has been conducted in [21]. A smart protection model for the transformer was proposed to address new network challenges due to integration of new types of load and generation. An online monitoring system was considered as essential to protect the transformer from abnormal loading and faults.

Authors in [22] have investigated the impact of additional EV load at a factory car-park, using lognormal probability distribution to predict the initial state of charge and using transient transformer aging model defined in IEEE 57.91 to calculate the transformer's LoL. The authors concluded that fast charging should be avoided as it overloads the transformer at penetrations as low as 15%. Further, given that factory workers park their cars for 8 hours, this allows sufficient time to fully charge vehicles using slow charging modes. Therefore, there is no need to consider fast charging. The authors propose a solution by only using slow charging modes as the car is normally parked for about 8 hours. Although this is feasible in some situations, in reality, some owners might have different requirements for charging duration depending on the use of their EV.

A methodology to determine the impact of high penetration of EVs on the thermal aging of distribution transformers was developed in [23]. It was concluded that transformer LoL is mainly dependent on ambient temperature and the loading of the transformer. It was also highlighted that shifting the charging load of EVs to off-peak hours, which are overnight and early morning hours, is not necessarily good for transformer aging, as it prevents the transformer from cooling down. One of the proposed solutions shifts some

of the charging load of residential areas to public charging in industrial and commercial areas, to reduce pressure on residential distribution transformers.

Authors in [24] and [25] have evaluated the impact of different types of charging strategies on transformer thermal aging. Charging strategies were categorized into central, decentralized, and hierarchical types. It was concluded that hierarchical charging strategies are most preferred in terms of transformer loss of life whereas centralized charging strategies (valley-filling) showed the greatest LoL.

A data-driven PEVs charging strategy based on a stochastic game model is used to measure the transformer aging [26]. Here a linear supply function is used for changing the charging behavior of EV owners. However, this article does not look into the thermal loading of the transformer. In [27], authors consider fixed ToU tariff and compares the EV load, when it acts only as a load and when EV participates in V2H (Vehicle to Home). Essentially the ToU tariff is predetermined by the utility and is independent of the load including the EV. Authors in [28] have considered an agent-based approach where real time price signal is used to minimize the congestion problem at MV/LV transformer. Although this article looks into the thermal loading of the MV/LV transformer, it does not consider the influence of ambient temperature on the thermal loading of the transformer. Authors in [29] have investigated several EV charging schemes in a parking lot. This article assumes that the operator can communicate with each car or charger at least every 15 minutes' interval. Again, the ToU price is predetermined and it is independent of the EV load.

As discussed above, while researchers have analyzed the impact on distribution transformers due to EV charging load, none of these paper provide a solution without augmentation to the distribution network. Most of the proposed solutions are based on the assumption that a very good communication link exists between the customers and utility or the aggregators. This article introduces a new ToU pricing mechanism based on the transformer's temperature to minimize distribution transformer loss of life. The method proposed in this article works without any modification to existing physical infrastructure.

III. PROPOSED SOLUTION TO REDUCE IMPACT ON TRANSFORMERS

A. SYSTEM MODEL

1) MODELING OF EV LOAD

Firstly, the Monte Carlo Simulation (MCS) is used to generate the aggregated EV load curve for uncoordinated charging. Secondly, it is used to estimate the total load demand by the EV fleet in the studied horizon, which is 24 hours. As EV charging is a stochastic process, MCS can be used to accurately estimate aggregated EV load demand over time [30].

Charging start time and charging duration data were acquired from NHTS (2017), accounting for 129,696 households [31]. The NHTS survey included 4,766 hybrid or

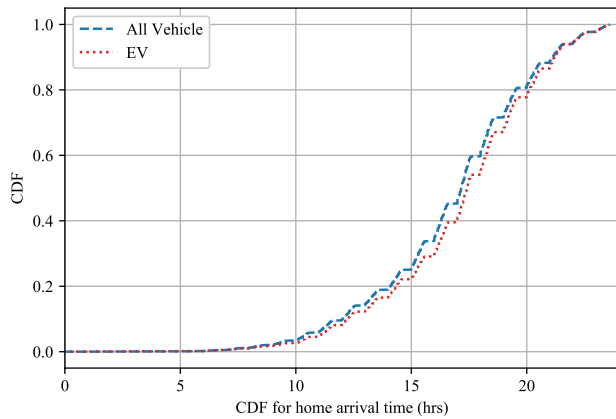


FIGURE 1. Home arrival time.

