Scientific African 20 (2023) e01683

Contents lists available at ScienceDirect

Scientific African

journal homepage: www.elsevier.com/locate/sciaf

Adaptive thermal model for loading of transformers in low carbon electricity distribution networks

Rilwan O. Oliyide[a,b,*], Liana M. Cipcigan[a]

[a] Institute of Energy, School of Engineering, Cardiff University, Cardiff, UK
[b] Department of Electrical/Electronic Engineering, Moshood Abiola Polytechnic, Abeokuta, Ogun State, Nigeria

ARTICLE INFO

Article history:
Received 14 September 2021
Revised 22 February 2023
Accepted 1 May 2023

Editor: DR B Gyampoh

Keywords:
Thermal loading
Dynamic loading
Distribution transformer
Electric vehicles
Heat pumps
GHG emissions

ABSTRACT

The uptake of low carbon technologies, particularly Electric Vehicles (EVs) and Heat-Pumps (HPs), at the low voltage (LV) distribution network, in the quest of cutting down on greenhouse gas (GHG) emissions in the transportation and residential sectors, has the potential to cause general load increase and may lead to higher and longer peak load demand. This development can, as hinted in previous studies, pose a real challenge of capacity overloading to transformers at the LV distribution network of electricity system. Prolonged periods of transformer overloading could lead to premature transformer failure and shortens transformer's life expectancy. A direct solution to addressing transformer overloading is the upgrading of the transformer capacity. However, the number of LV distribution transformers in electricity system to be upgraded and the resources needed for such operation make the solution less desirable to the Distribution Network Operators (DNOs). Therefore, it is important to develop cost-effective solutions for the optimal utilization of the existing transformer capacity. Adaptive thermal loading of transformers is one of such solutions. This paper focusses on the Adaptive Thermal Loading (ATL) of transformers in LV distribution networks with considerable penetration level of EVs and HPs. The thermal model of a 500-kVA, 11/0.415-kV (no load), 50-Hz, Dyn11, ONAN mineral oil filled, free breathing, ground mounted transformer serving a real and typical urban LV network in the United Kingdom (UK) is developed based on IEC 60,076–7:2005 standard and used as the case study. A method of adaptive thermal loading of the transformer is presented to examine its capacity performance when serving the future load of the LV network following the integration of projected uptake figures of EVs and HPs for the years 2020, 2030, 2040 and 2050 into the network. Given the load and temperature forecasts of a day, the method aims at optimizing, considering the real and present conditions of the operating environment, the overall daily transformer capacity utilization that gives maximum daily return on investment without undermining reliability of supply and normal life expectancy of the transformer. Results show improved performances of the transformer when the adaptive thermal loading method is used.

* Corresponding author.
E-mail address: oliyide.rilwan@mapoly.edu.ng (R.O. Oliyide).

https://doi.org/10.1016/j.sciaf.2023.e01683

Introduction

The energy consumption for residential heating in the United Kingdom (UK) in 2021 accounted for approximately 16% of all GHG gas emissions [1]. In the UK, most of the residential heating needs are met by gas-fired boilers [1]. In Great Britain (GB) alone, 84.2% of households use gas-fired boilers for heating [2]. Also, in 2021, the transport sector accounted for 26% of all GHG emissions in the UK [1]. The road transport, especially passenger cars, is the major contributor in this sector. Internal Combustion Engine (ICE) cars, as at the end of 2021, made up above 90% of all cars licensed by propulsion/fuel type in the UK [3].

To reduce emissions in the transport sector, EVs are expected to play a dominant role. The UK Government's ambition is that nearly all cars and vans on the roads are zero emission by 2040 [4]. Government says as this number grows EVs will become a "*resource for a smart electricity*" bringing benefits for drivers and creating a more flexible and efficient energy system [4].

Therefore, there is considerable potential in cutting down on GHG emissions in both residential and transport sectors by switching to low carbon sources and adoption of new technologies. Hence, the drive towards increasing awareness on the use of HPs for residential heating and EVs for road transportation. To this end, the UK Government initiated incentive schemes such as 'Plug-in Car Grant' to encourage uptake of EVs and 'Renewable Heat Incentive' to encourage the switching from fossil fuel heating to renewable heating [5,6].

A significant uptake of HPs and EVs in a geographical area will increase the load demand of that area and may also increase the magnitude and duration of its peak load demand. A number of studies [7–12] assessing the impacts of uptake of EVs and HPs on the electricity distribution networks concluded that the distribution transformers may be overloaded. Prolonged and/or accumulated periods of overloading could shorten transformer's life expectancy and leads to premature failure [13,14]. Transformer is one of the most critical equipment in the power system [15]. Amongst the impacts of an unplanned outage of a transformer are reduction in system reliability and economic losses to DNOs [16,17].

In previous literature many methods have been proposed for managing EVs and HPs load without overloading the transformer. In [11], a temperature-based smart charging algorithm was developed by combining a transformer thermal ageing model with empirical travel behaviour of the EVs owners. The study results claimed that delaying charging until after midnight can increase, rather than decrease the transformer ageing. However, the transformer thermal ageing model was based on 'Equivalent ageing Factor' averaged over a 12-hour period and not over a 24-hour period.

In [12], a Java-based simulation platform was developed to study the ageing Acceleration Factor and Loss-of-Life of a distribution transformer under different scenarios of EV battery charging. Results indicated that an intelligent management of EV battery charging profile, based on the assumption of communication between residential storage device and EV via an intelligent charge controller, could help manage the distribution transformer loss-of-life. The capital investment for the storage device and the communication set-up was, however, not costed.

Three different coordination mechanisms for negotiation between DNOs and EVs aggregators were proposed in [18] to manage load congestion problem. But none of these mechanisms considered the thermal behaviour of the transformer. In [19], an integrated approach for real-time load congestion management by combining a cost-based Demand-Response mechanism, real-time thermal model of transformer and active power curtailment was proposed. The integrated approach in [19] is however contingent on the availability of small-scale prosumers, i.e. end-users and local producers, in the distribution network.

In [20], an Enhanced Transformer Ratings Tool was developed based on the IEC 60,076–7 thermal model. The tool was tested on 33/11 kV primary distribution transformers with the aim of calculating enhanced seasonal transformer ratings for winter, summer, and spring/autumn. However, in the development of the tool in [20] which aims to calculate a single enhanced seasonal thermal rating, average seasonal temperatures were used, and not measured temperature.

In this paper, an Adaptive Thermal Loading (ATL) method of distribution transformer is proposed. In this method, a Non-Linear Programming (NLP) function is formulated and solved to determine optimal, considering the real and present conditions of the operating environment, overall daily transformer capacity utilization that will yield maximum daily return on the capital invested on the transformer without sacrifice of normal life expectancy of the transformer.

