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Impact on Distribution Transformer Life Using Electric Vehicles with Long-Range Battery Capacity

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Abstract: This paper presents a comparative analysis of the effects of short-range and long-range electric vehicles charging on transformer life. Long-range vehicles are expected to become more common in the future. They have higher battery capacity and charge at higher power levels, modifying demand profile. A probabilistic analysis is performed using the Monte Carlo Simulation, evaluating the transformer hottest-spot temperature and the aging acceleration factor. Residential demand is modeled based on real electricity measurements, and EVs' demand is modeled based on real data collected from a trial project developed in the United Kingdom. Simulations are conducted considering the influence of ambient temperature analyzing summer and winter seasons and several EV penetration levels. Results show the impacts caused by long-range vehicles are more severe because they charge at higher power levels, especially during winter, when residential demand is higher. For penetration level of 50% during summer, the use of long-range EVs brings a minimum equivalent aging factor of 5.2, which means the transformer aged 124.8 h in a cycle of only 24 h, decreasing its lifetime.

Keywords: distribution transformer; electric vehicles; hottest-spot temperature; Monte Carlo Simulation; transformer loss-of-life

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1. Introduction

Global warming and climate change have been driving a global decarbonization movement, seeking to reduce the use of fossil fuel and greenhouse gas emissions. The transport sector accounts for a huge part of total gas emissions, achieving 8 Gt. of CO_2 emissions in 2022 [1]. The use of electric vehicles (EVs) is essential to decarbonize this segment. Thus, governments in several countries have been promoting public politics with subsidies and incentives for the use of EVs. For example, Norway adopted a national goal that all new cars sold by 2025 should be zero-emission [2]. Germany agrees to ban internal combustion engines by 2030, and France and Great Britain plan to end the sales of fossil fuel-powered cars by 2040 [2].

Electric vehicles market sales have grown rapidly in the last years. The main barrier to widespread adoption of EVs is the battery, which still must overcome the high costs and low charging speed and range to dominate the market. To address the consumers' concern, the EV industry has been launching vehicle models with higher battery capacity that charge at higher power levels, increasing vehicle range and reducing the charging time [3]. EV models from 2014 have short-range batteries with capacity around 24 kWh. However, the latest EV models such as Tesla 3 have long-range batteries of 75 kWh and charge at 7–11 kW.

The increased use of EVs can have negative impacts on electrical energy distribution systems. EVs need to be frequently charged and consume a large amount of energy, causing excessive and undesirable peaks in energy demand. This can lead distribution transformers, which were sized before EVs' integration, to overload [4]. When transformers are exposed to high ambient temperatures and loading above the nominal value, transformers' windings may overheat, leading to deterioration and loss-of-life, incurring extra costs. Moreover, EV demand has uncertainties and randomness associated with user's behavior and battery specification, which brings extra challenge to this problem.

Numerous studies have been conducted analyzing EVs' impact on transformer loss-of-life. In [5], authors propose a reactive power compensation strategy during EV charging for transformer overloading mitigation in a residential feeder. In [6], authors analyze the impact of reactive power from public EV charging stations on transformer aging and active power losses. Simulations considered vehicles with battery capacity from 40 kWh to 80 kWh, charging at 3.4 kW and 7.2 kW.

Authors in [7] analyze the effects of EVs' charging demand on distribution transformer attending residential customers and propose demand side management with time-of-use (ToU) tariffs to minimize transformer aging. Vehicles with 16 kWh and 24 kWh charging at 3.7 kW are considered, and several EVs' penetration levels are analyzed. Authors in [8] propose a smart charging strategy to minimize electricity consumption costs and avoid transformer overloading by considering a charging station in a commercial building integrated with photovoltaic generation and a battery energy storage system. They adopt vehicles of 16 kWh and 24 kWh charging at 3.3 kW and 6.6 kW. Reference [9] proposes a smart charging algorithm with variable-rate to mitigate transformer overloading and loss-of-life. The method is compared with other strategies, such as uncontrolled charging and fixed-rate controlled charging, with promising results. EV demand is modeled based on a Bureau of Transportation Statistics survey, and simulations consider eight different types of EVs charging at different power levels varying from 1.9 kW to 11.5 kW.

In [10], authors evaluate the damaging impact of several EVs on distribution transformers life considering different penetration levels. Simulations consider EVs with 11 kWh battery capacity charging at 4 kW. Results show the loss-of-life rate during evening peak is 12.21 for a scenario with 40% EV penetration level. In [11], authors propose a risk assessment to quantify the severity and likelihood of transformer overload conditions due to high levels of EVs' demand coupled with rooftop solar generation. Probabilistic analysis is performed, and multiple EV penetration scenarios are analyzed. In [12], authors propose a fuzzy system to estimate distribution transformer aging and mitigation strategies combining battery energy storage systems and photovoltaic generation. Authors in [13] evaluate distribution transformer overload and aging in a residential feeder using probabilistic analysis. Simulations considered fast chargers with vehicles with 100 kWh charging at 50 kW, and vehicles with 16 kWh and 32 kWh charging at 3.7 kW and 6.6 kW. In [14], authors propose an approach to support EV charging that allows the transformer to operate beyond nameplate rating without compromising its life based on the knowledge of thermal inertia. Results show transformers can operate above the nameplate rating for periods without exceeding any relevant IEEE or IEC standards. In [15], authors propose a framework to assess distribution transformer aging using Time Series Decomposition and the Hidden Markov Model as forecasting tools. However, EV demand is modeled based on travel surveys and several assumptions instead of real data. In [16], authors analyze the potential impact of EV charging on transformer lifetime using a real distribution system from USA. Although a probabilistic analysis is adopted, EV demand is modeled based on projections, assumptions and travel surveys instead of real data.

