Impact of Reactive Power Assumptions on Physics-Informed Assessment of Transformer Ageing in Distribution Networks

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Abstract

Power distribution networks are undergoing a fundamental shift in their utilisation driven by the rapid increase in the prevalence of residential photovoltaic (PV) systems, coupled with the increasing penetration of inverter-based household loads (such as heat pumps), changing expected reactive power flows. However, many Distribution System Operators (DSOs) have limited reactive power monitoring and instead rely on historical constant power factor assumptions, masking the true transformer current and thermal stress, resulting in biased lifetime estimates. This paper proposes an assessment methodology that integrates a low-voltage distribution network model with the physics-based IEEE C57.91 transformer thermal-ageing model to quantify transformer loss of life. The methodology evaluates different LCT penetration levels using representative load and reactive-power profiles. The methodology is demonstrated using a spatially coherent real-world distribution network model, derived from geographical network data, with PV generation and residential load profiles. We conduct a comparative analysis between the standard DSO assumption (constant power factor) and the actual reactive power profile. The results indicate that the assumption of a constant power factor of 0.95 significantly over/underestimates total current and thermal stress, resulting in biased transformer health assessments. The study demonstrates that a revised reactive power assumption is an important consideration for transformer health assessment and asset-management decisions.

Keywords — Reactive Power, Distribution Transformers, LCTs, Physics-Informed Health Assessment, Loss of Life (LoL).

1. Introduction

With the increasing penetration of low-carbon technologies (LCTs) in low-voltage distribution networks, traditional fit-and-forget design paradigms are facing significant challenges. High-capacity distributed generation, such as solar PV, together with large customer demands from heat pumps and electric vehicles (EVs), are increasingly connected to distribution networks with limited operational visibility and control. As a result, DSOs must adopt more intelligent management strategies to maintain secure and reliable network operation. Within this context, the distribution transformer is a critical asset, and accelerated ageing has become a major concern. Since distribution transformers are among the most valuable assets in low-voltage networks, understanding their degradation is essential when assessing the capacity of a network to accommodate further LCT uptake. This ageing process is fundamentally governed by the transformer's internal thermal condition, particularly the winding hot-spot temperature, which drives the degradation of insulation materials.

A key factor limiting transformer lifetime is the degradation of the internal cellulosic paper insulation. The ageing of transformer insulation paper occurs through oxidation, hydrolysis, and pyrolysis, driven primarily by acidic conditions, moisture, and elevated temperature, respectively. As the cellulose structure degrades, both its mechanical strength and dielectric integrity are progressively reduced (Krause et al., 2022).

In Great Britain (GB), DSOs typically employ standardised condition and risk assessment methodologies aligned with regulatory asset-risk frameworks (Ofgem, 2021). Accordingly, transformer interventions are prioritised according to condition, age, duty cycle, and consequence of failure. For distribution transformers, common health indicators include oil quality, dissolved gas analysis (DGA), and moisture content. However, owing to cost and logistical constraints, many ground-mounted secondary substations still rely on periodically recorded peak seasonal loading together with simplified IEC thermal models, rather than continuous condition monitoring (Scottish and Southern Electricity Networks, 2024).

The increasing adoption of LCTs at the distribution level is beginning to undermine the validity of such historical peak-load assumptions. This issue is particularly important in relation to reactive power. Owing to limited LV observability, reactive demand across many secondary networks is still represented in planning studies using assumed load power factors, historically around 0.98 (Weatherhead & Higgins, 2015). However, the power-electronic interfaces associated with LCTs can introduce variable reactive power behaviour and harmonic distortion that deviate markedly from these historical assumptions. Continued reliance on outdated power factor assumptions may therefore lead to underestimation of transformer thermal stress and ageing, increasing the risk of unobserved degradation, asset failure, and costly network outages (Vita, Fotis, Chobanov, Pavlatos, & Mladenov, 2023).

Accordingly, a growing body of literature has investigated the impact of LCT adoption on distribution transformer ageing, considering both individual technologies and their combined effects. Representative studies include (Pezeshki & Wolfs, 2013), which highlights the beneficial effect of PV penetration on transformer thermal performance, (Pavlićević & Mujović, 2022), which identifies the adverse ageing effect of EV charging, and (McBee, 2017; Paterakis et al., 2016), which examine the combined influence of PV, EVs, and energy storage on transformer loss of life. Collectively, these studies indicate that PV can reduce transformer thermal stress by offsetting daytime demand, whereas EV charging tends to accelerate ageing through increased and concentrated loading, particularly during peak charging periods. When multiple LCTs are deployed simultaneously, their interactions can further modify transformer operating conditions through changes in loading patterns, cooling behaviour, and power quality. However, most existing studies above are based on test systems and may not fully reflect the diversity of practical distribution networks. In reality, network characteristics vary substantially according to asset age, transformer capacity, cable ratings, and local load density. Recently reinforced networks with upgraded transformers and cables may be able to accommodate additional LCT penetration, whereas older and more constrained networks may experience greater hot-spot temperature rise and faster insulation degradation. This motivates the use of digital twin frameworks, combined with active and reactive power assumptions, to support cost-effective and condition-informed asset management.