The aim of this study is to investigate to what extent the capacity headroom for the accommodation of more EVs and HPs load on the LV distribution network could be raised while asset reinforcement deferral is enforced. It is assumed here that associated equipment such as tap changers, switchgears, bushings, protection and metering instruments, busbars, etc., can withstand the additional stress that comes with the excess load above the transformer nameplate rating. The proposed method is applied on a distribution transformer serving a real urban LV network with projected uptake figures of HPs and EVs for the year 2050.

The rest of the paper is organized as follows: Section 2 describes the distinction and the relative merits/demerits between the adaptive thermal loading of transformer and static loading of transformer. In section 3, transformer thermal modelling based on IEC 60,076–7:2005 is presented. The NLP function for the adaptive thermal loading of the transformer is formulated in Section 4. Details of the real LV network used as the case study are presented in Section 5. The proposed method is implemented on the case study in Section 6. Results are presented and discussed in Section 7 and in Section 8 summary and conclusions are drawn.

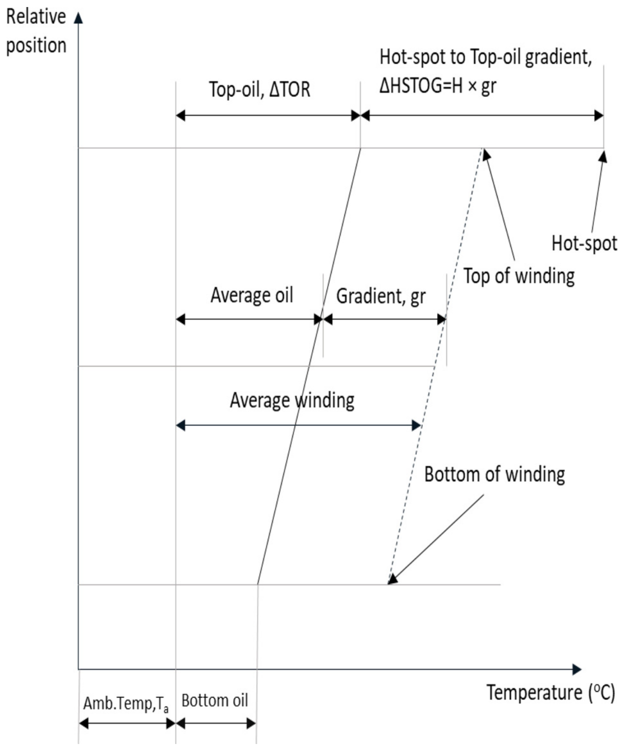

Fig. 1. Transformer thermal diagram [13].

Adaptive thermal loading versus static loading of transformer

The ageing process and hence the expected life of an oil-immersed transformer are principally determined by the ageing of the paper insulation of its winding [21]. The paper insulation degradation is a function of temperature, moisture content, oxygen content and time [22]. Moisture and oxygen contents of the insulation paper can be minimised with modern preservation techniques [23,24]. Temperature and time therefore remain as the major factors determining the degradation rate of paper insulation and therefore the expected life of the transformer [25]. The temperature of the hottest spot within the transformer winding, known as the 'Hot Spot Temperature' (HST) is reckoned as the operating temperature of the paper insulation [26]. The higher the HST, the quicker the winding insulation degrades and the faster the transformer ages. The degradation rate of insulation paper doubles for every 6 °C rise above the rated HST [13]. The HST is a function of ambient air temperature, oil temperature, and transformer design amongst others [27].

Static load rating is specified by the manufacturers to limit the operating temperature to less than 110 °C, for a thermally upgraded insulation paper, based on ambient temperature of up to 40 °C to ensure normal life expectancy of the transformer [14]. However, in most cases, the ambient temperature in UK is far below 40 °C and the transformers are operating, most of the time, below their temperature limits, i.e., thermally low loaded. This condition can be exploited to safely maximise the use of existing transformer capacity based on real conditions in which the transformer operates. Transformers can therefore be adaptive thermally loaded based on real environmental conditions and HST rather than on static load rating. The use of static load rating does not fully capture the real and present thermal conditions and can lead to false indication of capacity reinforcements and/or strategic measures to reduce load due to false indication of full capacity being exhausted.

In adaptive thermal loading of the transformer, load data is considered along with meteorological measurements. Using these pieces of information, transformers can be loaded in such a way to gain variable capacity headroom by leveraging on environmental cooling. This implies that adaptive thermal rating often exceeds the nameplate rating. However, under harsh environmental conditions, adaptive thermal rating may be lower than the nameplate rating of the transformer. The rationale behind adaptive thermal loading of transformer is to enable the DNOs use more intensively the distribution transformers and possibly achieve capacity reinforcement deferral in the wake of expected load increase due to the uptake of HPs and EVs in homes.

Transformer thermal modelling

IEC 60,076–7:2005 stipulates how oil-immersed transformer can be operated under different ambient temperature and time-varying load. Fig. 1 is the transformer thermal diagram per [13] which explains the temperature distribution inside the transformer.

The following assumptions are made about temperature distribution inside the transformer [13]:

- The oil temperature increases linearly from bottom to top of the tank irrespective of the cooling mode.
- The temperature rise of the winding increases linearly and is parallel to the oil temperature rise, with a constant difference (gr) between the two parallel lines.
- Due to the allowance being made for the increase in stray losses, the hot-spot temperature rise is higher than the temperature rise of the conductor at the top of the winding.

From Fig. 1, it is seen that the HST(t) is a sum of three components: the ambient temperature T_a(t), top-oil temperature rise ΔTOR(t) and the hot-spot to top-oil gradient $\Delta HSTOG$(t) as expressed in (1).

$$HST(t) = T_a(t) + \Delta TOR(t) + \Delta HSTOG(t) \tag{1}$$

The *HST*(t) during a transient period, i.e., load change from one steady state to another can be modelled by functions of the exponential forms of top-oil temperature and hot-spot to top-oil gradient as in (2) and (3) respectively:

For load increase:

$$\Delta TOR(t) = \Delta TOR(i) + [\Delta TOR(f) - \Delta TOR(i)] \times f_1(t) \tag{2}$$

$$\Delta HSTOG(t) = \Delta HSTOG(i) + [\Delta HSTOG(f) - \Delta HSTOG(i)] \times f_2(t) \tag{3}$$

Where $\Delta TOR(i)$ and $\Delta HSTOG(i)$ are initial top-oil temperature rise (°C) and initial hot-spot to top-oil gradient (°C) at the beginning of the load change. $\Delta TOR(f)$ and $\Delta HSTOG(f)$ are final top-oil temperature rise (°C) and final hot-spot to top-oil gradient (°C) at the end of the load change. $f1(t)$ and $f2(t)$ are exponential functions that describe the relative increase of top-oil temperature rise and hot-spot to top-oil gradient per unit of the steady state value respectively.

$$f_1(t) = 1 - e^{-t/(k_{11} \times \tau o)} \tag{4}$$

$$f_2(t) = \left[k_{21}\left(1 - e^{-t/(k_{22} \times \tau w)}\right) - (k_{21} - 1)\left(1 - e^{-t/(\tau o/k_{22})}\right)\right] \tag{5}$$

Where k_{11}, k_{21} and k_{22} are thermal model constants. τo, τ_{w} and t are oil time-constant (mins), winding time-constant (mins) and duration of the load (mins) respectively.

