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Published in:
Proceedings of the 59th International Universities Power Engineering Conference

DOI:
10.1109/UPEC61344.2024.10892501

Publication date:
2025

Document Version
Author accepted manuscript

Link to publication in ResearchOnline

Citation for published version (Harvard):
Anwar, AS, Farrag, ME & Baird, J 2025, Enhancing transformer ageing prediction in NOMs methodology: incorporating demand data analysis. in *Proceedings of the 59th International Universities Power Engineering Conference.* International Universities Power Engineering Conference (UPEC), vol. 59, IEEE, 59th International Universities Power Engineering Conference, Cardiff, United Kingdom, 2/09/24. https://doi.org/10.1109/UPEC61344.2024.10892501

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Enhancing Transformer Ageing Prediction in NOMs Methodology: Incorporating Demand Data Analysis

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***Abstract*— In response to escalating electrical demands from Electric Vehicles (EVs) and Heat Pumps (HPs), the impact on transformer aging has been comprehensively investigated. By incorporating extensive demand data analysis, this study enhances the Network Output Measures (NOMs) methodology to predict transformer aging more accurately. The penetration of EVs and adoption of HPs, which are expected to double the typical household electricity consumption, are quantified and simulated. This simulation uses detailed data from a lead asset database, applying comprehensive equations to predict the aging and degradation of transformers under increased load conditions. This study presents a critical advancement in the understanding and management of transformer aging under the increased stress imposed by modern energy demands. The results highlight the accelerated aging process, quantified as a rate substantially higher than under normal conditions. A revised approach to the NOMs methodology is proposed, emphasizing the need for integrating real-time monitoring and advanced analytics to better manage the life cycle of electrical network assets.**

Keywords — asset end of life, transformer ageing, demand data analysis, predictive modeling.

I. Introduction

Every energy transmission system is made up of assets that have an expected service life. It's crucial to monitor these assets for potential failures, as any interruptions could have serious repercussions for both the network's owner and its users. In the UK, the electricity supply industry is run by major private entities but falls under the regulation of the Office of Gas and Electricity Markets (Ofgem), which aims to safeguard consumers and ensure a more sustainable and equitable energy system [1]. Energy companies regularly develop capital replacement plans to preserve network reliability, which must be approved by Ofgem.

In the UK, electricity generation companies are privatized entities that produce and deliver power to the national grid. Similarly, privatized regional transmission companies own and manage the energy transmission networks, ensuring electricity is transmitted across the grid at high voltage with minimal loss. The entire system is managed by a single Electricity System Operator (ESO), which maintains the stability and security of the grid. Currently, the National Grid Electricity System Operator (NGESO) serves as the ESO in the UK [2]. There are three main transmission operators: National Grid Electricity Transmission plc (NGET) covering England and Wales, Scottish Power Transmission Limited for southern Scotland, and Scottish Hydro Electric Transmission plc for northern Scotland and the Scottish islands [3].

Load-related activities involve modifying the network to accommodate fluctuating demand, including connecting or disconnecting generators to meet the regulatory standards established by Ofgem [4]. Conversely, non-load-related activities encompass the monitoring, inspection, refurbishment, or replacement of infrastructure components such as transformers, substations, towers, overhead lines, and cables to maintain the reliability required by the regulator [4]. These components are referred to as non-load assets.

In contrast, lead assets, which are vital for transmitting electrical energy across the electricity transmission network at voltages above 132 kV include transformers, reactors, circuit breakers, overhead lines, and underground cables [5]. Non-lead assets comprise additional components of the electrical power transmission system that operate below 132 kV, and include similar types of equipment as the lead assets [5].