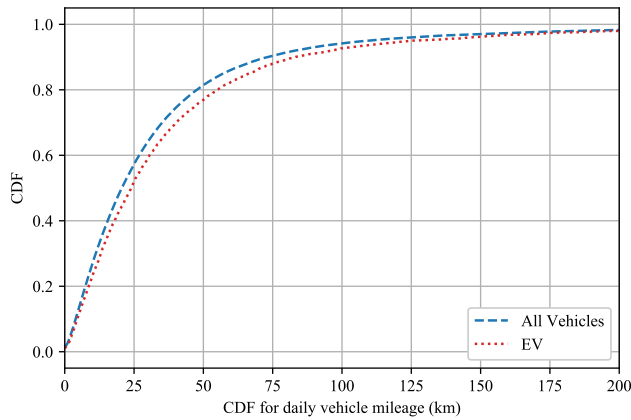


FIGURE 2. Daily mileage.

electric vehicles out of 222,183 vehicles. Previous survey data (2009 NHTS) did not include or specify electric vehicles separately, which would make assumptions derived from the previous survey for EV load modeling incorrect.

As reported in [32], more than 80% of EVs are charged at home; therefore, the time at which vehicle owners start charging is modeled using the final home arrival data of EVs. Charging duration is derived from the daily distance traveled. The cumulative distribution function (cdf) for home arrival time and daily mileage are derived similarly to [33] and [34] as shown in Fig.1 and Fig.2, respectively.

The number of EVs connected to the distribution network can be determined by (1). The penetration level of EVs varies from 0 to 50% as estimated in [3] and [35]. The value of μ is estimated as 2 based on the findings in the 2017 NHTS.

$$N_{EVs} = X_{pen} \times N_{House} \times \mu \quad (1)$$

EV charging load is estimated using Algorithm 1 [36], [37]. In this article, two types of EVs are selected for investigation: namely Nissan LEAF (24 kWh) and Chevy Volt (16 kWh). Charging level 2 with a charging capacity of 3.7 kW, is selected to estimate the energy required by the battery.

Algorithm 1 EV Load Computation

Input: E_{batt} : Capacity of battery in kWh

d : daily mileage driven in km

e : energy consumption in kWh/km

η : efficiency of charger

1: Set minimum state of charge

$$SOC_{min} = \begin{cases} 30\% & \text{if EV is Chevy Volt,} \\ 5\% & \text{if EV is Nissan LEAF,} \end{cases}$$

2: Compute the energy consumed by the vehicle

$$E_{cons} = \frac{d \times e}{E_{batt}}$$

3: Compute the state of charge (SOC) of the battery

$$SOC_{ini}^n = \max \left[SOC_{min}, \left(1 - E_{cons} \frac{d}{E_{batt}} \right) \right]$$

4: Calculate the energy required to charge the vehicle

$$E_{req} = \frac{1 - SOC}{\eta} \times E_{batt}$$

Output: Required energy to charge the vehicle E_{req}

2) MODELING OF THE RESIDENTIAL LOAD AND AMBIENT TEMPERATURE

It is important to model existing load properly, in order for results to be valid. Most researchers to date have represented existing load using a single load curve that shows an average load demand. This model does not include variations of load for different seasons. Therefore, the load model based on models developed in [38] are used in this article. The load profiles are taken from the National Feeder Taxonomy Study (NTFS) developed by the Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO).

Ambient temperature data was acquired from the Bureau of Meteorology, Australian Government [39]. Refined daily half-an-hour temperature data from May 2016 to April 2017 was used from a weather station located at Perth, Western Australia. Fig.3 shows four representative ambient temperature clusters based on a Euclidean K-mean method. Representative numbers of clusters were derived using (2) and (3). The maximum value of λ_K^{SSE} was used to determine the most suitable number of clusters [40].

$$SSE = \sum_{i=1}^K \sqrt{\sum_{p \in C_i} (d_i - p)^2} \quad (2)$$

$$\lambda_K^{SSE} = SSE_{K-1} + SSE_{K+1} - (2 \times SSE_K) \quad (3)$$

3) MODELING DISTRIBUTION TRANSFORMER LoL

Thermal aging equations from the IEEE Std. C57.91 [41] were used for dynamic modeling of the transformer. The LoL

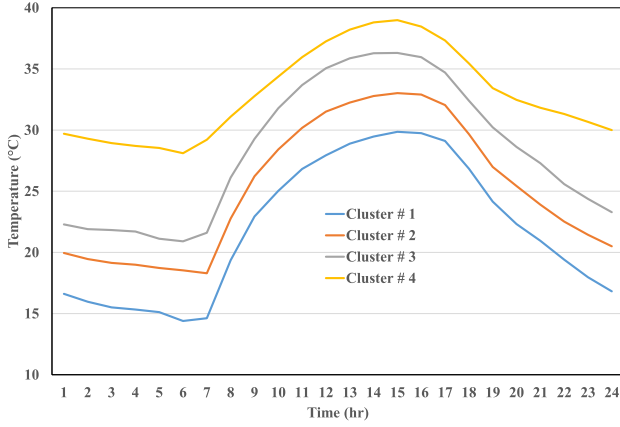


FIGURE 3. Ambient temperature clustering using Euclidean k-means.