For load decrease:

$$\Delta TOR(t) = \Delta TOR(f) + [\Delta TOR(i) - \Delta TOR(f)] \times f_3(t) \tag{6}$$

$$\Delta HSTOG(t) = \Delta HSTOG(f) + [\Delta HSTOG(i) - \Delta HSTOG(f)] \times f_4(t) \tag{7}$$

Where $f3(t)$ and $f4(t)$ are exponential functions that describe the relative decrease of top-oil temperature rise and hot-spot to top-oil gradient per unit of the steady state value respectively.

$$f_3(t) = e^{-t/(k_{11} \times \tau o)} \tag{8}$$

$$f_4(t) = \left[k_{21} \times \left(e^{-t/(k_{22} \times \tau w)}\right) - (k_{21} - 1) \times \left(e^{-t/(\tau o/k_{22})}\right)\right] \tag{9}$$

In (5) and (9), if k_{21} is unity and τ_{w} is negligible, then (3) and (7) become

$$\Delta HSTOG(t) = \Delta HSTOG(f) \tag{10}$$

The initial and final top-oil temperature rise after a load change over a period t are given by (11) and (12) respectively.

$$\Delta TOR(i) = \Delta TOR_{(R)} \times \left(\frac{(K_i^2 \times R) + 1}{(R+1)}\right)x \tag{11}$$

$$\Delta TOR(f) = \Delta TOR_{(R)} \times \left(\frac{(K_f^2 \times R) + 1}{(R+1)}\right)x \tag{12}$$

Where $\Delta TOR_{(R)}$ is the top-oil temperature rise (°C) at rated load. R is the ratio of loss at rated load to no-load loss. K_i is the ratio of initial load to rated load. K_f is the ratio of final load to rated load and x is the oil exponent constant.

Similarly, the initial and final hot-spot to top-oil gradient after load change are given by (13) and (14) respectively.

$$\Delta HSTOG(i) = \Delta HSTOG_{(R)} \times (K_i)y \tag{13}$$

$$\Delta HSTOG(f) = \Delta HSTOG_{(R)} \times \left(K_f\right)y \tag{14}$$

Where $\Delta HSTOG_{(R)}$ is hot-spot to top-oil gradient (°C) at rated load and y is the winding exponent constant.

The degradation rate of the transformer winding insulation obeys the Arrhenius reaction rate theory [28]. Therefore, the per-unit life (PUL) of transformer is given by (15):

$$PUL(t) = 9.8 \times 10^{-18} \times, e^{\left(, \frac{15000}{HST(t)+273}\right)} \tag{15}$$

The inverse of the PUL is the ageing Acceleration Factor (AAF).

$$AAF(t) = \frac{1}{PUL(t)} \tag{16}$$

From (15) and (16), for HST of 110 °C both PUL and AAF are unity. For HST greater than 110 °C, PUL is less than unity and AAF is higher than unity. Conversely, for HST less than 110 °C, PUL is higher than unity and AAF is less than unity.

The estimate of the transformer loss life (LoL) in percentage of normal life expectancy after a 24-hour operating period can be determined by (17):

$$LoL_{(24hr)} = \frac{\sum_{t=1}^{T} \left(AAF(t) \times T_s(t)\right)}{\sum_{t=1}^{T} T_s(t)} \times \frac{24}{N_{life}} \times 100\% \tag{17}$$

In (17), t is the index of time interval. T is the total number of time intervals. T_s is the duration of time interval in hours. N_{life} is the normal life expectancy of the transformer in hours.

Transformer adaptive thermal loading: mathematical formulation

Transformers are important components, in terms of both capital investment and reliability of the power system. High-capacity utilisation factor of transformers and good returns on investments are therefore the expectations of the DNOs. The adaptive thermal loading of transformer is formulated as an optimisation problem with the objective of maximising daily return on the transformer utilisation in accordance with the real and present operating and environmental conditions. Constraints to the optimisation problem are the thermal and load conditions that ensure the normal life expectancy of the transformer. The objective function is formulated and expressed in (18):

$$DRU = max \sum_{t=1}^{24} \left[\left(L_{(t)} \times EP_{(t)}\right) - \left(TOC_{(t)} \times LoL_{(t)}\right)\right] \tag{18}$$

Where DRU is the 'Daily Return on transformer Utilisation' in currency unit (£). $L_{(t)}$ is the load on transformer at time t in kW. $EP_{(t)}$ is the 'Energy Price' at time t. $TOC_{(t)}$ is the 'Total Owning Cost' of the transformer in currency unit (£). $LoL_{(t)}$ is the loss of life of the transformer at time t in per unit.

Total owning cost $TOC_{(t)}$ not only takes the initial cost of buying the transformer into account but also the cost to operate and maintain the transformer [29]. TOC can be determined as the sum of the initial cost price C_p, the cost of no-load C_{NL}, and the cost of load-loss C_{LL} [29].

$$TOC_{(t)} = C_P + C_{NL} + C_{LL(t)} \tag{19}$$

The objective function in (18) is subject to the constraints of (20) to (23):

$$K(t) \le 1.8 \tag{20}$$

$$\Delta TOR(t) \le 110^\circ C \tag{21}$$

$$HST(t) \ \le 140^\circ C \tag{22}$$

$$LoL_{(24hr)} \le 0.0133\% \tag{23}$$

The constraint expressed in (20) limits the transformer loading to 1.8 per unit of its rated capacity. In (21), the top-oil temperature rise is limited to 110 °C to manage pressure build-up. This is to prevent expansion of oil which could lead to overflow of oil in the tank. The HST is kept under 114 °C in (22) to prevent formation of gas bubbles in the oil and paper insulation. Eq. (23) ensures that the daily cumulative loss of life of the transformer insulation does not exceed that of normal operation of the transformer at HST of 110 °C for 24 h.

Fig. 2 shows the algorithm for adaptive thermal loading of transformer and optimal DRU.