Most studies mentioned above model EVs' demand based on national surveys or projection scenarios, instead of using real data collected from trial projects, which directly impacts the estimation of transformer life. Another important aspect is that these studies do not capture stochasticity in transformer life due to EV charging demand, because only EVs' profile is generated probabilistically. Moreover, despite some studies adopting long-range EV models, to the best of the author's knowledge, no study has been reported in the literature comparing the effects of long-range and short-range EVs on transformer life. Table 1 provides an overview of the most recent studies in this area.

Table 1. Literature review of recent papers analyzing the impacts of EVs on transformer life.

Reference	Probabilistic Analysis	Real EVs' Database from Trial Project	Diverse EVs' Penetration Levels	Comparative Analysis (Long × Short-Range)
[5]	-	-	-	-
[6]	-	-	✓	-
[7]	-	-	✓	-
[8]	-	-	-	-
[9]	-	-	-	-
[10]	✓	✓	✓	-
[11]	-	-	-	-
[12]	✓	-	✓	-
[13]	✓	-	-	-
[14]	-	-	-	-
[15]	✓	-	✓	-
[16]	✓	-	✓	-
This paper	✓	✓	✓	✓

This paper addresses this knowledge gap in the literature, comparing the effects of long-range and short-range EVs' charging on transformer life. A probabilistic analysis is employed using the Monte Carlo (MC) Simulation considering uncertainties from residential and EV demand. Residential demand is modeled based on real data from the UK Data Service [17], and EVs' charging demand is modeled based on real data from the Electric Nation Project developed in the United Kingdom [18]. The deterioration of the transformer is investigated through the analysis of transformer hottest-spot winding temperature and equivalent aging factor, according to the thermal model presented in IEEE Guide [19]. Simulations are conducted considering seasonal variations, adopting winter and summer profiles for residential demand, EVs' demand and ambient temperature. Besides, several EV penetration levels are analyzed. The key contributions of this work are as follows:

- Models EVs' demand based on real data collected from trial projects;
- Employs a probabilistic analysis on transformer life due to EV charging demand under different EVs' penetration levels;
- Compares long-range and short-range EVs' charging impact on transformer life.

This work is organized as follows. Section 2 presents the proposed methodology and the probabilistic models adopted for residential and EVs' demand. The results are presented in Section 3, followed by main conclusions in Section 4.

2. Proposed Methodology

Figure 1 shows the proposed method to quantify the impacts that long-range and short-range EVs' charging demand cause on transformer life. The Monte Carlo Simulation is used to consider model uncertainties [20]. First, residential and EVs' demand are sampled according to probabilistic models developed based on real data. Then, the transformer load is computed for summer and winter, accounting for residential load and EVs' charging demand. Based on transformer demand and ambient temperature, transformer indices are evaluated for summer and winter to estimate its loss of life.

To guarantee simulation's reproducibility, Mersenne Twister pseudorandom number generator with a seed equal to 3000 was used, as suggested in [21], to perform 1000 simulations and achieve convergence, using Random Number Generation toolbox of MATLAB 2021. Simulation period of 24 h is considered with sampling interval of 10 min.

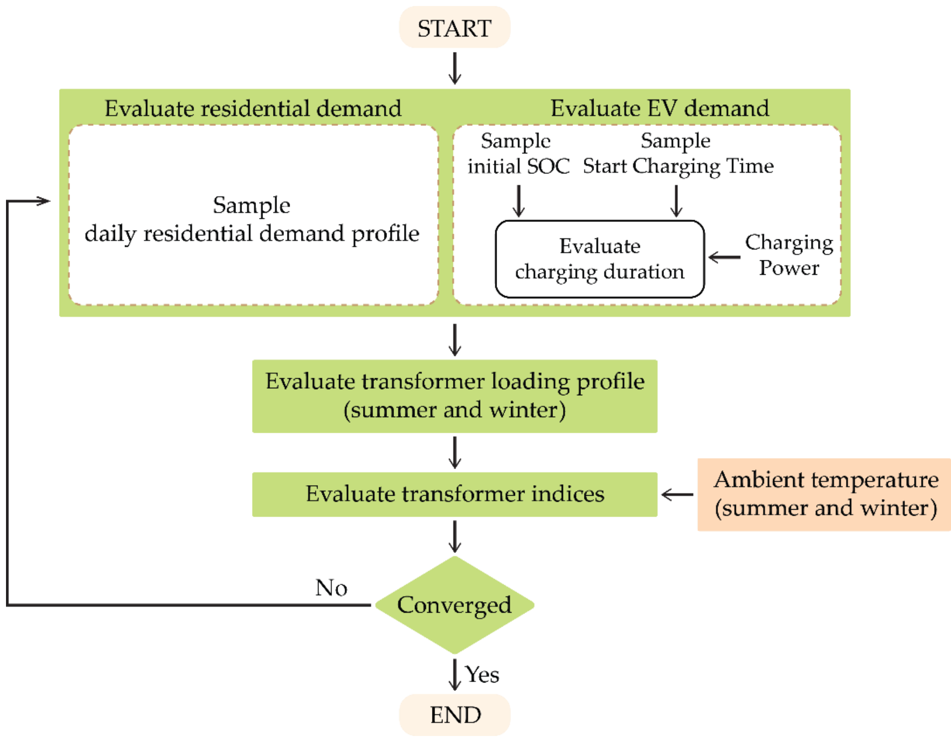

Figure 1. Flowchart of the proposed impact assessment methodology using probabilistic analysis.