A key lead asset in the electrical network is the transformer, whose lifespan is influenced by various factors, primarily the electrical load it carries. Increased load results in more current flowing through the transformer, which heats the windings and can lead to insulation degradation primarily due to chemical reactions between the insulation and the cooling oil. The impact of high levels of EVs charging on transformer aging has been explored by authors in [6]. This study delves into the loss of life of transformers across various EV penetration levels and charging scenarios. Leveraging the loss of life methodology established in [6], the authors of this research proceed to adapt and refine the NOMs methodology, subsequently evaluating its implications on the analysis outcomes.

Over the time, transformers generally degrade, with the insulation aging more rapidly than other components. The insulation's condition deteriorates during the operational life of the transformer. Given the expense associated with replacing insulation and the overall value of the transformer, it is frequently more practical to replace the entire transformer rather than just the insulation. This makes the condition of the insulation a critical factor in determining a transformer's lifespan.

The authors of [7] have detailed various types of transformer insulation and the mechanisms of insulation aging. The insulation system is subject to thermal, electrical, and chemical stresses that cause irreversible degradation. The primary mechanisms of thermal degradation are oxidation and hydrolysis [8], [9]. In the presence of oxygen, water, and acids, which are found in the oil, the cellulose-based insulation system degrades, a process that is exacerbated by high temperatures [8]. These chemical reactions double in rate with every 6-8 degree celsius increase in temperature [10], [11]. Typically, transformers operate at temperatures ranging from 40-80 degree celsius, where insulation aging occurs slowly and steadily. However, as the operational load increases and temperatures rise above 110 degrees Celsius, the rate of insulation degradation accelerates significantly. Insulation

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made from thermally upgraded paper is designed to withstand these higher temperatures.Transformers feature two categories of insulation: major and minor. Major insulation is located between; the core and Low Voltage (LV) winding, between LV and High Voltage (HV) winding, at the top and bottom of the winding and yoke, between HV winding and the tank, and around the bushings. Minor insulation is found between conductors, turns, layers, laminations, joints, and connections. The materials used for these insulation types include paper, pressboard, and transformer board, all of which are derived from plant cellulose. A significant issue with this cellulose-based insulation is its hygroscopic nature, meaning it readily absorbs moisture from the environment.

Hot-spot temperature represents the highest temperature point within a transformer, typically located at the top of the winding. The rate of insulation aging is greatly influenced by temperature, and because the hot-spot temperature is the peak internal temperature, it is where the insulation degrades most rapidly. Consequently, hot-spot temperature is deemed a crucial factor in the aging process of transformers.

Dissolved Gas Analysis (DGA) is a diagnostic tool used to assess the condition and detect early issues in transformers [12]. This process involves extracting oil from a transformer and analyzing it in a laboratory to measure the concentrations of nine specific gases Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), Acetylene (C_2H_2), Carbon Monoxide (CO), Carbon Dioxide (CO_2), Oxygen (O_2), and Nitrogen (N_2). Using Duval's Triangle, which interprets the ratios of Methane, Ethylene, and Acetylene, six distinct types of faults can be identified [13]: high energy arcing, low energy arcing, corona discharge, and hot spot temperatures categorized as less than 200°C, between 200°C and 400°C, and greater than 400°C. Additionally, transformer furfuraldehyde (FFA) analysis evaluates the degradation of transformer insulation and helps estimate its remaining lifespan. The concentration of furan derivatives in transformer oil correlates directly with the degree of polymerization (DP) of the insulation [7], allowing the determination of the transformer's likelihood of failure based on the severity of detected faults.

The probability of failure is defined as the likelihood that an asset will not perform its designated function, either completely or partially [14]. This metric assesses whether the asset will fail to meet its operational expectations, which could potentially lead to the malfunctioning of other assets linked directly or indirectly to it.

Transformers, reactors, circuit breakers, underground cables, overhead lines, towers, conductors, and fittings represent the main lead assets within the power transmission system, all of which are at risk of failure. The system also includes tap-changers and bushings. Overhead lines consist of towers, conductors, and various fittings. The steelwork of a tower includes legs, step bolts, bracing, crossarms, and the peak structure. The fittings category encompasses insulators, arcing horns or corona rings, jumpers, vibration dampers, U-bolts or other tower attachments, shackles or links, suspension clamps, tension clamps, and the conductors at these clamps. Despite the variety and complexity of these components, the transformer is considered the most costly asset in the system.