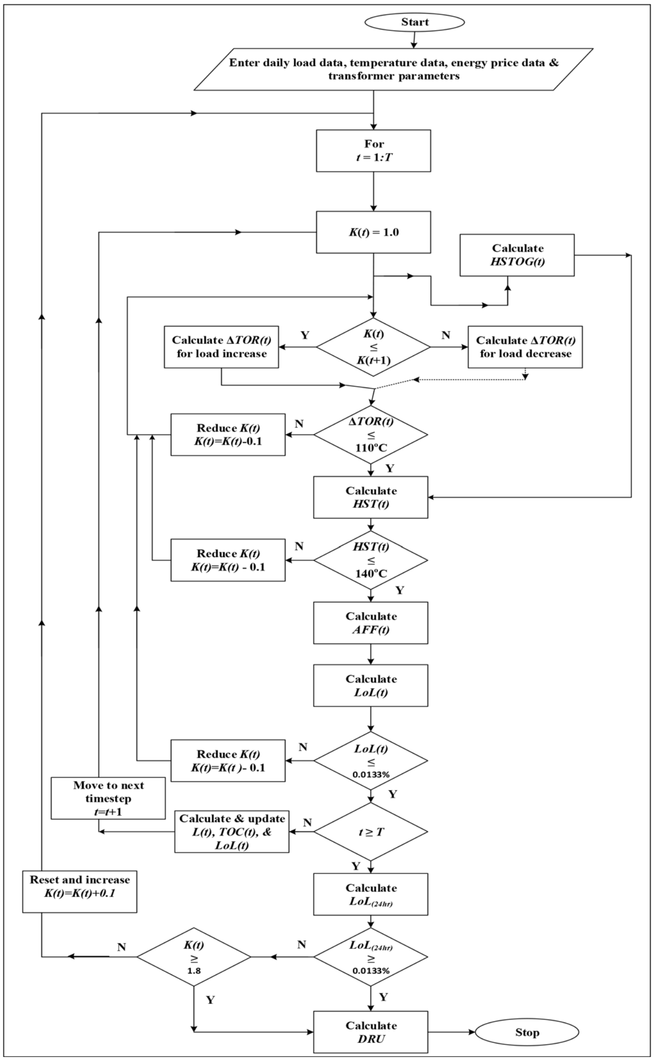

Fig. 2. Algorithm for adaptive thermal loading of transformers and optimal *DRU*.

Table 1
Feeders Analysis.

Feeder	2014 Annual load (MWh)	Length (m)	No of Buildings
1	360.78	1190	95
2	202.29	555	51
3	402.70	1155	120
4	108.94	250	32
Total	1074.71		298

Case study

A distribution transformer serving a real urban residential LV network in Cardiff is the case study. The area is supplied by a 500-kVA, 11/0.415-kV (no load), 50-Hz, Dyn11, ONAN mineral oil filled, free breathing, ground mounted transformer. The transformer supplies 347 households consisting of 298 buildings in four feeders. Fig. 3 shows the simplified diagram of the LV network and Table 1 gives the analysis of the number of buildings per feeder, annual baseline load of the feeders in the year 2014 and the length of the feeders.

In this work, residential baseline electricity demand is described as the household electricity demand which excludes the electricity demand of EVs and HPs. In 2014, the uptake levels of both EVs and HPs were very small, and their combined electricity demand was not visible in the total residential annual electricity demand presented in [30,31]. Therefore, residen-

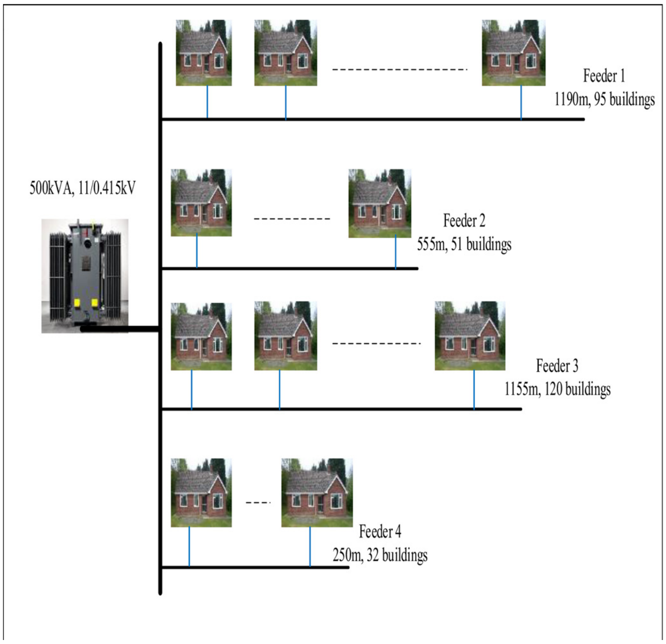

Fig. 3. Simplified diagram of the case study LV network.

Table 2
Number Of EVs And HPs in the LV Network Under TD Scenario, 2020–2050 [32].

Year	Number of EVs (Units)	Number of HPs (Units)
2020	23	5
2030	93	45
2040	167	95
2050	256	207

tial annual electricity demand in 2014 is regarded as 'reference baseline' in the context of this work. Projected residential annual baseline electricity demand for 2020, 2030, 2040 and 2050 of GB are estimated from the breakdown analysis of the annual demand presented in National Grid's Future Energy Scenarios (FESs) [30].

National projection figures of the different uptake scenarios of EVs and HPs as presented in the National Grid's FESs document [30] were scaled down to the level of the LV network. The process of scaling down was well detailed in [32]. National Grid's FESs presents a number of "plausible and credible pathways for the future of energy for GB, from today out to 2050″. These scenarios are developed based on the energy trilemma of security, affordability and sustainability [30].

In the FESs, the most optimistic uptake scenario for low carbon technologies (LCTs) in general and EVs and HPs in particular is called the 'Two Degrees' (TD). The scenario name 'TD' is derived from the Article 2 of the Paris Agreement [33]. It indicates the target of holding the increase in global average temperature to well below 2 °C above the pre-industrial levels. The TD depicts a scenario of prosperous economic growth, increased focus on RESs and LCTs, and strong political drive to achieve the renewable integration and all of UK's 2050 emissions reduction targets. It is a scenario in which technology and investment are focused on innovation in renewable energy sources (RESs) (solar and wind) and low carbon (nuclear) generation.

Table 2 presents the number of EVs and HPs the LV network is hosting under the TD scenario in the years 2020, 2030, 2040 and 2050.

By the year 2050, the LV network is hosting 256 EVs and 207 HPs. The EVs and the HPs are distributed amongst the feeders based on the ratio of the number of buildings per feeder. Table 3 gives detailed distribution of EVs and HPs between the feeders of the LV network in TD scenario.

Future load profiles of the LV network for the years 2020, 2030, 2040 and 2050 were respectively created considering the baseline load growth and uptake of EVs and HPs by the residents of the area. Based on the normalisation of load profiles from [34], projected annual baseline demand of the LV network for the years 2020, 2030, 2040 and 2050 are converted to half-hourly seasonal (summer weekday and winter weekday) daily profiles.