This paper proposes an assessment methodology that integrates a low-voltage distribution network model with the physics-based IEEE C57.91 transformer thermal-ageing model (IEEE C57.91-2025, 2025) to quantify transformer loss of life. The methodology evaluates different LCT penetration levels using representative load and reactive-power profiles. By comparing representative reactive-power profiles with conventional fixed power-factor assumptions, the proposed methodology supports more informed distribution network planning and transformer health assessment.

The remainder of this paper is organised as follows: Section 2 reviews reactive power behaviour in low-voltage networks and discusses how LCT-driven changes in power factors can affect transformer loading and thermal stress. Section 3 describes the proposed methodology, including the low-voltage network model and the IEEE C57.91 physics-based transformer thermal ageing model used to estimate loss of life. Section 4 presents the case-study configuration and penetration scenarios. Section 5 presents and critically discusses the simulation results and their implications for transformer ageing under different LCT conditions. Finally, Section 6 concludes the paper and outlines its limitations and directions for future work.

2. REACTIVE POWER AND ITS IMPACT IN THE MODERN DISTRIBUTION NETWORK

Compared with active power, reactive power has long been under-emphasised in both operational practice and the research literature. This is partly because reactive power is less directly associated with end-use energy consumption, and instead is shaped by local voltage conditions, power-factor variability, capacitor-bank switching, tap-changer operation, and inverter-based Volt-VAR control. In typical 11 kV / 0.415 kV secondary networks, substantially less utility-side reactive compensation is deployed on the 415 V side than on the 11 kV side. Consequently, reactive power is more frequently exchanged across the distribution transformer, increasing current magnitude and associated copper losses. This can elevate winding hot-spot temperatures and, under sustained high-loading conditions, contribute to accelerated insulation ageing.

2.1. Reactive Power Behaviour of Residential Loads

Residential HVAC demand varies across Europe because of differences in climate, building stock, and heating systems. Cooling can contribute significantly to summer electricity demand in Southern Europe, but cooling-dominated conditions are outside the scope of this study. The analysis focuses on GB and European regions with similar climatic and residential-demand characteristics. Heat pumps are therefore modelled as an additional electrical load using profiles derived from GB data.

Other major residential end-uses, including water heating (13.6%) and refrigeration (7.0%), also exhibit favourable electrical characteristics. In particular, resistive water heating operates at an approximately unity power factor ($\mathrm{PF} \approx 1.0$), while modern refrigerators commonly achieve power factors in the range of 0.80 to 0.99. By contrast, several motor- and compressor-driven appliances with smaller aggregate energy shares, including washing machines (0.55–0.59), dehumidifiers (0.30–0.80), and pool or hot tub pumps (0.35–0.80), exhibit substantially lower power factors. Although these appliances contribute less to total active energy consumption, they may impose a disproportionately large reactive power burden on low-voltage distribution networks.

The increasing adoption of advanced power electronic interfaces is beginning to mitigate these inefficiencies. Modern washing machines, for example, increasingly employ inverter-controlled motor drives. Through pulse-width modulation, such systems enable the fundamental input current to remain more closely aligned with the supply voltage waveform, thereby reducing the reactive component of the current. Comparative experimental studies support this trend. Inverter-driven washing machines have been reported to achieve a displacement power factor of 0.94–0.95 and an overall power factor of 0.69–0.80 across 30–60°C wash cycles. In contrast, conventional induction motor-based machines exhibit a $\cos\varphi$ of 0.73–0.75 and a total power factor of only 0.55–0.59 (Anderson, Al Hadi, Jones, & Ionel, 2021).

Despite the technical advantages of inverter-based appliances in reducing reactive power demand, their rate of market penetration remains limited by the long service life of domestic equipment. This transition is further slowed by consumer purchasing behaviour, as households often prioritise initial capital cost over electrical performance metrics such as power factor. Consequently, DSOs continue to represent the aggregate residential network using an assumed power factor typically in the range of 0.95–0.98.

2.2. Impact of LCTs on Reactive Power in Modern Distribution Networks

While reactive power challenges are evident at the household level, a more significant challenge in modern distribution networks arises from the increasing uptake of LCTs, including rooftop PV, heat pumps, and EV chargers. Because the power ratings of these devices are comparable to those of small generators or sizeable discrete loads, their aggregated behaviour can materially affect feeder operation (Protopapadaki & Saelens, 2017; Hungbo, Gu, Meegahapola, Littler, & Bu, 2023). Although interconnection is governed by established standards, including legacy guidance such as IEEE 929-2000 (Refaat, Kalas, Daoud, & Bendary, 2012) and more specific guidance such as IEEE 1547.6-2011 (IEEE, 2011); however, compliance with these standards alone does not eliminate local voltage problems under high LCT penetration.