The transmission networks and their assets are anticipated to experience considerable changes, especially in the way energy is distributed throughout the network. This shift is expected due to two main factors: (a) the expanded use of renewable energy sources, which are geographically dispersed, and (b) the decarbonization efforts at the household level, facilitated by the increasing adoption of EVs and air source low-grade HPs.

Transformers stand as critical infrastructure within power distribution systems, facilitating the transfer of electricity from generation sources to end-users. In the context of the United Kingdom's evolving energy landscape, characterized by a growing adoption of EVs and HPs, the operational demands on transformers have undergone significant shifts [15]. Amidst these changes, the NOMs Incentive Methodology, a foundational framework in the UK's energy sector, has been instrumental in monitoring network performance and incentivizing efficiency improvements [14].

The conventional NOMs methodology typically characterizes average demand as the mean consumption level observed over a designated period, while maximum demand is identified as the highest point of consumption recorded within that timeframe [14]. This sole reliance on average and maximum demand levels fails to capture the transient spikes in demand that can significantly impact transformer ageing. For instance, during events like a football match where there's a sudden surge in electricity consumption, even if it occurs infrequently, it can exert substantial stress on transformers. In this scenario, the NOMs calculation, which considers the higher value between maximum and average demand, would prioritize that short peak demand observed during the football match over the typical average load, skewing the assessment of the transformer's operational stress. Similarly, the increasing adoption of EVs and HPs introduces additional challenges, as these technologies can also contribute to demand spikes on a broader scale and over more prolonged durations compared to isolated events like a football match. Additionally, the concurrent peak demands from EVs and HPs can overlap, significantly elevating the stress on transformers. This overlapping results in demand peaks that are not only higher but also more sustained than those caused by isolated events, such as a football match. Consequently, even if the transformer operates at a relatively low average load for the majority of its service life, the presence of occasional high-demand events could mask its actual performance and ageing rate in the NOMs analysis.

This highlights the limitation of the current NOMs methodology in accurately reflecting the operational conditions experienced by transformers and their associated ageing effects. As a result, there's a critical need to revise the NOMs framework to incorporate real-time demand data and account for transient load fluctuations more effectively. By doing so, the modified NOMs methodology can provide a more comprehensive and accurate assessment of transformer health, enabling better-informed decision-making for grid management and infrastructure planning.

At the heart of this research lies a recognition of the limitations inherent in current NOMs frameworks, particularly in their ability to account for the cumulative effects of routine peak demands on transformer health. By exploring modifications to calculation methodologies and system parameters, researchers of this paper seek to establish a more robust framework capable of accurately predicting transformer ageing in real-world operational conditions. Simulation studies and data analytics methodologies serve as essential tools for validating the proposed enhancements and assessing their efficacy in capturing the intricacies of transformer performance.

The significance of this research extends beyond academic inquiry, holding implications for energy policy, infrastructure planning, and the broader transition towards sustainable energy systems in the UK. Accurate ageing prediction methodologies are integral to ensuring the resilience and efficiency of power distribution networks, particularly amidst the ongoing transformation of the transportation and heating sectors. By advancing the NOMs methodology to align with contemporary energy trends, this study aims to contribute to the optimization of network performance and the promotion of grid sustainability.

Through the synthesis of theoretical frameworks, empirical analysis, and practical insights, this paper presents a pioneering approach to enhancing transformer ageing prediction within the NOMs Incentive Methodology. The findings of this research have the potential to inform regulatory decisions, guide investment strategies, and drive innovation in the UK's energy sector, ultimately fostering a more reliable and sustainable power infrastructure for the future.