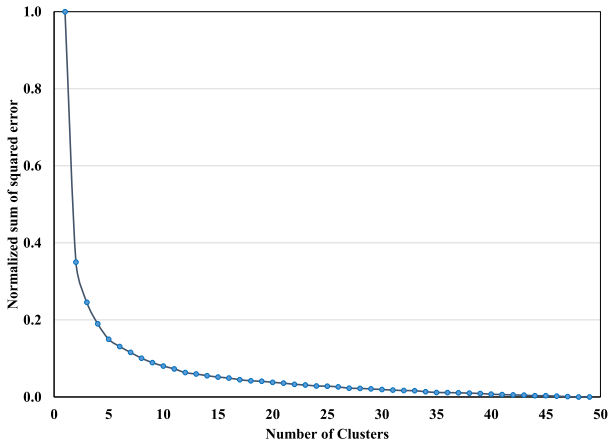


FIGURE 4. Sum of square error for ambient temperature dataset.

of the transformer was calculated using (4), where T is the number of time slots, usually chosen as 24 and L_{normal} is the nameplate insulation life of the transformer at rated load which is usually considered to be 180000 hours.

$$LoL(\%) = \frac{F_{EQA} \cdot T \cdot 100}{L_{normal}} \quad (4)$$

The average aging factor F_{EQA} is given by (5). For every time step, the actual accelerated aging factor F_{AA} is given by (6), determining the transformer's lifetime degradation. This empirical formula is dependent on the hot-spot temperature of the transformer. If the hot-spot temperature is higher than the reference hot-spot temperature (usually its 110°C), the F_{AA} is greater than 1 and vice versa.

$$F_{EQA} = \frac{\sum_{n=1}^N F_{AA,n} \cdot \Delta t_n}{\sum_{n=1}^N \Delta t_n} \quad (5)$$

$$F_{AA} = e^{\frac{15000}{383} - \frac{15000}{\theta_H + 273}} \quad (6)$$

Transformer lifetime aging is dependent on hot-spot temperature and is given by (7).

$$\theta_H = \theta_A + \Delta\theta_{TO} + \Delta\theta_H \quad (7)$$

where θ_H is the distribution transformer's hot-spot temperature, θ_A is the ambient temperature, $\Delta\theta_{TO}$ is the top-oil temperature rise over the ambient temperature, and $\Delta\theta_H$ is the winding hot-spot temperature over top-oil temperature.

The increases in hot-spot temperature due to winding and oil are given by 8 and 9, respectively.

$$\Delta\theta_{H,t} = \theta_{HR} \left\{ \left(L_t^{2m} - L_{t-1}^{2m} \right) \left(1 - e^{-\frac{\Delta t}{\tau_W}} \right) \right\} + \left\{ L_{t-1}^{2m} \cdot \theta_{HR} \right\} \quad (8)$$

where θ_H is the change in hot-spot temperature for every time step t , θ_{HR} is the winding hot-spot temperature at rated load over top-oil temperature, L_t and L_{t-1} are the ratios of final load to rated load and the initial load to the rated load, m is the exponent of load squared versus the winding gradient, and τ_W is the winding time constant at the hot-spot location.

$$\Delta\theta_{TO,t} = \Delta\theta_{TOR} \left\{ \left(\frac{L_t^2(r+1)}{r+1} \right)^{\rho} - \left(\frac{L_{t-1}^2(r+1)}{r+1} \right)^{\rho} \right\} \times \left\{ 1 - \exp \left(\frac{r \left(\phi_t^{\rho-1} - \phi_{t-1}^{\rho-1} \right) \Delta t}{\tau_{TOR} \left((\phi_{t-1}^{\rho} - \phi_t^{\rho}) \right)} \right) \right\} \quad (9)$$

where,

$$\begin{aligned} \phi_t &= L_t(r+1) \\ \phi_{t-1} &= L_{t-1}(r+1) \\ t &= 1, \dots, 24 \\ n &= 1, \dots, N \end{aligned}$$

where $\Delta\theta_{TOR}$ is the top-oil temperature rise at rated load over ambient temperature, r is the ratio of load loss at rated load to no-load loss, τ_{TOR} is the rated load oil thermal time constant, and ρ is the loss function exponent versus the rise in top-oil temperature.