The average daily EVs charge requirements of the LV network as determined in [32] and the half-hourly percent of average daily charge in [35] are adopted to generate the actual average half-hourly EV charging profile. Fig. 4 shows the EVs daily charge requirements distribution and Fig. 5 is the average half-hourly EV charging profile. The daily average electricity

Table 3
EVs And HPs distribution between the feeders in TD scenario.

Feeder	Year	No of EVs (Units)	No of HPs (Units)
1	2020	7	1
	2030	28	14
	2040	50	29
	2050	77	62
2	2020	5	1
	2030	19	9
	2040	33	19
	2050	51	41
3	2020	9	2
	2030	37	18
	2040	67	38
	2050	102	83
4	2020	2	1
	2030	9	5
	2040	17	10
	2050	26	21

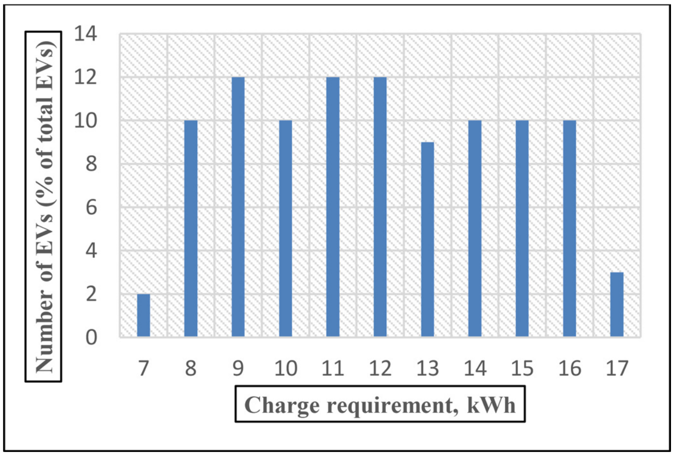

Fig. 4. EVs daily charge requirement distribution [32].

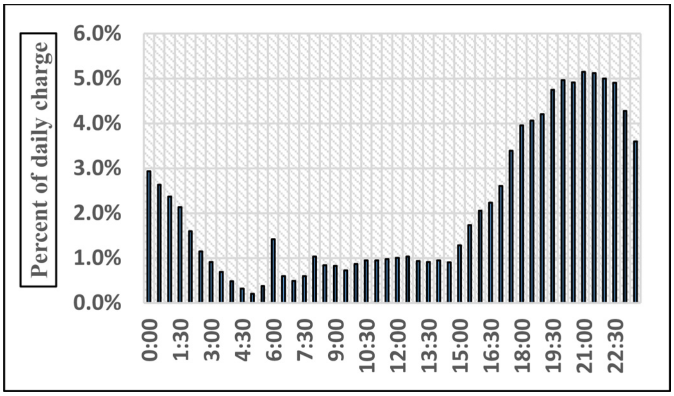

Fig. 5. Average half-hourly EV charging profile [35].

demand of a 6-kW variable speed air-source HP, shown in Fig. 6, whose operating profile for the provision of both residential space heating and hot water was derived from the simulation described in [32] was used in this study.

Powerflow simulation study of the created future load profiles of the LV network was performed for the years 2020, 2030, 2040 and 2050. GridLAB-D power system simulation software was used for the powerflow simulation study. The powerflow simulation showed the impacts of the load demand of the uptake of EVs and HPs in the LV network on the transformer loading. Fig. 7 shows the transformer loading under the TD scenario on a typical summer weekday (TDSmrWd) in the years 2020, 2030, 2040 and 2050. Fig. 8, on the other hand, shows the transformer loading under the TD scenario

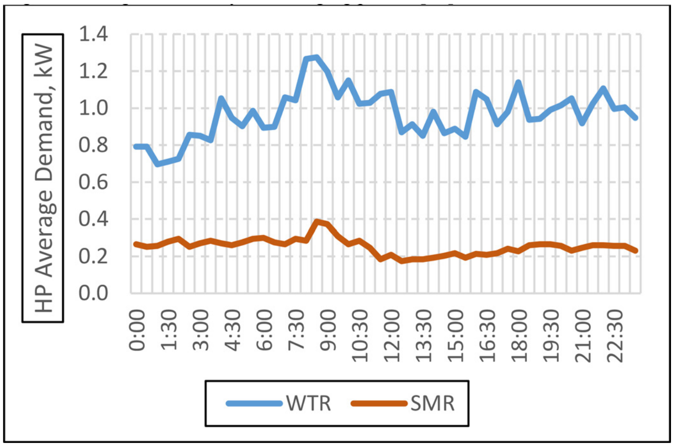

Fig. 6. HP daily average demand [32].

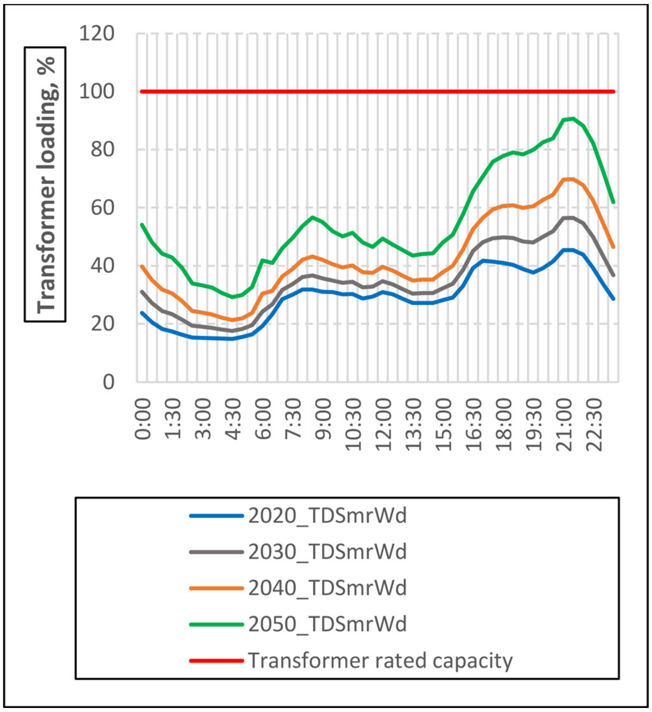

Fig. 7. Half-hourly transformer loading, TDSmrWd, 2020 – 2050.

on a typical winter weekday (TDWtrWd) in the years 2020, 2030, 2040 and 2050. The transformer is adequate to meet the load requirements of the network in the TDSmrWd scenario for all the years considered (see Fig. 7). Whereas in Fig. 8, the transformer experienced sustained overload of more than 30% in 2050_TDWtrWd.