2.1. Residential Demand

The database used to generate residential load profiles comprehends real electricity measurements from 22 residences in the East Midlands, United Kingdom, from 2008 to 2009 [17]. This data is divided into 2 sets according to the season: summer (June to September) and winter (December to March). Since no parametric distribution function fits the original data, a non-parametric Gaussian kernel with 0.01 bandwidth is considered for each 10-min interval. The Kolmogorov-Smirnov statistic test (KS-test) is applied to the data generated with the obtained probabilistic models. Figure 2 shows the results which indicate a good fit.

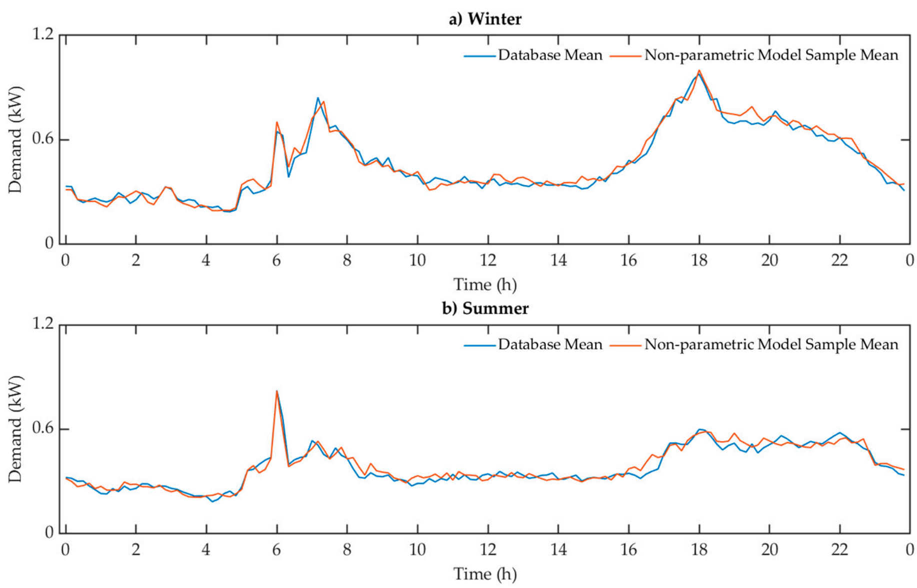

Figure 2. Mean value from measured residential load and data generated with the proposed probabilistic model. (**a**) Winter. (**b**) Summer.

2.2. Electric Vehicles Demand

EVs' demand is modeled based on a real database from Electric Nation Project, which collected data from 673 smart chargers installed at participants' homes in United Kingdom from January 2017 to July 2018 [18]. The database contains information, such as participant identification, day of the week, start charging time, battery capacity (kWh) and energy consumed (kWh).

First, data was pre-processed, filtered and separated to consider only measurements taken in two seasons: summer (June to September) and winter (December to March). Based on this data, the initial state-of-charge (SOC) is evaluated according to (1) [8].

$$SOC_i(\%) = \left(1 - \frac{E}{B_c}\right) \times 100 \quad (1)$$

where SOC_i is the initial state-of-charge, E is the energy consumed while charging the vehicle (kWh) and B_c is the battery capacity (kWh).

Then, the start charging time and SOC_i collected from the database were fitted to a non-parametric distribution function, with Gaussian kernel and 0.01 of bandwidth, to obtain their corresponding probabilistic distribution function (PDF). The goodness-of-fit is evaluated employing the KS-test and results indicate a good fit as shown in Figures 3 and 4.

Based on these probabilistic models, random samples of the SOC_i and start charging time are generated, and the charging duration is evaluated as shown in (2) [8].

$$\Delta T_{charge} = \left(\frac{SOC_f - SOC_i}{\eta P_{ch}}\right) \times C_b \quad (2)$$

where SOC_f is the final state-of-charge, η is the charger's efficiency assumed as 99% and P_{ch} is the charging power (kW).

The EV charging demand profiled is obtained for a period of 24 h with 10-min resolution according to the flowchart shown in Figure 5. Two EV models are considered varying the EV battery capacity and the charging power level:

- short-range vehicles with 24 kWh charging at 7.4 kW.
- long-range vehicles with 75 kWh charging at 11 kW.