High demand and rapid duty cycles can produce local voltage excursions, particularly on feeders with limited voltage support. For example, PV export may lead to voltage rise, whereas coincident EV charging and heat pump operation may cause voltage drop, potentially violating operating limits and degrading power quality (Protopapadaki & Saelens, 2017). Behind-the-meter and centralised energy storage are often proposed as mitigation options, but their wider deployment remains constrained by techno-economic considerations and customer-side adoption (Rezaeimozafar, Monaghan, Barrett, & Duffy, 2022). Inverter-based mitigation strategies are typically classified as local schemes, which rely only on terminal measurements and operate autonomously, and coordinated schemes, which can offer better network-wide performance but depend on communications and monitoring infrastructure that is often limited and not possible in LV networks (Efkarpidis, De Rybel, & Driesen, 2016).

Accordingly, this study adopts publicly available representative profiles for PV, heat pumps, and EV charging and assumes no additional active control beyond baseline regulatory compliance. These LCT-integrated profiles are then compared against the Elexon Class 1 profile baseline (Elexon, 2013), which represents the average domestic unrestricted customer and is commonly used for demand estimation where real-time smart meter data are unavailable.

2.2.1. Heat pump loads

The heat-pump profiles are derived from the Low Carbon London dataset, which contains measurements from 19 residential customers (UKPN, 2014). Figure 1 compares these profiles with the standard Elexon Class 1 profile (Elexon, 2013). The selected heat-pump profile exhibits increased early-morning and overnight active-power demand together with leading reactive-power behaviour. This differs from the conventional assumption of a fixed 0.95 lagging power factor. A power factor of 0.92 leading is therefore considered as a sensitivity case rather than a universal heat-pump assumption.

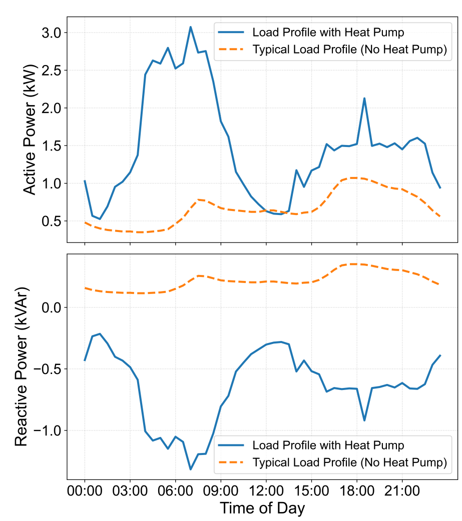

Figure 1. Active and reactive power profiles for the Elexon Class 1 and heat-pump-integrated loads.

2.2.2. Photovoltaics

The PV profiles are obtained from the open-source OPSCI dataset, which contains four years of rooftop PV measurements (Elektro, 2023). As shown in Figure 2, PV generation offsets residential demand and can cause substantial midday reverse power flow. The selected profile also exhibits leading reactive-power behaviour during PV generation (Elektro, 2023; UK Power Networks, 2026). A fixed lagging power-factor assumption may therefore inaccurately represent transformer loading in PV-rich networks.

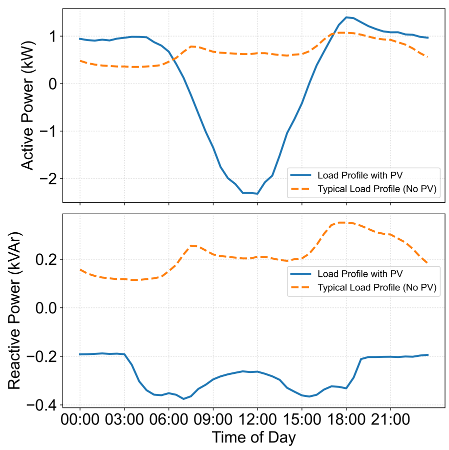

Figure 2. Active and reactive power profiles for the Elexon Class 1 and PV-integrated loads on a sunny day.

2.2.3. Electric vehicles

EV charging is inherently uncertain because it depends on travel behaviour, battery state of charge, user preferences, and electricity tariffs (Quiros, Ochoa, & Lees, 2015). Figure 3 therefore applies an hourly charging probability, with its maximum between 19:00 and 20:00. The resulting short-duration active-power peak exceeds twice the typical residential peak demand (Azadfar, Sreeram, & Harries, 2015). Unlike the selected heat-pump and PV profiles, the EV-integrated profile remains lagging, although reactive-power demand decreases slightly during the main charging period. Its network impact is therefore dominated by concentrated evening active-power demand.