The challenge is therefore the overloading of the transformer which could lower the headroom for the uptake of EVs and HPs in the LV network. Upgrading the transformer capacity to meet the winter load demand will be uneconomical as the transformer is underutilised even on a typical summer weekday in 2050. The proposed adaptive thermal loading of transformer is therefore applied. The goal is to optimize the capacity utilization of the transformer in an attempt to meet all the load requirements of the network without undermining system reliability and normal life expectancy of the transformer. This can be achieved by leveraging on the real weather conditions of winter to thermally load the transformer.

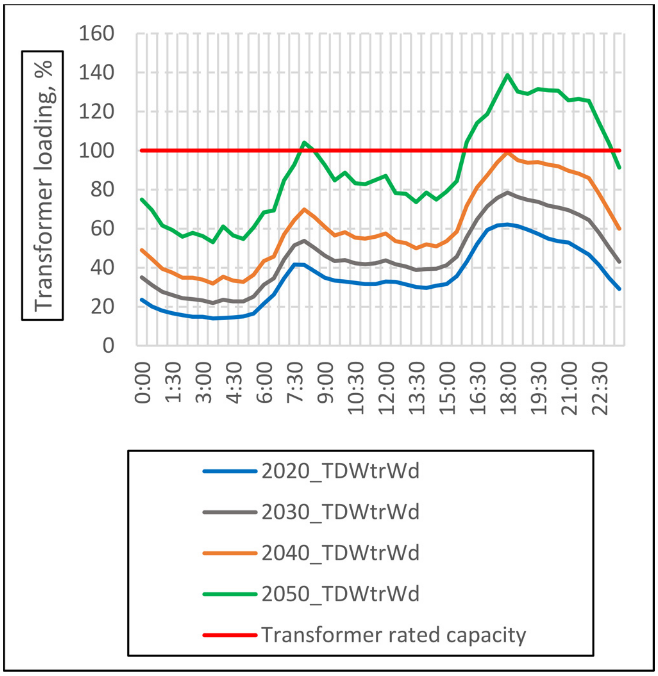

Fig. 8. Half-hourly transformer loading, TDWtrWd, 2020 - 2050.

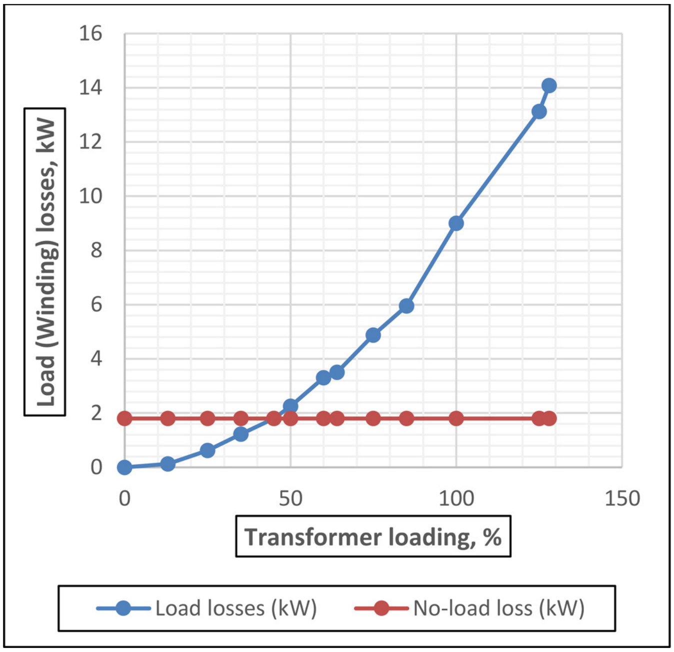

Fig. 9. Transformer Loading and load losses.

Implementation

The transformer was studied, and its thermal behaviours analysed when carrying the load demand of the LV distribution network under **TDWtrWd** scenario in **2050**. Three situations were investigated to verify the usefulness of the proposed adaptive loading method:

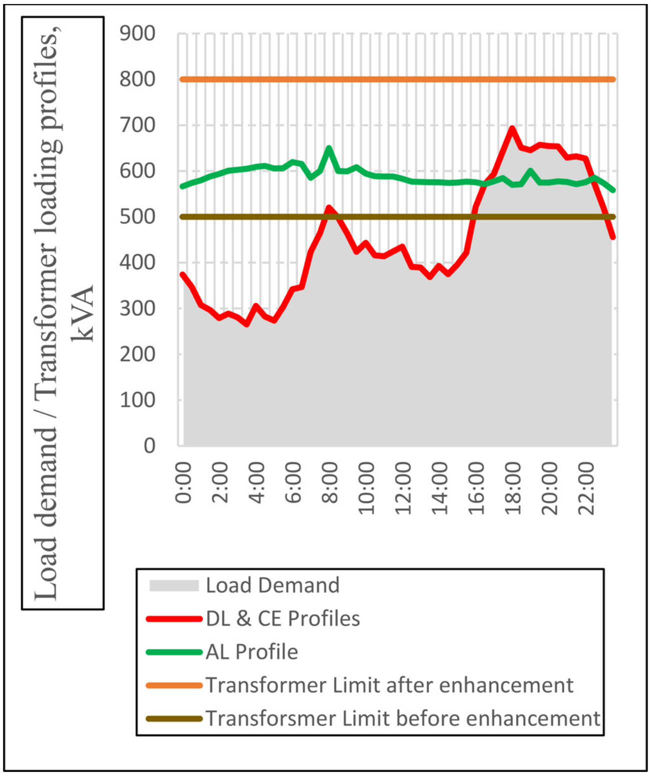

Fig. 10. Transformer Loading profiles on a winter weekday in 2050.

1) **Dumb loading (DL):** The transformer is allowed to carry the load demand of the LV area without any intervention. This is a do-nothing situation. To simulate the situation, Eq. (18) is applied on the transformer without imposing the constraints of Eqs. (20) to (23) while the thermal condition of the transformer is evaluated.
2) **Capacity enhancement (CE):** The capacity of the transformer is upgraded to a higher rating. To simulate this situation, the capacity of the case study transformer is upgraded to 800kVA and then allowed to carry the load demand of the LV area without any further intervention. That is according to Eq. (18) without imposing the constraints of Eqs. (20) to (23).
3) **Adaptive loading (AL):** The transformer is allowed to carry the load demand of the LV area based on the proposed adaptive thermal loading method. The objective function of Eq. (18)) was implemented on the transformer subject to the constraints of Eqs. (20) to (23).

In each of the three situations, the following plots of the transformers were obtained and compared.

- Transformer loading profile
- Transformer utilisation factor
- Daily *HST* plot
- Daily cumulative *LoL* plot
- Daily cumulative *DRU* plot

The parameters of the transformer of the LV distribution network are given in Table 4.

Ambient temperature data for a typical winter day and a typical summer day are from the MET Office [36]. The rated load loss of the transformer was determined from the power flow simulation. Fig. 9 is the plot of transformer loading against the load losses for some data points. From the plot of Fig. 9, the winding resistance of the secondary is estimated to be 0.02Ω.