Here, LoL of the transformer is derived as a function of the transformer's load and ambient temperature. All the symbols in (8) and (9) are constants except L_t and L_{t-1} .

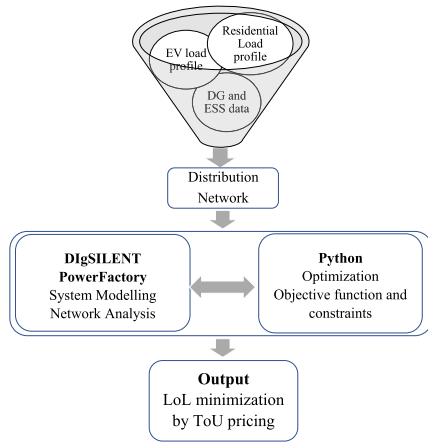
Since the maximum loading of the transformer is dependent on the hot-spot temperature as given in (6), the amount of additional EV load, a particular transformer can support at any point of time is mainly dependent on the following factors as per (7):

- 1) Ambient temperature.
- 2) Existing residential load.

Out of the two factors listed above, residential load is further dependent on ambient temperature. The maximum load that the transformer can support depends on the difference between the maximum transformer temperature (given by the manufacturer) and the ambient temperature. Since the ambient temperature of the next day's is a known priori with very high accuracy, the allowable transformer loading is calculated using (6) – (9). The allowable loading of the transformer based on hot-spot temperature without the EV is due to existing residential load and ambient temperature.

TABLE 1. Summary of optimization parameters and variables.

Type	Parameters/Variables
Input Parameters	Network Data, Residential Load Profile, EV Load Profile
Output Parameters	F_{AA}
Decision Variables	P_t^{peak} and th_{peak}

**FIGURE 5.** Proposed methodology.

B. PROPOSED MODEL

The proposed methodology to find optimal ToU price and time subject to objective function constraints is given in Fig. 5. The summary of input variables, output variables, and decision variables are given in Table 1.

The main idea is to determine optimal ToU pricing dependent on ambient temperature. The relationship between customer demand and price of electricity is given in (10) and is based on [42]. It proposes two demand response models based on TOU and emergency demand response method. The same model is expanded and used in [43], and [44]. This model uses the demand-price elasticity concept based on the principle of psychology and economy. The model can be used for both price-based or incentive-based programs. However, in this article, only the price-based program is used.

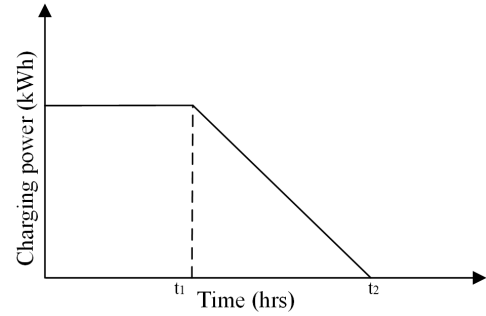
$$L_t = L_{t-1} + E_t \frac{L_{t-1}}{\beta_0} [\beta_t - \beta_0 + A_t] + \sum_{\substack{k=1 \\ k \neq t}}^{24} E_{t,k} \frac{L_{t-1}}{\beta_0} [\beta_k - \beta_0 + A_k] \quad (10)$$

where

$$t, k = 1, \dots, 24$$

The starting time and duration of the various electricity ToU price can be determined based on the percentage loading of the transformer. From this, the share of peak load, shoulder load, and off-peak load can be calculated and using (10), various tariffs can be determined.

The following objective function and the associated constraints define the optimization problem. The objective is to

**FIGURE 6.** Typical charging power profile of EV [30].

minimize the F_{AA} of the transformer which is a function of existing residential load and additional EV load.

$$\min \sum_{t=1}^{24} [F_{AA} (L_{R,t} + L_{EV,t}) \Delta t] \quad (11)$$

The constraints that must be met during the process of optimization are as follows:

Transformer Capacity Limit:

$$S_t \leq S_{nom} \quad (12)$$

Transformer Demand:

$$L_{T,t} = L_{R,t} + \sum_{n=1}^N L_{EV,t}^n \quad (13)$$

Electrical Vehicle SOC:

$$SOC_t^n = SOC_{t-1}^n + \left(\eta L_{EV,t}^n \frac{\Delta t}{E_{batt}} \right) \quad (14)$$

$$SOC_{ini}^n = \max \left[SOC_{min}, \left(1 - E_{cons} \frac{d}{E_{batt}} \right) \right] \quad (15)$$

$$SOC_{dep}^n = SOC_{req} \quad (16)$$

Lithium-ion Battery Charging Characteristics:

$$L_{EV,t}^n = \begin{cases} L_{EV}^{max} & \text{if } 0 \leq t \leq t_1, \\ L_{EV}^{max} \left(\frac{t_2-t}{t_2-t_1} \right) & \text{if } t_1 \leq t \leq t_2, \end{cases} \quad (17)$$

Constraint (12) shows that the total apparent power after the addition of EV must not exceed the rated capacity of the transformer in order to avoid accelerated aging due to high temperature. Constraint (13) gives the total demand/load experienced by the transformer at any given time t . Constraint (14) gives the SOC of n^{th} EV at time t for a period of time Δt . The initial SOC_{ini}^n of n^{th} EV depends on the previous driving distance and is calculated by (15). SOC_{min} is selected if the calculated SOC falls below the minimum value in order to avoid the degradation of the battery. The EV must be sufficiently charged to be used for the next day, where this condition is given in (16). Constraint (17) gives the charging power of EV based on the typical charging profile of Fig. 6. The actual charging profile is simplified by piecewise linearization [23], [45], and [46].

TABLE 2. Self and cross elasticity.

	Peak	Shoulder_1	Shoulder_2	Off_Peak
Peak	-0.1	0.009	0.009	0.01
Shoulder_1	0.009	-0.1	0.009	0.01
Shoulder_2	0.009	0.009	-0.1	0.01
Off_Peak	0.01	0.009	0.009	-0.1

IV. NUMERICAL SIMULATION AND RESULTS

A. INPUT DATA AND PARAMETERS

Decision variables are P_t^{peak} and th_{peak} (time at which the peak price starts). The relationship between four different ToU tariffs and the threshold temperature at which each tariff is applied is given in (18). To determine the ToU tariff using (10), Table 2 shows the self and cross elasticity used between the various tariffs based on the work in [47].

The values of the decision variables are optimized using the Simplicial Homology Global Optimization (SHGO) algorithm. It is a promising derivative free and recently published global optimization (GO) algorithm based on integral homology and combinatorial topology [48], [49]. The main advantage of SHGO is that it can determine unique local minima which are locally convex (approximately) with relative ease compared with other optimization algorithms. A core i7 PC with 8 GB RAM was used for the simulation, where it was able to solve the problem within a few minutes.

In this work; three penetration levels of EVs, namely 10%, 25%, and 50% (based on (1)); three representative residential load profiles (i.e. summer load, winter load, and shoulder load); and four representative temperature profiles have been considered (as given in Fig.3).

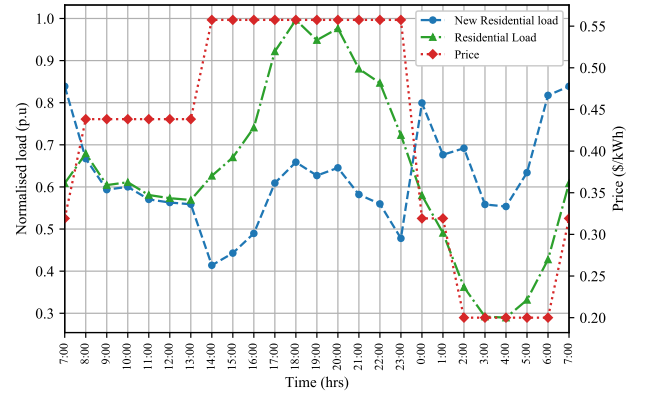
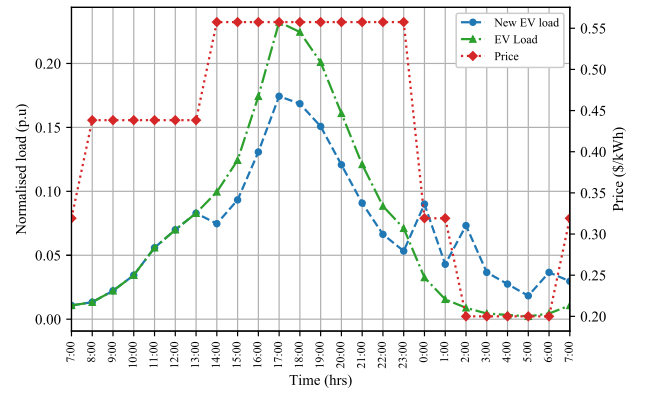
$$P_t = \begin{cases} P_t^{peak} & \text{if } \theta_H \geq th_{peak} \\ P_t^{sdr_1} & \text{if } th_{sdr_1} \leq \theta_H \leq th_{peak} \\ P_t^{sdr_2} & \text{if } th_{sdr_2} \leq \theta_H \leq th_{sdr_1} \\ P_t^{offpeak} & \text{if } th_{min} \leq \theta_H \leq th_{sdr_2} \end{cases} \quad (18)$$