3. DISTRIBUTION NETWORK AND ASSET MODELLING

In both the EU and GB, a substantial proportion of distribution network assets currently in service were installed during the 1950s and 1960s. Although heat pumps, photovoltaic systems, and electric vehicles are relatively recent technologies, they are increasingly connected to these legacy networks. These networks were originally designed for conventional, largely unidirectional residential demand rather than the higher, more variable and bidirectional power flows associated with modern low-carbon technologies. As the underlying infrastructure has not been upgraded accordingly, a growing mismatch exists between its original design assumptions and current operating conditions.

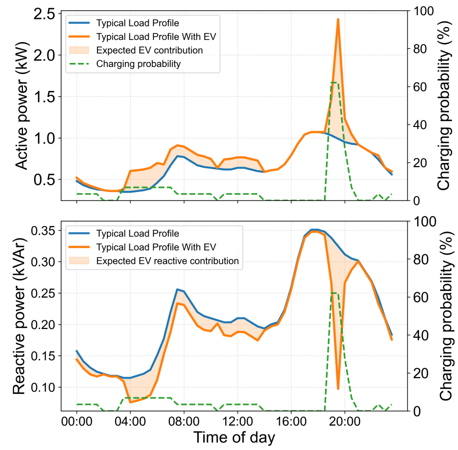

Figure 3. Active and reactive power profiles for the typical residential and EV-integrated loads.

As a result, many DSOs do not possess the detailed and fully digitised network models required for modern analysis of these evolving operating conditions. The development of accurate network models is therefore essential, as it enables advanced power flow analysis to estimate transformer loading and current flows with greater precision. These outputs provide the basis for transformer thermal ageing assessment, where the resulting loading profiles are used to quantify thermal stress and insulation loss of life. This integrated analysis enables a clearer understanding of how modern demand patterns affect legacy network assets.

3.1. Distribution network model

The distribution network is represented using a bus-line model comprising transformers, cables, link boxes, fuses, and loads. Although the DSO maintains fixed asset records for these components, the available data are often incomplete and may contain errors. Consequently, a systematic approach is required to establish the connectivity of all network elements and to identify or estimate modelling inaccuracies. Developing a runnable network model is therefore essential for enabling network operators to understand the actual condition and behaviour of the system.

To obtain high-fidelity power flow results in OpenDSS (EPRI, 2024), the proposed method corrects connectivity gaps and erroneous links in the baseline model while operating strictly at feeder level. This constraint avoids the introduction of non-existent cable impedance and prevents the incorrect merging of adjacent electrical circuits. The resulting model can then be used to perform power-flow simulations in OpenDSS based on the specified load inputs and to extract the corresponding transformer operating characteristics.

3.2. Physics-based transformer thermal ageing model

The transformer thermal ageing model adopted in this work is based on IEEE C57.91 (IEEE C57.91-2025, 2025) and is used to evaluate the effect of load variation on transformer operating temperature and insulation ageing. This model was selected because it is specifically developed for mineral-oil-immersed transformers and provides a standard framework for thermal assessment. By representing both top-oil and winding temperature rises through dynamic thermal equations, the model captures the delayed thermal response of the transformer to changing load, which is essential for accurate hot-spot temperature estimation and loss-of-life calculation. In addition, its parameter-based structure allows implementation using time-series current data from the network model.

The model is particularly appropriate for the present study because the power flow results provide time-varying transformer loading information. These quantities are then used to estimate the top-oil temperature rise, the winding hot-spot temperature rise, and, ultimately, the insulation ageing rate. In this way, the model establishes a direct and physically meaningful link between network operating conditions and transformer degradation. The rated transformer current is first calculated as

$$I_{\text{rated}} = \frac{S_{\text{rated}}}{\sqrt{3}V_{LL}} \tag{1}$$

where S_{rated} is the rated transformer apparent power and V_{LL} is the rated line-to-line voltage.

Based on the three-phase transformer currents obtained from the network power flow model, the equivalent current used for top-oil estimation is calculated as

$$I_{\text{eq},n} = \sqrt{\frac{I_{1,n}^2 + I_{2,n}^2 + I_{3,n}^2}{3}} \tag{2}$$

The top-oil loading factor is then expressed in per unit as

$$K_{\text{topoil},n} = \frac{I_{\text{eq},n}}{I_{\text{rated}}} \tag{3}$$

To represent the most heavily loaded phase, the maximum phase loading factor is defined as

$$K_{\max,n} = \frac{\max(I_{1,n}, I_{2,n}, I_{3,n})}{I_{\text{rated}}} \tag{4}$$