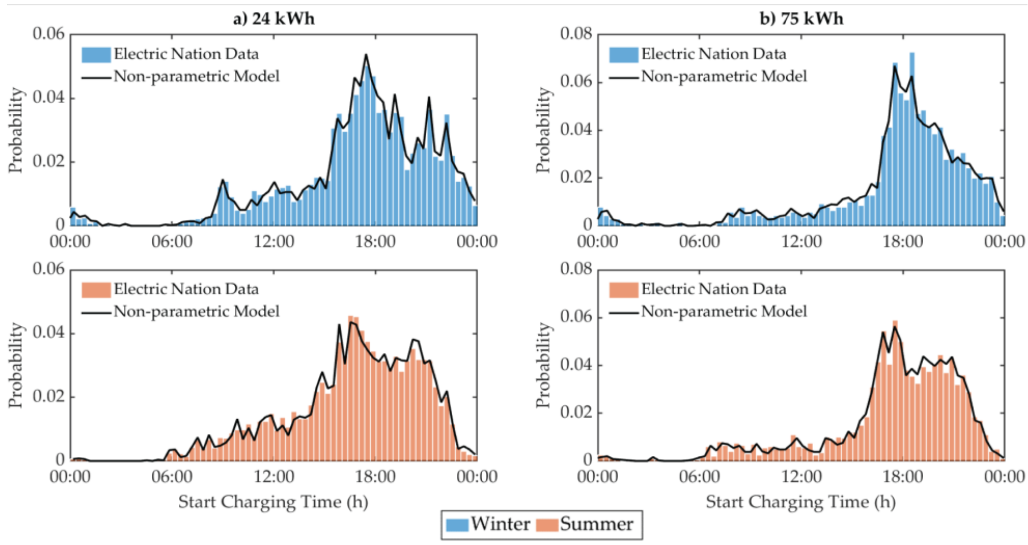

Figure 3. Histograms of Start Charging Time and PDF models for different battery capacities. (**a**) 24 kWh. (**b**) 75 kWh.

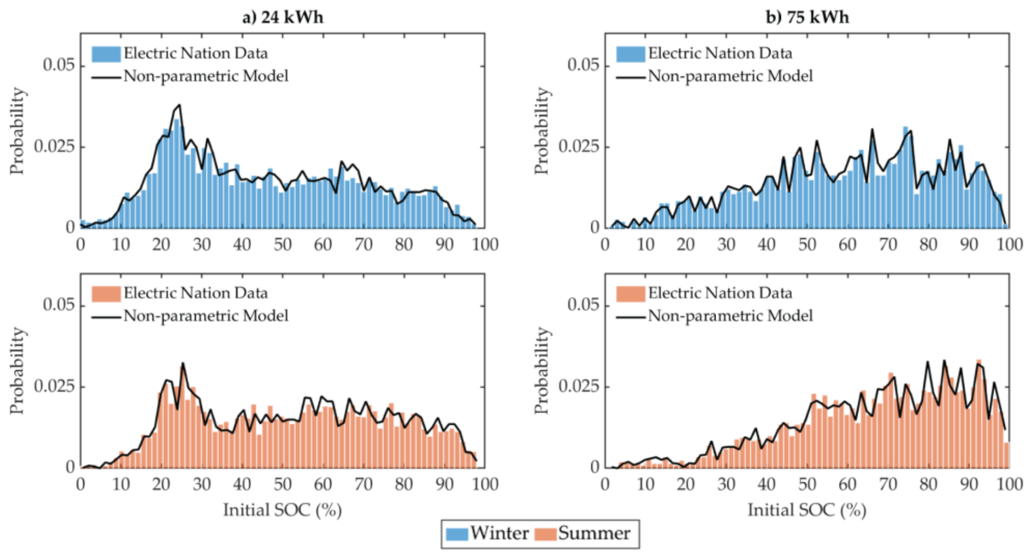

Figure 4. Histograms of initial state-of-charge and PDF models for different battery capacities. (**a**) 24 kWh. (**b**) 75 kWh.

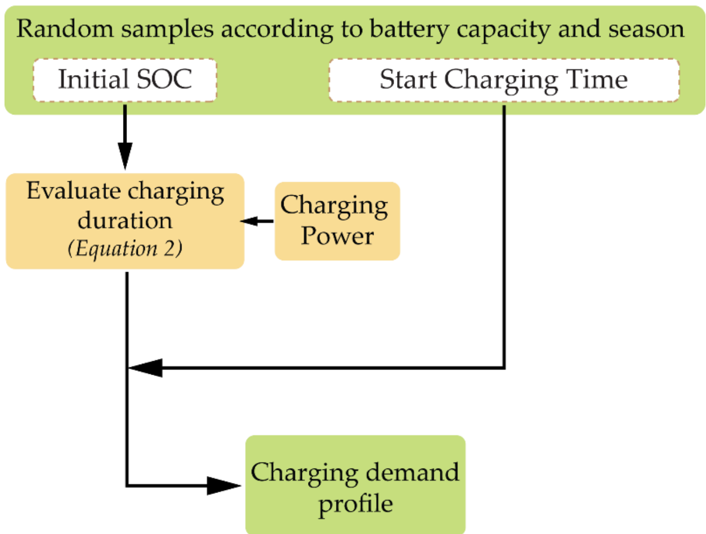

Figure 5. Electric vehicle charging demand profile calculation.

2.3. Transformer Aging Model

Transformers are one of the most important and expensive devices in the distribution grid, and the efficiency of these assets is vital to ensure reliability and power delivery. Transformer service life is mainly related to insulation degradation. Under normal operating conditions, core and coil losses generate significant internal heat, which if not dissipated, can shorten the life of transformers [19].

Insulation aging or deterioration is a function of temperature, moisture content and oxygen content over time. With modern oil preservation systems, moisture and oxygen contributions to insulation deterioration can be minimized by leaving insulation temperature as the control parameter. Since, in most appliances, the temperature distribution is not uniform, that part which is operating at the highest temperature will normally suffer the most deterioration. Therefore, in aging studies it is usual to consider the effects of aging produced by the higher temperature (hottest-spot temperature).