where

$$\begin{aligned} th_{sdr_1} &= (th_{peak} - th_{min}) \frac{2}{3} + th_{min} \\ th_{sdr_2} &= (th_{peak} - th_{min}) \frac{1}{3} + th_{min} \\ P_t^{sdr_1} &= \left(P_t^{peak} - P_t^{offpeak} \right) \frac{2}{3} + P_t^{offpeak} \\ P_t^{sdr_2} &= \left(P_t^{peak} - P_t^{offpeak} \right) \frac{1}{3} + P_t^{offpeak} \end{aligned}$$

B. RESULTS AND DISCUSSION

This article analyzed the load experienced by the distribution transformer. Load varies throughout the year and is comprised of residential load and additional load from EV, which is further dependent on penetration levels. The demand response of residential load and EV load is carried out separately, as residential load can be shifted to either side of the time duration as the loads are more flexible. Since EV cannot

**FIGURE 7.** ToU tariff based on residential load.**FIGURE 8.** ToU tariff based on EV load.

be charged before its arrival time, EV charging loads are only shifted to the later time based on the ToU tariff signal.

The results for a case with 25% EV penetration, winter load, and representative ambient temperature-4 are shown in Fig. 7 to Fig. 12. The demand response of residential load is shown in Fig. 7, where it can be seen that the load is shifted to either side of the load profile depending on the ToU tariff. A major portion of the load from peak hours and a small portion of the load from shoulder-1 period are shifted to off-peak time and shoulder-2 time periods, respectively. Fig. 8 shows the demand response of the EV charging load. Since most EVs will be used during the day time, where survey data shows that about 20% of the EVs return home after 15:00 hr and about 80% by 20:00 hr; therefore, EV loads are only shifted to the later time after arrival based on ToU tariff.

Fig. 9 shows the demand response of the total load based on the ToU tariff signal. The hot-spot temperature goes above its threshold temperature from 14:00 hrs to 22:00 hrs for uncoordinated charging. The demand response proposed here is able to shift the load to off-peak hours and maintain the temperature of the transformer within the limit. The peak load of about 1.22 p.u. at 18:00 hr is shifted to a peak load of 0.845 p.u. at 00:00 hr. The ToU tariff varies in-between AUD 0.2 per kWh to AUD 0.8 per kWh. The optimization finds the best value of TOU tariffs and the start time of

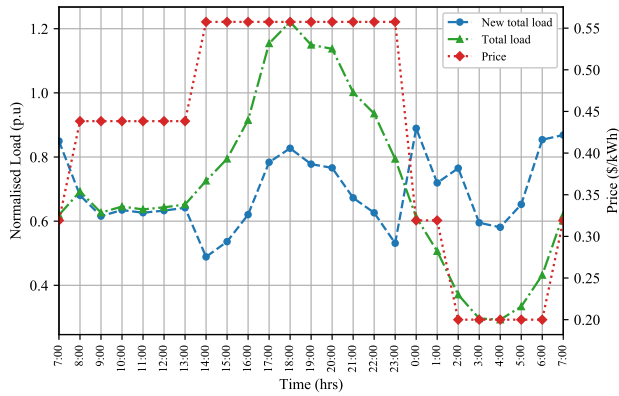


FIGURE 9. ToU tariff based on total load.

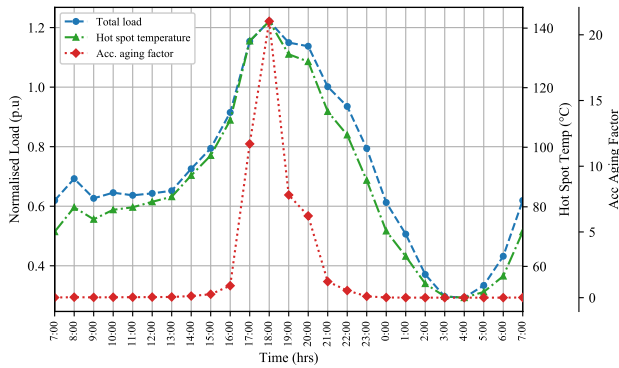


FIGURE 10. Hot-spot temperature and Accelerated ageing factor for uncoordinated charging.