The UK day-ahead wholesale electricity price from N2EX [37] divided by a factor of 0.363 to reflect the total electricity price, in line with the Office of Gas and Electricity Markets (Ofgem) electricity bill breakdown [38] gives the energy price used in the objective function. The cost price of transformers was supplied by a UK-based power equipment marketing company on a non-disclosure agreement.

Analytical Solver®, a commercial optimization software package from the Frontline Solvers [39], was used to solve the optimization problem. The problem model was diagnosed as Non-Convex Non-Linear Programme (NonCvx NLP) and it was solved with KNITRO (V10.3.0.0) Solver Engine.

Table 4
Distribution Transformer Parameters.

Parameters	Values
Rating	11/0.4 kV,500kVA
Cooling type	ONAN
x	0.8
y	1.6
k_{11}	1.0
k_{21}	1.0
k_{22}	2.0
$\Delta TOR_{(R)}$	65 °C
$\Delta HSTOG_{(R)}$	23.0 °C
N_{life}	180,000hours
τo	180minutes
τw	10minutes
R	5
Rated load current (L_r)	722.5A

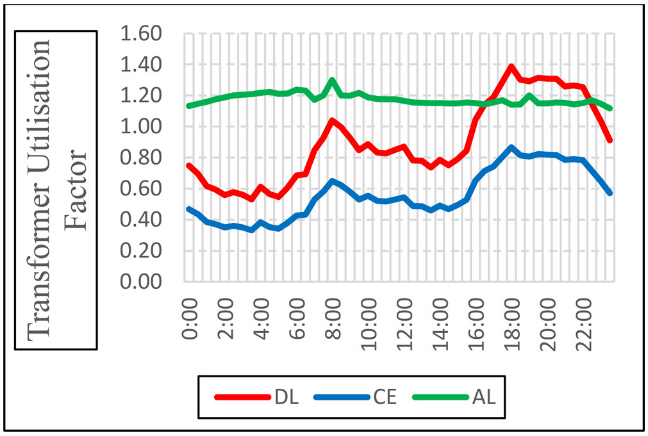

Fig. 11. Transformer Utilisation Factors on a winter weekday in 2050.

Results and discussion

Fig. 10 shows the load demand of the LV area and the transformer loading profiles of the three investigated situations on a typical winter weekday in 2050. The load demand exceeds the transformer limit before enhancement by an average of about 30% throughout the evening period in the DL profile. In the AL profile, the loading capability of the transformer is above the transformer limit before enhancement throughout the whole period. However, it is deficient by about 15% on average in meeting the evening load demand of the LV area. After the transformer capacity is upgraded, the CE profile shows, as seen in Fig. 10, that the load demand of the LV area is satisfied with the transformer having surplus capacity.

Fig. 11 shows the utilisation factors of the transformers in each of the loading profiles. In the DL profile, the transformer has an average daily utilisation factor of about 0.9. In the AL profile, the transformer has an almost constant utilisation factor averaging 1.18 throughout the day. However, it is observed in the AL profile that the transformer utilisation factor at night time slightly decreases with time into the day.

This is because as the temperature rises from the night to the day, the transformer adapts and adjusts its loading capability accordingly. In the CE profile, the transformer has an average daily utilisation factor of about 0.56.

Thermal behaviours (HST curves) of the transformers under the three investigated loading profiles are presented in Fig. 12. As seen, the HST of the transformer in the DL profile is well below the 110 °C mark that ensures normal life expectancy until 17:00 h when the HST increases rapidly.

Between 17:00 h and 22:30 h the HST is above 120 °C reaching 138 °C between 18:00 h and 19:00 h. This implies that the transformer in the DL profile is thermally under-loaded up until 17:00 h when it is now thermally overloaded for the rest of the evening. The HST of the transformer in the AL profile, as seen in Fig. 12, is almost constant at 110 °C throughout the day. This implies that the transformer in the AL profile is adequately thermal loaded throughout the day. In the CE profile (see Fig. 12), the HST of the transformer is below 110 °C throughout the day reaching a maximum of 72 °C at 18:30 h. The transformer is therefore thermally under-loaded.

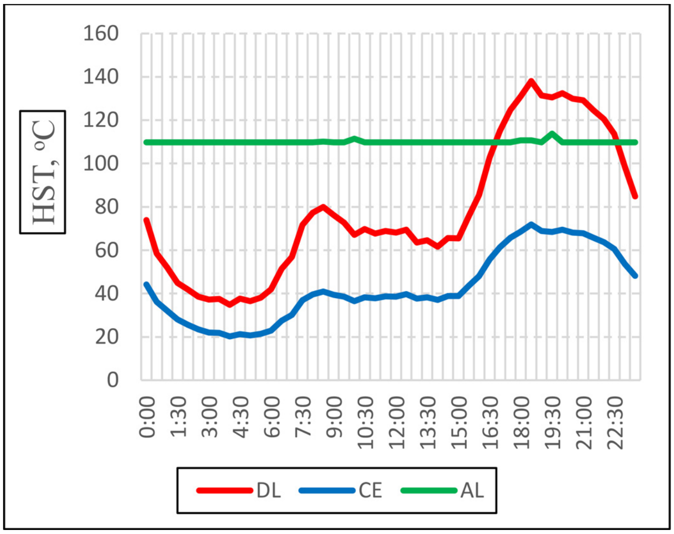

Fig. 12. HST curves of transformers on a winter weekday in 2050.

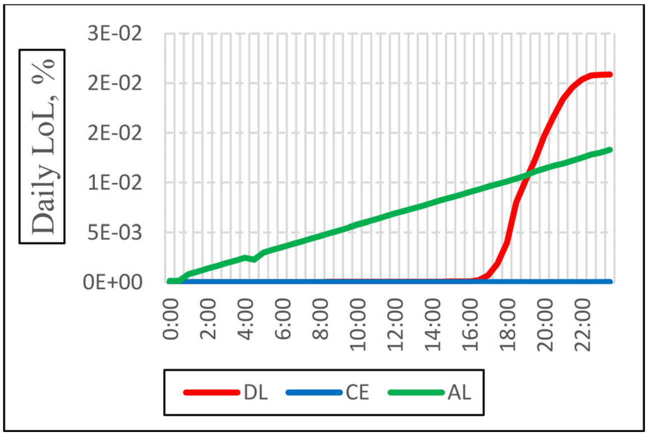

Fig. 13. Daily cumulative LoL plots of transformers on a winter weekday in 2050.

The daily cumulative loss of life of the transformers in each of the loading profiles on a winter weekday in 2050 are presented in Fig. 13. For the DL profile, the cumulative loss of life of the transformer is almost nil until 17:00 h when it increases rapidly to reach a maximum of 0.02% at the end of the day.