II. THE IMPACT OF EV CHARGING AND HP UTILIZATION ON NETWORK DEMAND

Peak demand is expected to rise due to additional loads from EV charging and HP usage, along with an overall increase in power demand. This surge may lead to voltage drops, known as voltage sag, at distribution feeders—a significant power quality concern. The increased load from EV charging and HP operation will cause additional current to pass through transformers, creating more heat in the windings and hastening the degradation of their insulation. Power system operators typically prioritize the use of cost-effective generators, considering both fuel costs and environmental impacts like carbon emissions, before resorting to more expensive options. With heightened demand, it's likely that less efficient generators will need to be used during peak times. This scenario could not only lead to higher costs for consumers but also greater environmental damage due to increased carbon emissions.

Therefore, it is essential to accurately estimate the increased demand attributed to EVs. This involves assessing the penetration levels of EVs within the electrical network. As of September 2023, the UK's vehicle fleet included 41.3 million vehicles, comprising 33.6 million cars, 4.7 million light goods vehicles, 542,700 heavy goods vehicles, and 142,920 buses and coaches [16]. Specifically, the EV segment included 1.1 million pure-electric cars, 645,580 plug-in hybrid EVs, and 60,000 plug-in vans [17].

Currently, EV penetration in the UK stands at 5.14% [17]. According to the latest car registration data from the Society of Motor Manufacturers and Traders (SMMT), EVs now constitute approximately 23.3% of all new car sales, with expectations for annual increases in adoption rates [15]. By 2030, 70% of all new car and 80% of all van sales are required to be electric, and by 2035, petrol and diesel vehicle sales will be banned [18]. By 2030, there could be as many as 11 million EVs, representing 26.6% of the UK's vehicle fleet. By 2040, this number could increase to 36 million EVs, accounting for approximately 87.2% of the fleet [19]. In this study, the authors will simulate market penetration levels ranging from 0% to 100%. Additionally, the UK is witnessing a rise in the adoption of electric trains, notably with the High Speed 2 (HS2) line, which is expected to become operational within the next decade. This new rail line will utilize 25 kV AC overhead line equipment (OHLE) [20].

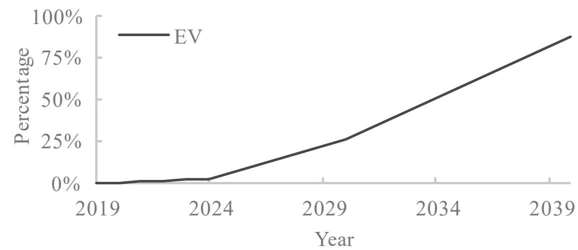

Fig 1. Percentage of EVs in the transportation sector from 2019. Graph projected to 2040 [19]

Starting in April 2024, the Scottish government has implemented the New Build Heat Standard, mandating that all new construction utilize HPs for heating systems instead of conventional gas boilers [21]. HPs are considerably more energy-efficient compared to oil or gas boilers [22], [23]. Consequently, it is anticipated that the use of HPs in UK homes will increase significantly. The committee on climate change recommended that 27 million HPs will need to be installed in the UK by 2050, covering 100% of the UK's dwellings [24]. However, it's important to acknowledge that the actual heat pump penetration may reach around 80%, considering that a portion of the housing stock may be unsuitable for heat pumps due to various factors [25]. With annual heating energy usage for medium-sized homes typically standing at 11,500 kWh [26], and considering the average coefficient of performance of Air Source Heat Pumps as 3 [27], it can be estimated that homes equipped with HPs would consume approximately 3,833 kWh annually, averaging about 10.5 kWh per day.