each tariff (namely, peak, shoulder-1, shoulder-2, and off-peak) and time duration, which gives the minimum F_{EQ} . For this particular case, the tariff starts with shoulder-2 of AUD 0.319 per kWh at 07:00 hr and changes to shoulder-1 of AUD 0.438 per kWh for the time period between 08:00 hr to 13:00 hr. At 14:00 hr the peak tariff of AUD 0.557 per kWh is applied to divert the EV charging load and the residential load to minimize the F_{AA} of the transformer. The tariff only changes to shoulder-2 at 00:00 hr, so that the EVs can start charging, and it further decreases to an off-peak tariff of AUD 0.2 per kWh after 01:00 hr until 06:00 hr.

The F_{AA} for uncoordinated EV charging is given in Fig. 10. The hot-spot temperature crosses the threshold temperature of 110°C in between 16:00 hr to 21:00 hr and F_{AA} reaches a peak of 20 at 18:00 hr. The F_{AA} only becomes more than 1 at 17:00 (i.e. one hour later than the time hot-spot temperature crosses its threshold of 110°C) hrs due the thermal time constant of the transformer. The proposed solution of shifting the load of the transformer based on the temperature of the transformer is shown in Fig. 11. It can be observed that the load profile changes based on the response to the ToU tariff signal and the optimization has done so by minimizing the equivalent aging of the transformer (F_{EQ}). The hot-spot temperature due to the new load of the transformer reaches very near to the threshold temperature at 18:00 hr and 00:00 hr, but

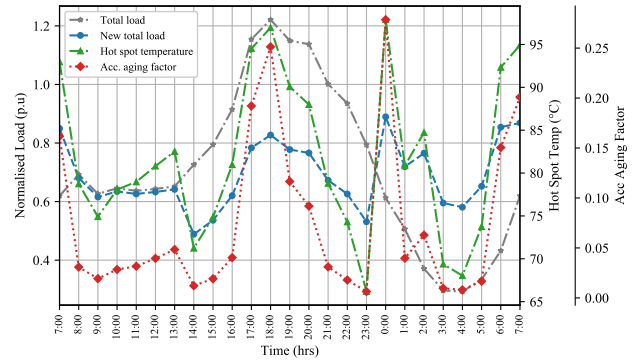


FIGURE 11. Hot-spot temperature and Accelerated ageing factor based on the proposed strategy.

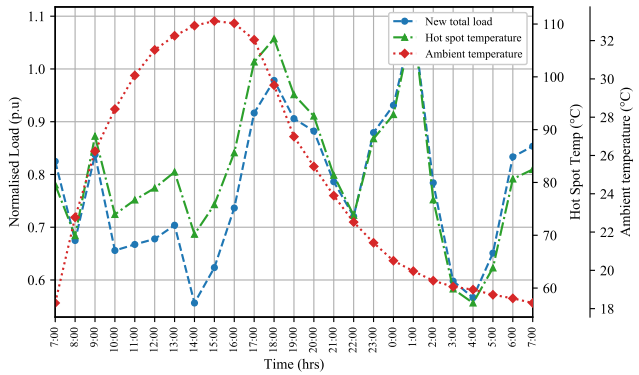


FIGURE 12. Influence of ambient temperature on the hot-spot temperature.

the F_{AA} only reaches a value of 0.28. This happens due to the thermal time constant of the transformer, where if managed properly, a higher amount of load can be accommodated by the transformer. The new load of the transformer significantly decreases F_{AA} , and it never crosses the limit.

The influence of ambient temperature on the transformer's hot-spot temperature is shown in Fig. 12 (case with 50% EV penetration, winter load, and representative ambient temperature-3). Accordingly, the hot-spot temperature rises significantly between 12:00 hrs till 16:00 hrs due to high ambient temperature between 25°C and 30°C. Therefore, it is important to manage the total load of the transformer based on the hot-spot temperature, which is further dependent on the ambient temperature. The amount of additional EV charging load that a particular transformer can handle without overloading can vary significantly for a place where ambient temperature varies throughout the day and throughout the year.

Table 3 shows the life expectancy of the transformer for thirty-two scenarios. The accelerated aging of the transformer is not affected by 10% of EV penetration. Accelerated aging of the transformer goes above 1 after the EV penetration reaches 25%. The impact of ambient temperature is evident as the F_{EQA} is below 1, for representative ambient temperature-1, but it is more than one for other ambient temperatures. The same trend can be seen for EV penetration

TABLE 3. Aging of transformer.