In this paper, transformer hottest-spot temperature (Θ_H) is evaluated based on the classic thermal model presented in IEEE Standard C57.91 [19]. All equations used in this section are from this reference.

The main factor contributing to transformer insulation degradation is transformer winding hottest-spot temperature, which can be computed as in Equation (3):

$$\Theta_H = \Theta_A + \Delta\Theta_{TO} + \Delta\Theta_H \tag{3}$$

where Θ_A is the average ambient temperature during the load cycle under analysis, $\Delta\Theta_{TO}$ is the top-oil rise over ambient temperature and $\Delta\Theta_H$ is the winding hottest-spot rise over top-oil temperature, all in °C.

The ambient temperature is an important parameter in determining the transformer's load capacity. This paper adopted ambient temperatures' curves over a period of 24 h, with average values extracted from the National Solar Radiation Database [22] for the location of the United Kingdom. Two curves are considered as shown in Figure 6, one for summer season and the other for winter season.

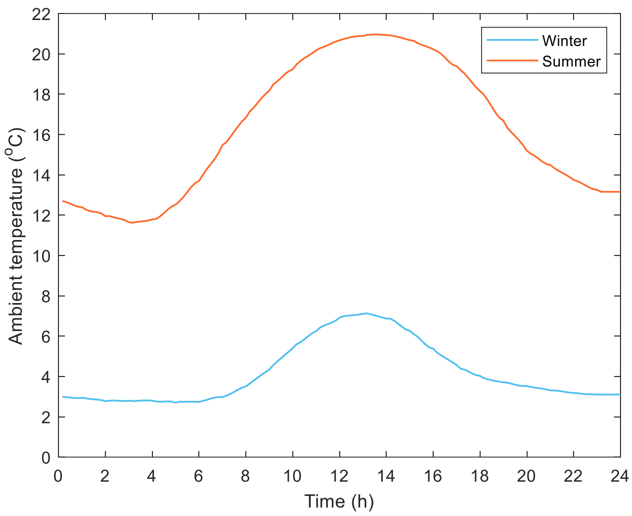

Figure 6. Average values of ambient temperature for a 24-h period.

The rise in top oil temperature at one time after a step load change ($\Delta\Theta_{TO}$) is given by the exponential expression as shown in Equation (4). This equation is used for each load step of a load cycle. The top-oil rise calculated for the end of the previous load step is used as the initial top-oil rise for the next load step calculation.

$$\Delta\Theta_{TO} = (\Delta\Theta_{TO,U} - \Delta\Theta_{TO,i})\left(1 - exp^{\frac{-1}{\tau_{OT}}}\right) + \Delta\Theta_{TO,i} \tag{4}$$

where τ_{OT} is the transformer oil time constant in hours, $\Delta\Theta_{TO,U}$ is the ultimate top-oil rise over ambient temperature in °C and $\Delta\Theta_{TO,i}$ is the initial top-oil rise over ambient temperature in °C.

The ultimate top-oil rise $\Delta\Theta_{\mathrm{TO,U}}$ is given by Equation (5):

$$\Delta\Theta_{TO,U} = \Delta\Theta_{TO,R}\left[\frac{(K_U^2 R + 1)}{(R+1)}\right]^n \tag{5}$$

where K_U is the ratio of ultimate load to rated load in per unit, R is the ratio of load loss to no-load loss and n is an empirically derived exponent whose value depends on transformer cooling mode.

The rise of the winding hottest-spot over the upper oil is evaluated according to Equation (6):

$$\Delta\Theta_H = \Delta\Theta_{H,R} K^{2m} \tag{6}$$

where $\Delta\Theta_{H,R}$ is the winding hottest-spot temperature at rated load in °C and m is an empirical exponent whose value depends on transformer cooling mode.

Based on the transformer hottest-spot temperature, some important indices can be evaluated. The transformer aging acceleration factor (F_{AA}) can be evaluated as shown in Equation (7) for a given load and temperature. F_{AA} is greater than 1 if the hottest-spot temperature is above the reference temperature of 110 °C and less than 1 if the hottest-spot temperature is below 110 °C.

$$F_{AA} = EXP^{\left[\frac{15000}{383} - \frac{15000}{\Theta_H + 273}\right]} \tag{7}$$

where Θ_H is the winding hottest-spot temperature (°C).

The equivalent transformer aging factor can be evaluated as in Equation (8), expressed in days for a varying load and temperature profile over the entire 24-h period analyzed.

$$F_{EQA} = \frac{\sum_{i=1}^{N} F_{AA_i} \Delta t_i}{\sum_{i=1}^{N} \Delta t_i} \tag{8}$$

where i is index of the time interval (t), N is total number of time intervals and Δt_{i} is time interval in hours.

An equivalent aging factor equal to 1 means that the transformer aged 1 day (24 h) in a cycle of 24 h, early deterioration not occurring. On the other side, an equivalent aging factor equal to 1.5 means that the transformer aged 36 h in a cycle of 24 h, implying premature aging. Transformer normal insulation life is 20.55 years, equivalent to 180,000 h. However, if this transformer operates continuously under the foregoing conditions with daily aging of 36 h, its useful life will be significantly reduced. The distribution transformer used in this paper has 200 kVA and supplies 100 residences. The thermal parameters provided by the manufacturer are listed in Table 2.