In the UK, the average household electricity consumption is currently 8 kWh per day [28]. With widespread adoption of EVs, this figure is expected to potentially double. The impact of a high penetration level of EVs on electrical networks is discussed in [6]. Additionally, the adoption of HPs is set to increase the demand further. The overloading of transformers due to increased EV charging and HP usage will cause distribution transformers face unprecedented stress. To address this, either the capacity of transformers and transmission lines would need to be increased, or load leveling mechanisms would need to be implemented. Load leveling might involve shifting some of the electrical demand to off-peak hours, thereby reducing peak demand and increasing off-peak demand, which would help to flatten the demand profile at the distribution end. This could be achieved by increasing electricity prices during peak hours and reducing them during off-peak hours.

III. SIMULATION AND RESULTS

The researchers were given a segment from a lead asset database provided by a major transmission company and utilized the comprehensive equations detailed in [14]. In the upcoming simulation, a 30 MVA transformer from this database was chosen. Each transformer in the database is uniquely identified by a distinct ID, which includes details about its manufacturer, location, specifications, and other relevant information. This particular transformer operates at 132 kV and is housed in a fully enclosed environment.

The simulation initially focused on a medium-sized household in the UK, modeling its electricity load without the additional demands from EVs and HPs. It was then rerun to include these extra loads. The EVs are charged between 6 pm to 9 pm. This time is selected to check the extreme cases when residents come back from work and charge EVs. The usage is 100% in this simulation. HP usage pattern is taken from [29]. To extrapolate this data to the transmission level, the load of a single household was scaled up by a factor of 12,000, representing the number of households serviced by this particular transformer across different distribution transformers. The results compared the accelerated aging effects due to the increased loads, and this additional aging was quantified and expressed as a single factor, illustrating the relative aging of the transformer under the heightened demand conditions. Fig 2 highlights the significant differences in load patterns that can be expected as the adoption of EVs and HPs increases. The graph clearly demonstrates how the additional demands impact the overall load on the transformer, emphasizing the need for enhanced capacity and load management strategies to accommodate these changes effectively.

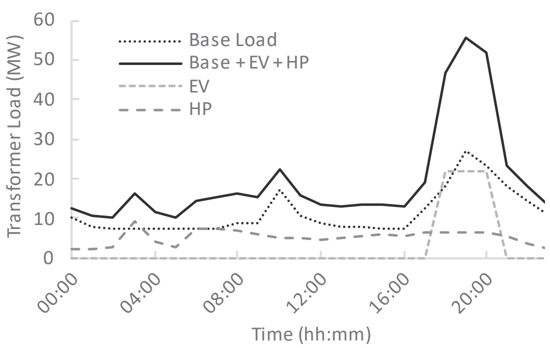

Fig 2. Comparative Load Analysis with and without the additional demands from EVs and HPs

In the context of assessing transformer load impacts under varying conditions, Fig 3 displays the top oil temperature and hot spot temperature corresponding to the typical ambient temperatures in Scotland for the same load pattern analyzed previously. This visualization underscores the thermal dynamics within the transformer, critical for understanding insulation degradation and overall asset health as influenced by environmental and operational conditions.

Fig 4 presents the relationship between the load factor and the accelerated aging factor (FAA) for the transformer. It illustrates how varying load levels directly influence the rate of aging, providing key insights into the durability and lifecycle management of transformer assets under different operational stresses.

The calculation revealed a loss of life amounting to 115.84 hours within a 24-hour cycle, indicating that the aging process is occurring at a rate 4.83 times comparing with normal. According to the NOMs methodology, the average duty factor for both maximum and average demand in this scenario would be set at 1.5. However, the observed aging rate of 4.83 times the aging at the rated load, highlighting a significant disparity and underscoring the need for adjustments in operational strategies to manage this accelerated aging process effectively.