EV Penetration (%)	Seasons	Ambient Temp	P_t^{peak} (\$/kWh)	th_{peak} (°C)	F_{EQA}^{Un}	F_{EQA}^{Smart}	$Life_{exp}^{Un}$ (years)	$Life_{exp}^{Smart}$ (years)
10	Winter	1	0.523	87.5	0.218	0.014	20.55	20.55
10	Winter	2	0.507	87.5	0.294	0.022	20.55	20.55
10	Winter	3	0.513	87.5	0.395	0.029	20.55	20.55
10	Winter	4	0.531	87.5	0.545	0.043	20.55	20.55
10	Summer	1	0.621	60	0.183	0.004	20.55	20.55
10	Summer	2	0.572	85	0.247	0.008	20.55	20.55
10	Summer	3	0.559	85	0.330	0.012	20.55	20.55
10	Summer	4	0.673	60	0.447	0.015	20.55	20.55
10	Threshold	1	0.546	87.5	0.155	0.007	20.55	20.55
10	Threshold	2	0.510	87.5	0.210	0.012	20.55	20.55
10	Threshold	3	0.524	87.5	0.285	0.014	20.55	20.55
10	Threshold	4	0.501	87.5	0.402	0.026	20.55	20.55
25	Winter	1	0.527	87.5	0.920	0.028	20.55	20.55
25	Winter	2	0.526	87.5	1.206	0.041	17.04	20.55
25	Winter	3	0.522	87.5	1.573	0.061	13.06	20.55
25	Winter	4	0.558	87.5	2.091	0.079	9.83	20.55
25	Summer	1	0.584	87.5	0.895	0.010	20.55	20.55
25	Summer	2	0.565	87.5	1.169	0.017	17.58	20.55
25	Summer	3	0.551	87.5	1.517	0.027	13.54	20.55
25	Summer	4	0.651	65	1.990	0.029	10.32	20.55
25	Threshold	1	0.550	87.5	0.711	0.013	20.55	20.55
25	Threshold	2	0.532	87.5	0.934	0.020	20.55	20.55
25	Threshold	3	0.539	87.5	1.231	0.027	16.69	20.55
25	Threshold	4	0.525	87.5	1.663	0.049	12.35	20.55
50	Winter	1	0.545	87.5	8.409	0.098	2.44	20.55
50	Winter	2	0.544	87.5	10.648	0.145	1.93	20.55
50	Winter	3	0.525	87.5	13.414	0.287	1.53	20.55
50	Winter	4	0.587	87.5	17.166	0.241	1.20	20.55
50	Summer	1	0.573	110	10.149	0.051	2.02	20.55
50	Summer	2	0.586	65	12.789	0.101	1.61	20.55
50	Summer	3	0.545	110	15.999	0.116	1.28	20.55
50	Summer	4	0.682	65	20.185	0.121	1.02	20.55
50	Threshold	1	0.574	87.5	6.346	0.033	3.24	20.55
50	Threshold	2	0.570	87.5	8.065	0.050	2.55	20.55
50	Threshold	3	0.576	87.5	10.267	0.068	2.00	20.55
50	Threshold	4	0.563	87.5	13.290	0.120	1.55	20.55

levels of 25% and 50% for all seasons, as the expected life of the transformer lowers as ambient temperature profile increases.

The expected life of the transformer is assumed to be 180,000 hours, which is about 20.55 years. The last two columns of Table 3 show the expected life of the transformer for uncontrolled charging of EV load and charging based on temperature as proposed. The obtained results show that with the use of the proposed strategy, the transformer will last until its lifetime of 20.55 years for all scenarios.

V. CONCLUSION

This article has presented a comprehensive methodology to measure a rise in the loss of life of power transformers due to EV charging loads to power distribution systems. Comprehensive and realistic data were used to model EV load and applied into the thermal model of the transformer. A new ToU

pricing to shift the EV load based on temperature is proposed and it does not need any new augmentation to the network, unlike methods proposed in other papers.

Thirty-two charging scenarios with three levels of EV penetrations with three real representative residential loads, and four real representative ambient temperatures were considered in the paper. The paper makes the following conclusions:

- 1) Results show that the annual LoL of the residential transformer will reach 98.23% with a 50 percent penetration of EVs in summer, corresponding to 1.02 years of transformer life expectancy for the 'worst case' charging scenario.
- 2) Results indicate that the smart charging scenario provides a better outcome from the loss of life reduction perspective. Results also reveal that, under the same EV loading conditions, the LoL of the transformers differs significantly over different seasons of the year. The

values of LoL due to EV charging are mainly increased with higher ambient temperature and higher residential load. This problem is mitigated as the results show that the proposed method is able to manage EV integration up-to 50%.

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