The ultimate top-oil temperature rise over ambient is then calculated as

$$\Delta\theta_{o,n}^{\text{ult}} = \Delta\theta_{or}\left(\frac{1 + RK_{\text{topoil},n}^2}{1+R}\right)^x \tag{5}$$

where $\Delta\theta_{or}$ is the rated top-oil rise over ambient, R is the ratio of load loss to no-load loss, and x is the oil exponent. To account for thermal inertia, the top-oil rise is updated dynamically using

$$\Delta\theta_{o,n} = \Delta\theta_{o,n-1} + \left(1 - e^{-\Delta t/\tau_o}\right)\left(\Delta\theta_{o,n}^{\text{ult}} - \Delta\theta_{o,n-1}\right) \tag{6}$$

where τ_o is the oil time constant. The corresponding top-oil temperature is then given by

$$\theta_{o,n} = \theta_a + \Delta\theta_{o,n} \tag{7}$$

where θ_a is the ambient temperature.

The ultimate winding hot-spot rise over top-oil is similarly obtained from the maximum phase loading factor as

$$\Delta\theta_{h,n}^{\text{ult}} = \Delta\theta_{hr}K_{\max,n}^y \tag{8}$$

where $\Delta\theta_{hr}$ is the rated winding hot-spot rise over top-oil and y is the winding exponent. Its transient behaviour is represented by

$$\Delta\theta_{h,n} = \Delta\theta_{h,n-1} + \left(1 - e^{-\Delta t/\tau_w}\right)\left(\Delta\theta_{h,n}^{\text{ult}} - \Delta\theta_{h,n-1}\right) \tag{9}$$

where τ_w is the winding time constant.

The winding hot-spot temperature is therefore expressed as

$$\theta_{h,n} = \theta_{o,n} + \Delta\theta_{h,n} \tag{10}$$

For non-thermally upgraded insulation, the ageing acceleration factor is defined as

$$V_n = 2^{(\theta_{h,n}-98)/6} \tag{11}$$

where $98\ ^\circ\mathrm{C}$ is the reference hot-spot temperature corresponding to a unit ageing rate, and the denominator 6 reflects the empirical six-degree ageing rule, according to which an increase of approximately $6\ ^\circ\mathrm{C}$ doubles the ageing rate.

Finally, the cumulative transformer loss of life over the study period is calculated as

$$\mathrm{LOL}(\%) = \frac{100}{L_{\mathrm{norm}}} \sum_{n=1}^{N} V_n \Delta t_n \qquad (12)$$

where L_{norm} is the normal insulation life in hours, Δt_n is the duration of time step n, and N is the total number of time steps.

4. CASE STUDY

To improve transparency and facilitate replication of the case study, a publicly available distribution network model is employed. The model assumptions, input profiles, parameters, and simulation procedure are described in the paper. The impact of low-carbon technologies on network reactive power is evaluated using a baseline power factor of 0.95, commonly assumed by DSOs in planning studies. The simulation results are then compared with high-resolution monitoring data.

4.1. Network Model

The study area is a radial distribution network located in Slovenia, comprising eight feeders supplied from a 20 kV substation. A satellite view of the network is shown in Figure 4. In the figure, each coloured line denotes a different LV feeder, each numbered point corresponds to an individual customer load, and the transformer is located at load point 1. This geographic layout defines the feeder topology, transformer location, and customer connection points used to construct the OpenDSS power-flow model, from which the time-varying transformer phase currents and loading profiles are extracted as inputs to the physics-informed thermal ageing assessment.

The network serves 158 customers in total, including 29 single-phase connections and 129 three-phase connections. It includes 8,614 m of underground cable with the corresponding cable parameters and four existing PV installations. In accordance with local standards, the allowable voltage variation in the network is limited to $\pm 10\%$. The network topology shown in Figure 4 is implemented in the OpenDSS model using the corresponding feeder, cable, customer-load, and LCT data. The power-flow simulation calculates the time-varying transformer phase currents, which are then used as electrical loading inputs to the physics-informed thermal-ageing model. The model uses these currents to estimate transformer hot-spot temperature and insulation loss of life.

4.2. Asset Assumption

The open-source dataset contains time-series monitoring data obtained directly from consumer smart meters over the period from September 2019 to November 2023. Analysis of these measurements indicates a peak demand of 292 kW on the low-voltage side of the transformer. In addition, inspection of satellite imagery suggests that the building stock is composed primarily of detached residential dwellings, some of which are accompanied by small-scale agricultural outbuildings.

As the detailed type and operating settings of the transformer in the study network are not available, a representative 500 kVA oil-immersed distribution transformer is adopted in this study. The transformer is modelled using specifications consistent with a commonly used Datsan unit (Datsan Transformer, 2020), rated at 20 kV/400 V, three-phase, 50 Hz, with ONAN cooling and compliance with IEC 60076. Within Datsan's 20 kV distribution transformer series, 500 kVA is listed as a standard rating, with five tap positions over a range of $\pm 2 \times 2.5\%$ and a normal insulation life of 180,000 hours.