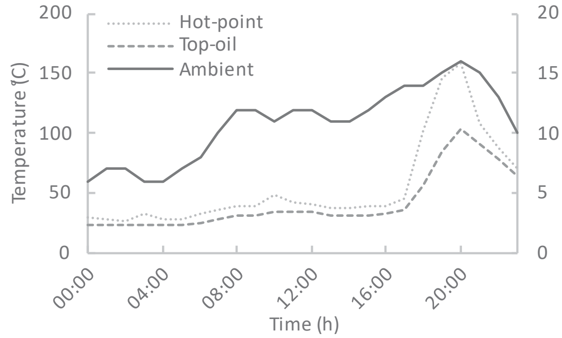

Fig 3. Thermal Dynamics of a Transformer: Illustrates how hot spot temperatures can exceed 110 degrees during peak demand, underscoring the critical thermal effects on transformer health

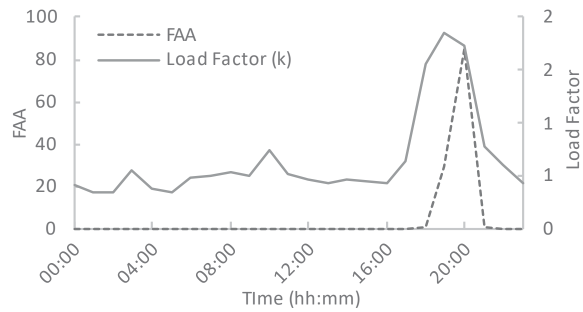

Fig 4. Load Factor and Aging: Shows how varying load levels impact transformer aging rates

The variable representing the transformer's end of life, labeled as $TxEoL_{Y0}$, is simulated by altering values of various variables and applying equation (1).

$$TxEoL_{y0} = \min\left(Max\left(EoL_{DGA}, EoL_{FFA}, EoL_{max,min}\right), EoL_{Y0,\max}\right) \quad (1)$$

End of life (EoL) is a continuous variable that ranges from 0.5 to 15. A value between 0.5 and 2.5 signifies that the transformer is either new or like new. Values ranging from 2.5 to 4.5 indicate that the transformer is in good or serviceable condition. A rating from 4.5 to 6.0 suggests the beginning of significant deterioration. Ratings from 6 to 8 indicate substantial deterioration, while a value above 8 points to severe deterioration and imminent failure [14]. EoL_{Y0} denotes the current end of life status, while $TxEoL_{Y0}$ represents the current end of life of the transformer.

A. Transformer End of Life: Standard vs. Modified NOMs

In assessing transformer durability under different load conditions, the average load was found to be 65%, while the maximum load reached 185%. The overall duty factor applied in this comparison was 1.5. When applying a duty factor of 1.5, the calculated end of life for the transformer was 2.85. However, for the more severe duty factor of 4.83, the initial end of life measurement was capped at 5.5. This capping reveals a limitation of the NOMs methodology, where, at this higher stage of stress, the methodology relies more heavily on DGA and Furanic Compound Analysis (FFA) to gauge transformer health, indicating a shift from purely load-based assessments to more diagnostic approaches under extreme conditions.

IV. Recommendations

A data-centric approach to estimation is highly recommended for enhancing the accuracy of predictions and facilitating effective planning for asset upgrades. Analyzing historical data allows for more precise forecasting and strategic decision-making. To further strengthen this approach, it is advisable to integrate real-time monitoring and advanced analytics into the existing asset management framework. This integration can help in detecting early signs of deterioration and in performing condition-based maintenance, thus preventing unexpected failures and optimizing lifecycle costs. Additionally, continuous updating of the data models with new information will ensure that the predictive analytics evolve in line with changing operational conditions and technological advancements.

V. Summary

The NOMs methodology, traditionally effective under standard loading conditions, has shown limitations with the evolving energy landscape where households increasingly adopt EVs and HPs. These technologies introduce new dynamics to the load profile, including overlapping demands and generally higher overall demands. This shift highlights the necessity for a more precise aging calculation methodology that can accurately reflect the increased stress on assets and ensure more reliable long-term asset management.

Acknowledgment

The authors would like to thank Energy Technology Partnership (ETP) Energy Industry Doctorate Programme.

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