Table 2. Transformer thermal parameters [23].

Parameter Description	Value
Rated Power	200 kVA
Maximum Temperature Rise of Oil ($\Delta\Theta_{TO,R}$)	50 °C
Maximum Temperature Rise for Winding ($\Delta\Theta_{H,R}$)	55 °C
No-load losses	500 W
Copper losses	2400 W
Transformer oil time constant (τ_{TO})	4.9 h
ONAN Cooling Method	$m = n = 0.8$

3. Simulation Results

In this section, the impact of EV charging on transformer life is analyzed considering different penetration levels and vehicles with different battery capacities: 75 kWh (long-range) and 24 kWh (short-range). In addition, the effects of winter and summer seasons are verified.

3.1. Base Scenario

The base scenario considers no household carries EVs. Results are separated according to winter and summer seasons. Figure 7 shows the boxplot of transformer load and hottest-spot temperature due to residential demand for a period of 24 h. In the boxplot, the horizontal line inside the box is used to mark the median, while the upper and bottom of the box represent 75th and 25th percentiles. The two horizontal lines outside of the box represent the maximum and minimum of the data. Note that residential demand is below the transformer nameplate rating of 200 kVA. Therefore, the hottest-spot temperature does not violate the reference temperature of 110 °C, and the transformer does not experience loss-of-life.

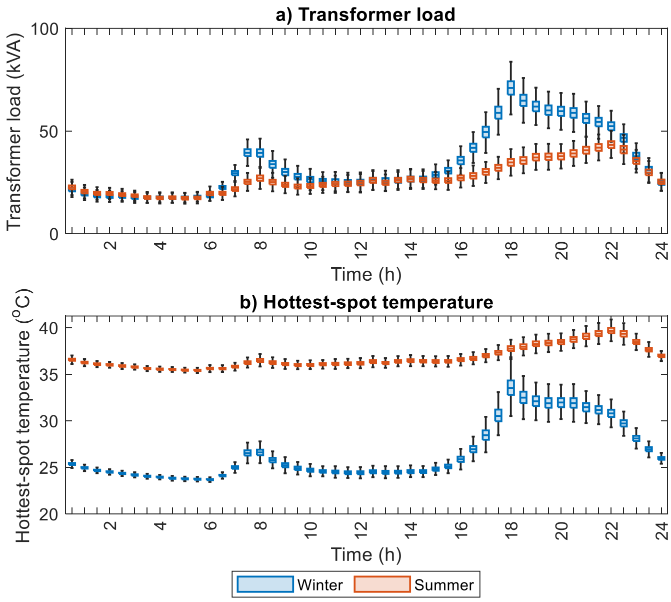

Figure 7. Boxplot for 24-h period. (**a**) Transformer load. (**b**) Hottest-spot temperature.

3.2. Penetration Level Impact

This section evaluates the impact of different EVs' penetration levels on transformer aging. In this study, the penetration level is defined as the ratio between the number of EVs and the number of households, which is 100. EVs' penetration level gradually increases from 0% up to 60% in steps of 10%.

Figure 8 shows the boxplot of maximum transformer load and hottest-spot temperature to each penetration level. During winter, residential demand is higher and transformer violates its rated capacity limit for lower penetration levels compared to summer. Also, the impacts caused by EVs with 75 kWh batteries are more severe because they charge at higher power levels, increasing peak demand. The total load already exceeds transformer-rated capacity for penetration levels of 20% in both winter and summer with long-range batteries.

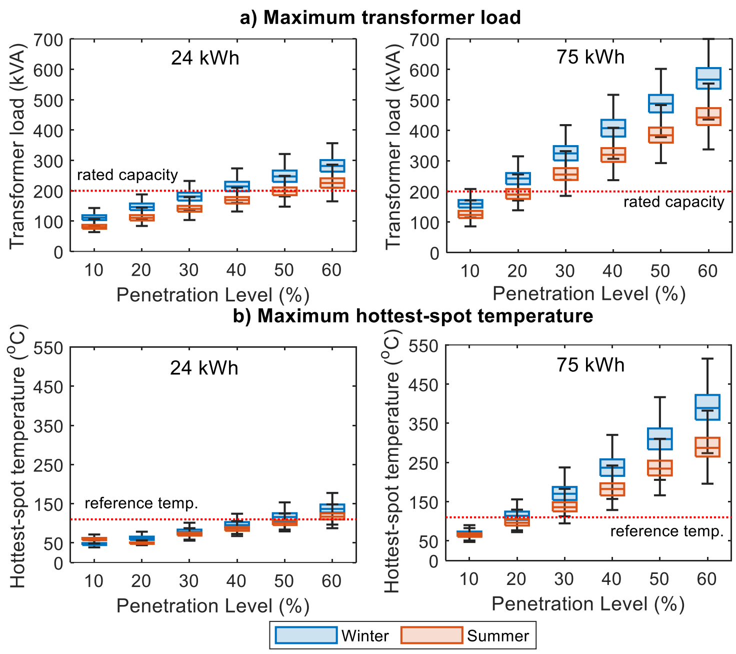

Figure 8. Boxplot for different EVs' penetration levels. (**a**) Maximum transformer load. (**b**) Maximum hottest-spot temperature.