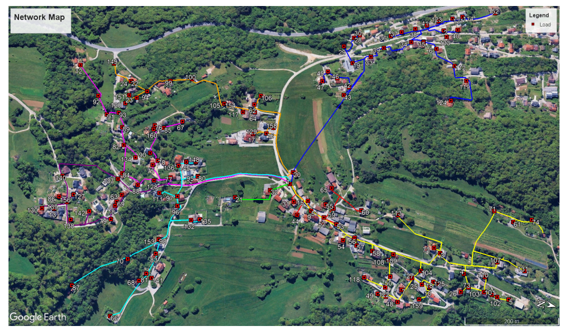

Figure 4. Geographic Layout of the Low-Voltage Distribution Network.

5. RESULTS AND DISCUSSION

5.1. Results

The network was assessed in terms of transformer loss of life during a winter period under sunny-day conditions. Heat pump, PV, and EV penetration levels of 25%, 50%, and 100% were considered. For each scenario, the use of actual reactive power was compared with the commonly adopted DSO assumption of a fixed 0.95 lagging power factor.

For each scenario, 1,000 Monte Carlo realisations were performed by varying network loading, ambient temperature, and transformer thermal parameters. The solid lines in Figures 5–7 represent the median cumulative loss of life, while the shaded regions indicate the 10th–90th percentile range.

Figure 5 shows that transformer ageing increases considerably with heat-pump penetration. At 25% and 50% penetration, the actual reactive-power cases produce slightly higher loss of life than the fixed power-factor cases. At 100% penetration, the increase becomes much more pronounced, and the fixed 0.95 lagging power-factor assumption substantially underestimates transformer ageing. The wider uncertainty range at this penetration level also indicates greater sensitivity to variations in loading, ambient conditions, and transformer parameters.

Figure 6 presents the corresponding results for PV. The effect of the fixed power-factor assumption varies with penetration level. The largest difference occurs at 25% penetration, where the fixed 0.95 lagging power factor produces a higher ageing estimate than the actual reactive-power case. At higher penetration levels, the differences become smaller and the uncertainty ranges overlap. This shows that the influence of PV depends on the interaction between local demand, reverse power flow, and reactive-power behaviour.

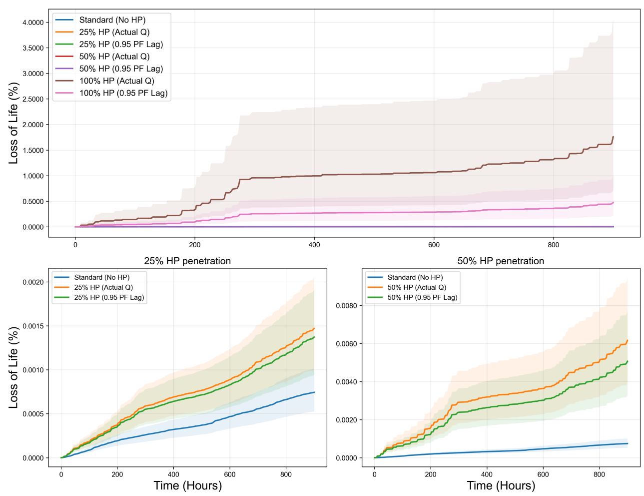

Figure 5. Probabilistic cumulative transformer loss of life for different heat-pump penetration levels and reactive-power assumptions.

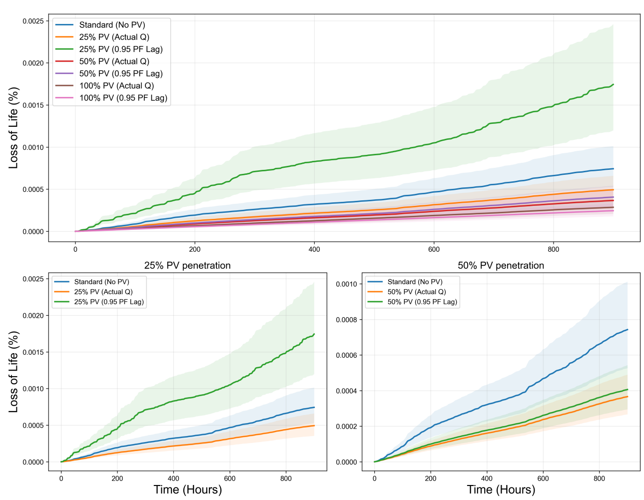

Figure 6. Probabilistic cumulative transformer loss of life for different PV penetration levels and reactive-power assumptions.

Figure 7 shows that the EV scenarios have a smaller effect on transformer loss of life than the heat-pump scenarios. The differences between the actual reactive-power and fixed power-factor cases are also relatively small, particularly at high EV penetration. This is mainly associated with the shorter and more diversified charging periods in the selected EV profiles.

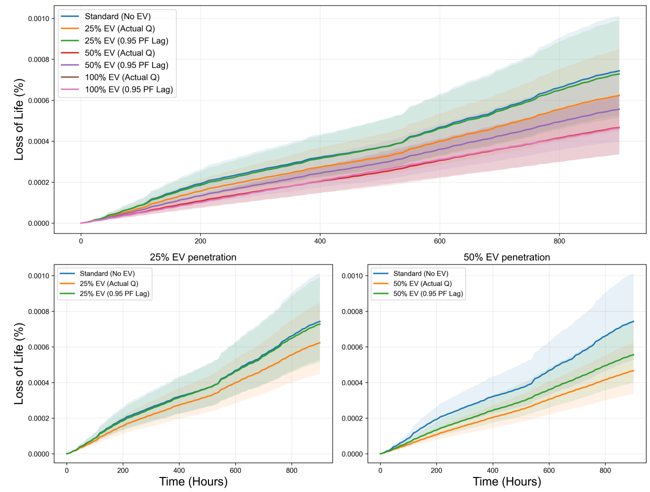

Figure 7. Probabilistic cumulative transformer loss of life for different EV penetration levels and reactive-power assumptions.

5.2. Discussion

The results show that reactive-power assumptions can have a significant effect on transformer ageing estimates, but the magnitude and direction of the effect depend on the type and penetration of the low-carbon technology. The greatest discrepancy is observed for high heat-pump penetration, where the fixed 0.95 lagging power factor underestimates thermal ageing. For PV, the assumed power factor can either increase or reduce the estimated loss of life depending on the operating condition, while the approximation performs more consistently for the selected EV profiles.

The probabilistic analysis further shows that transformer loss of life cannot be represented fully by a single deterministic trajectory. The uncertainty ranges generally become wider under more highly stressed operating conditions. However, the main trends remain visible, particularly the strong impact of high heat-pump penetration and the sensitivity of PV results to reactive-power assumptions.

These findings highlight the importance of using representative active- and reactive-power profiles when assessing transformer health. The results are specific to the investigated network, selected profiles, and assumed uncertainty ranges. Future work will extend the analysis using longer measurement periods and will propagate customer, weather, and network uncertainty directly through the OpenDSS model.

6. CONCLUSION

This paper has presented a physics-informed methodology for assessing transformer thermal health in low-voltage distribution networks with increasing LCT penetration. The methodology combines time-series power-flow simulation with a physics-based thermal-ageing model to estimate hot-spot temperature, ageing acceleration, and cumulative insulation loss of life. These outputs are interpreted as transformer health indicators. The proposed methodology does not perform fault detection, fault identification, or remaining-useful-life prediction.

The results show that reactive power assumptions have a significant effect on the estimated transformer loss of life. In the heat pump case study, the commonly used DSO assumption of a fixed 0.95 lagging power factor consistently underestimates transformer ageing compared with the Actual Q cases, with the discrepancy becoming particularly large at high penetration levels. At 100% heat pump penetration, the loss of life increases sharply, suggesting that the existing 500 kVA transformer is unlikely to support this level of uptake without reinforcement or replacement. In the PV case study, the direction and magnitude of the error vary with penetration level, indicating that a fixed power-factor assumption does not consistently represent PV-dominated operation.

This work therefore highlights the importance of combining realistic distribution network modelling with transformer ageing analysis for condition-informed asset management and network planning. Future work will extend the methodology by using more detailed transformer and network models, incorporating condition-monitoring data, and expanding the analysis from a single month to a full year to better capture the seasonal and operational effects of PV, heat pumps, and EVs on transformer ageing.

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REFERENCES

Anderson, H. C., Al Hadi, A., Jones, E. S., & Ionel, D. M. (2021). Power factor and reactive power in us residences – survey and energyplus modeling. In *2021 10th international conference on renewable energy research and application (icrera)* (p. 418-422). doi: 10.1109/ICRERA52334.2021.9598561

Azadfar, E., Sreeram, V., & Harries, D. (2015). The investigation of the major factors influencing plug-in electric vehicle driving patterns and charging behaviour. *Renewable and Sustainable Energy Reviews*, *42*, 1065–1076.

Datsan Transformer. (2020, January 18). *500 kva 20/0.4 kv copper winding standard losses transformer.* Retrieved 2026-03-22, from https://www.datsan.com.tr/en/products/three-phase-distribution-transformers/101-20-kv-series-distribution-transformers/274-500-kva-20-400-copper-standard%20losses-oil-immersed-distribution-transformer.html

Efkarpidis, N., De Rybel, T., & Driesen, J. (2016). Technical assessment of centralized and localized voltage control strategies in low voltage networks. *Sustainable Energy, Grids and Networks*, *8*, 85–97.