For EVs with 24 kWh, the maximum hottest-spot temperature remains below the reference value until the penetration level of 50%. For EVs with 75 kWh, the maximum hottest-spot temperature reaches undesirable values for penetration levels as from 20%.

It is important to analyze the evolution of EVs' penetration level to evaluate transformer life. Compared to the base scenario, there is a considerable increase in transformer load and hottest-spot temperature as the penetration levels of EVs increase, especially for vehicles with 75 kWh, where low penetration levels above 20% already lead to severe violations. To better understand the impact of EV charging on transformer hottest-spot temperature and loss-of-life, the penetration level of 50% is investigated in the following section.

3.3. Case Study (Penetration Level of 50%)

This scenario assumes that out of 100 households, 50 have an electric vehicle. Figure 9 shows the boxplot of transformer load for winter and summer seasons, considering EVs with battery capacity of 24 kWh and 75 kWh. In a residential area, users typically charge their vehicles when returning home at the end of the day. Residential demand is also high during this time, causing a considerable increase in peak demand overloading the transformer. Results show the transformer is more likely to exceed its rated capacity for EVs with higher battery capacity during the winter season.

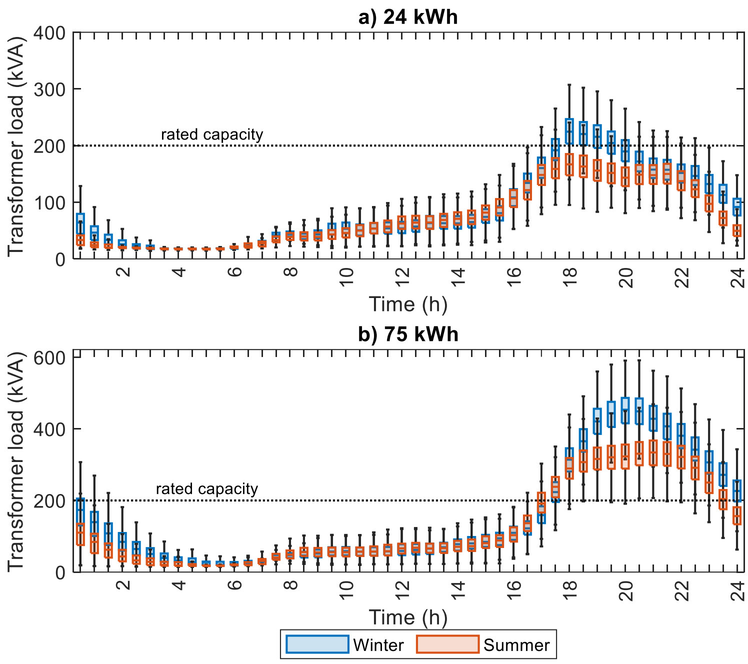

Figure 9. Boxplot of transformer load for 24-h period. (**a**) 24 kWh. (**b**) 75 kWh.

Figure 10 shows the cumulative distribution function of transformer hottest-spot temperature, and the same behavior is observed. The worst scenario is when using vehicles with higher battery capacity during the winter season. For vehicles with 24 kWh, the probability of transformer hottest-spot temperature achieving values above the reference temperature of 110 °C is 64.5% during winter and 17.6% during summer. For vehicles with battery capacity of 75 kWh, the probability increases to 100% for both winter and summer seasons. The main factor that affects the transformer is its insulation temperature, which in turn is mainly related to overload operation and exposure to high ambient temperatures. Since the ambient temperature at this location (England) is not very high during summer season (maximum of 21 °C), transformer operating life is mainly affected by load, which is higher during winter.

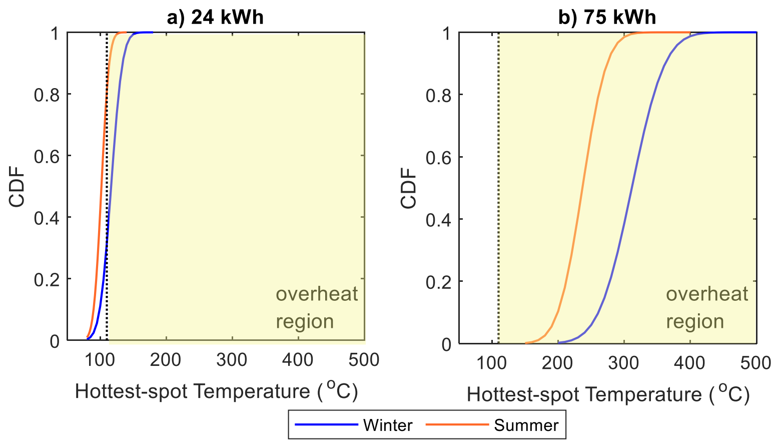

Figure 10. Cumulative distribution function of transformer hottest-spot temperature for 24-h period. (**a**) 24 kWh. (**b**) 75 kWh.

Figure 11 shows the boxplot of the transformer equivalent aging factor. Under normal operating conditions, the transformer should have a maximum equivalent aging factor of 1 day for a 24-h load cycle to prevent premature degradation. The results show the occurrence of transformer aging is very rare when EVs with battery capacity of 24 kWh are adopted both in winter and summer scenarios. However, when EVs with battery capacity of 75 kWh are used, transformer aging always occurs, with minimum values of 127.8 during winter and 5.2 during summer. As an example, an equivalent aging factor equal to 5.2 means that the transformer aged 124.8 h (5.2 × 24) in a cycle of 24 h, implying premature aging. If this transformer is subjected under the foregoing conditions during the whole year, its useful life will be shortened from 20.55 years (normal insulation life) to 4 years, which is not acceptable.

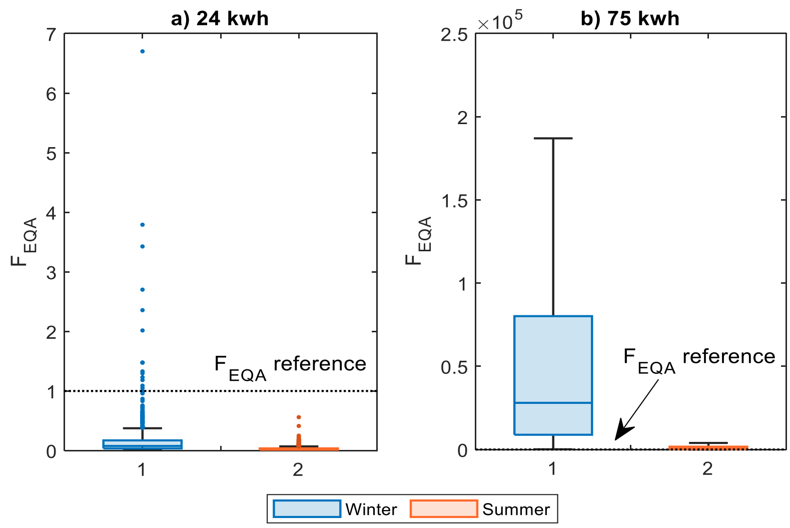

Figure 11. Boxplot of transformer equivalent aging factor (F_{EQA}). (**a**) 24 kWh. (**b**) 75 kWh.

Figure 12 shows the boxplot of transformer overload duration during a day. The results clearly show the negative effect of using EVs with higher battery capacity as transformer overload duration increases significantly. For EVs with battery capacity of 24 kWh, overload duration has median value of 130 min (approximately 2 h) during winter and 0 min during summer. For EVs with battery capacity of 75 kWh, overload duration has median value of 410 min (approximately 7 h) during winter and 380 min (approximately 6 h) during summer. This confirms that, when the transformer operates overloaded for long periods, it will accelerate transformer aging and shorten its service life.

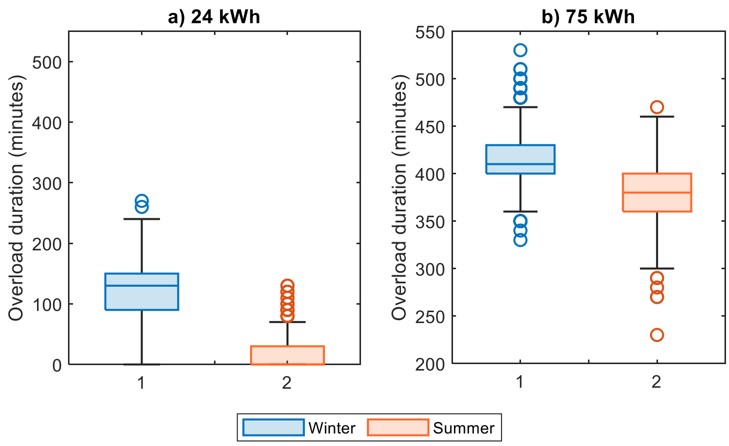

Figure 12. Boxplot of transformer daily overload duration. (**a**) 24 kWh. (**b**) 75 kWh.

4. Conclusions

This paper analyzed the impacts of long-range EVs on transformer life and compared results with the effects caused by short-range EVs. A probabilistic analysis is employed using the Monte Carlo Simulation. Residential demand is modeled based on real household curves from the UK Data Service, and EVs' pattern is modeled based on data collected from the Electric Nation Project developed in the United Kingdom. Several EVs' penetration levels are analyzed from 0% to 60% in steps of 10% for winter and summer seasons. From the results, important conclusions can be addressed:

- The impacts caused by EVs with 75 kWh batteries are more severe because they charge at higher power levels, increasing total peak demand;
- Transformer life is mainly affected by load and ambient temperature. Since ambient temperature at the site of the study is not very high during summer and residential demand is higher in winter, transformer is more likely to exceed its rated capacity during winter;
- Transformer overload duration is significantly higher when EVs with higher battery capacity are used, accelerating transformer aging and shortening its service life;
- As EVs' penetration level increases, there is a considerably increase in transformer load and hottest-spot temperature, especially for vehicles with 75 kWh, where low penetration levels above 20% already lead to severe violations on hottest-spot temperature;
- For penetration level of 50% during summer, the use of long-range EVs leads to a minimum equivalent aging factor of 5.2, which means a transformer aged 124.8 h in a cycle of 24 h, decreasing its lifetime.

As in most studies, EV demand is modeled in this paper assuming an everyday plug-in charging behavior. More research should be carried out modeling EVs' charging pattern for a week-long period since some studies already demonstrated that vehicles with higher battery capacity do not charge every day [24]. This behavior directly affects the number of vehicles charging simultaneously and, therefore, EV peak load. Besides, as high ambient temperatures directly impact transformer loss-of-life, more analysis should be conducted using data from a different location with warmer weather.

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