Elektro. (2023). *OPSCI.* Retrieved 2025-11-09, from https://www.elektro-ljubljana.si/projekti/ArtMID/1374/ArticleID/2156/OPSCI-Open-SCI

Elexon. (2013). *Load profiles and their use in settlement* (Tech. Rep.). Elexon. Retrieved from https://www.elexon.co.uk/guidance-note/load-profiles/ (Accessed: 2024-05-22)

EPRI. (2024). *Opendss documentation.* Retrieved from https://opendss.epri.com/ (Accessed: 2026-03-24)

Hungbo, M., Gu, M., Meegahapola, L., Littler, T., & Bu, S. (2023). Impact of electric vehicles on low-voltage residential distribution networks: A probabilistic analysis. *IET Smart Grid*, *6*(5), 536–548.

IEEE. (2011). *Ieee recommended practice for interconnecting distributed resources with electric power systems distribution secondary networks.* The IEEE Standards Association Piscataway, NJ, USA.

IEEE C57.91-2025. (2025). *IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators* (No. IEEE Std C57.91-2025).

Krause, C., de Pablo, A., Devaux, F., Ding, H., Katshuna, V., Lukic, J., ... Walker, D. (2022, April). The condition of solid transformer insulation at end-of-life. *ELECTRA*(321), 1–18. Retrieved 2026-03-02, from https://electra.cigre.org/321-april-2022/reference-paper/the-condition-of-solid-transformer-insulation-at-end-of-life.html

McBee, K. D. (2017). Transformer aging due to high penetrations of pv, ev charging, and energy storage applications. In *2017 ninth annual ieee green technologies conference (greentech)* (p. 163-170). doi: 10.1109/GreenTech.2017.30

Ofgem. (2021). *Dno common network asset indices methodology* (Tech. Rep.). Ofgem. Retrieved 2026-03-02, from https://www.ofgem.gov.uk/sites/default/files/docs/2021/04/dno_common_network_asset_indices_methodology_v2.1_final_01-04-2021.pdf

Paterakis, N. G., Pappi, I. N., Erdinç, O., Godina, R., Rodrigues, E. M. G., & Catalão, J. P. S. (2016). Consideration of the impacts of a smart neighborhood load on transformer aging. *IEEE Transactions on Smart Grid*, *7*(6), 2793-2802. doi: 10.1109/TSG.2015.2501380

Pavlićević, A., & Mujović, S. (2022). Impact of reactive power from public electric vehicle stations on transformer aging and active energy losses. *Energies*, *15*(19), 7085.

Pezeshki, H., & Wolfs, P. (2013). Impact of high pv penetration on distribution transformer life time. In *2013 ieee power energy society general meeting* (p. 1-5). doi: 10.1109/PESMG.2013.6672074

Protopapadaki, C., & Saelens, D. (2017). Heat pump and pv impact on residential low-voltage distribution grids as a function of building and district properties. *Applied Energy*, *192*, 268–281.

Quiros, J., Ochoa, L. F., & Lees, B. (2015). A statistical analysis of ev charging behavior in the uk. In *2015 ieee/pes innovative smart grid technologies latin america (isgt latam)* (pp. 1–6).

Refaat, A., Kalas, A., Daoud, A., & Bendary, F. (2012). A control methodology of grid-connected pv system to verify the standard ieee 929-2000. *energy*, *1*, 2.

Rezaeimozafar, M., Monaghan, R. F., Barrett, E., & Duffy, M. (2022). A review of behind-the-meter energy storage systems in smart grids. *Renewable and Sustainable Energy Reviews*, *164*, 112573.

Scottish and Southern Electricity Networks. (2024, February). *Network visibility strategy.* Retrieved from `https://www.ssen.co.uk/globalassets/about-us/stakeholder-engagement/annual-engagement-plans-and-reports/ssen-network-visibility-strategy-feb-2024.pdf` (Accessed: 2026-03-24)

UK Power Networks. (2026). *Photovoltaic (pv) solar panel energy generation data.* London Datastore. Retrieved from `https://data.london.gov.uk/dataset/photovoltaic-pv-solar-panel-energy-generation-data-2nlqm/` (Maintainer: Greater London Authority. Accessed: 22 March 2026)

UKPN. (2014). *Low carbon london: Heat pump load profiles.* London Datastore. Retrieved from `https://data.london.gov.uk/dataset/low-carbon-london-heat-pump-load-profiles-2nlrm/` (Accessed: 2024-05-22)

Vita, V., Fotis, G., Chobanov, V., Pavlatos, C., & Mladenov, V. (2023). Predictive maintenance for distribution system operators in increasing transformers' reliability. *Electronics*, *12*(6), 1356.

Weatherhead, S., & Higgins, C. (2015, September). *Future roadmap for improvement of hv & lv network modelling* (Technical Report No. 7640-08-R0). SP Energy Networks.