The trend is due to the fact that the transformer in DL profile is initially thermally under-loaded until 17:00 h and thereafter thermally overloaded for the rest of the evening. The daily cumulative loss of life of the transformer in DL profile is about two times above normal. For the AL profile, the cumulative loss of life of the transformer gradually increases from zero at 00:00 h and reaches a maximum of about 0.01% at 23:30 h. This is the normal daily loss of life for a full life expectancy of the transformer. The daily cumulative loss of the transformer in the CE profile is almost zero as seen in Fig. 13. This is because the transformer is thermally under-loaded throughout the day. This practically implies that under this condition the transformer could out-live its normal life expectancy.

The daily return on utilisation of the transformer in each of the loading profiles on a winter weekday in 2050 are presented in Fig. 14. The daily return on utilisation of transformer in DL and CE profiles are almost equal.

This is because their *TOCs* are almost equal. The high cost of loss of life of transformer in DL profile almost balances the initial high cost of a higher rating transformer in CE profile. The daily return on utilisation of transformer in AL is the highest at a value of £4350, which is £835 more than *DRU* of CE. AL profile has the highest *DRU* because the transformer utilisation factor is relatively high and the loss of life of the transformer is moderately normal.

Conclusions

An adaptive thermal loading method of distribution transformer serving LV area distribution network characterised by significant uptake of EVs and HPs is presented. The aim is to provide a cost-effective solution to the problems of transformer

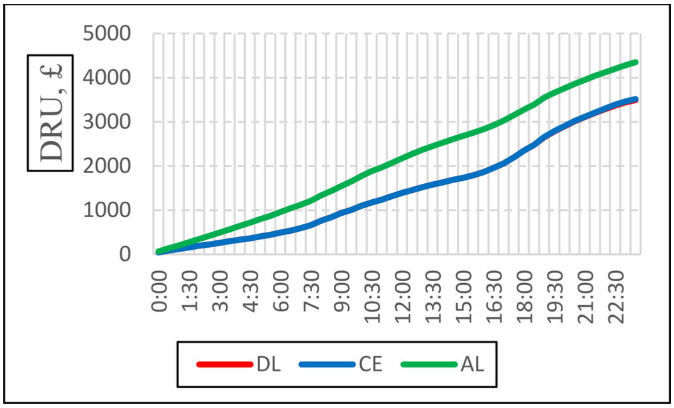

Fig. 14. Daily return on utilisation of transformers on a winter weekday in 2050.

overloading and its attendant consequences of possible premature failure of transformer and restriction of further uptake of EVs and HPs.

A distribution transformer serving a typical real urban LV network in the UK is used as the case study. Future load profiles of the LV network for the years 2020, 2030, 2040 and 2050 were respectively created considering the uptake of EVs and HPs by the residents of the area. In the method, a Non-Linear Programming (NLP) optimization function is formulated and solved to determine optimal, considering the real and present conditions of the operating environment, overall daily transformer capacity utilization that will yield maximum daily return on the capital invested on the transformer without sacrifice of normal life expectancy of the transformer. The optimisation problem of the proposed adaptive thermal loading method was solved using Analytical Solver® – a commercial optimization software package from the Frontline Solvers. To verify the usefulness of the proposed method, three situations were investigated:

1) **Dumb loading (DL)**: The transformer is allowed to carry the load demand of the LV area without any intervention. This is a do-nothing situation.
2) **Capacity enhancement (CE)**: The capacity of the transformer is upgraded to a higher rating, i.e. replace the transformer with one of higher rating.
3) **Adaptive loading (AL)**: The transformer is allowed to carry the load demand of the LV area based on the proposed adaptive thermal loading method.

Results showed that the loadability of the transformer increased by about 18% over its static rating in winter with the proposed method of loading. Before the proposed method, the transformer was overloaded by about 30% for not less than five hours and suffered a daily loss of life of 0.02%, which is twice above normal daily loss of life. With the proposed method, the overloading was reduced to 15% and the daily loss of life of the transformer was also reduced to 0.01% that ensures full life expectancy of the transformer. Upgrading the transformer capacity resulted in low-capacity utilisation factor.

The proposed adaptive thermal loading of distribution transformers would particularly be useful to the DNOs for the following reasons:

- It provides DNOs with information on the loading and thermal limits of distribution transformers at different time of the day.
- The information on the thermal limit of distribution transformers would enable DNOs to make better informed decisions about transformer loading, capacity reinforcement and load management techniques that are not based on static rating of transformers.

Future research on this topic will be focused on load management techniques that complement the adaptive thermal loading of the transformer to cost-effectively meet all the load demand of the LV network.

To bring Africa and the African Union (AU) Agenda 2063 into the perspective of this paper, the proposed adaptive thermal loading of distribution transformers would help in achieving the priority areas of the seventh goal of the AU Agenda 2063. The seventh goal of the AU Agenda 2063 is about environmental sustainability and climate resilient economies and communities. An effect of the climate change is extreme weather conditions – high temperatures especially in Africa. Adaptive thermal loading of transformers rather than static (or nameplate capacity) loading would ensure that transformers are not dangerously overloaded and prevent premature failure of transformers. The proposed model presented in this paper is extendable and deployable even in Africa.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Rilwan Oliyide would like to acknowledge the Nigeria Tertiary Education Trust Fund (TETFund) for sponsoring his Ph.D. in Cardiff University. He also would like to appreciate Moshood Abiola Polytechnic (MAPOLY), Abeoukta, Nigeria for the support received during his Ph.D. studies.

References

[1] Department for business energy and industrial strategy (DBEIS), “2021 UK grenhouse gas emissions, final figures,” *Statistical Release: National Statistics*, no. February 2023. London, pp. 1–47, 2023.
[2] Office of Gas and Electrcity Market (Ofgem), “Insights paper on households with electric and other non-gas heating,” no. December, pp. 1–84, 2015.
[3] Department for Transport (DfT) and driver and vehicle licensing agency (DVLA), “vehicle licensing statistics : 2021,” *Stat. Release*, no. December 2022. Available: https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables [Accessed: 20-Feb.-2023].
[4] U.K. Parliament of, *Automated and Electric Vehicles Act* 2018, House of Commons, London, 2018.
[5] Office for Low Emission Vehicles (OLEV), “Reformed plug-in car grant extended into next decade - GOV.UK,” *News story*, 2018. [Online]. Available: https://www.gov.uk/government/news/reformed-plug-in-car-grant-extended-into-next-decade. [Accessed: 10-Dec-2018].
[6] Department for Business Energy and Industrial Strategy (DBEIS), “The Renewable Heat Incentive: A Reformed Scheme.” London, pp. 1–116, 2016.
[7] R.O. Oliyide, C. Marmaras, E.T. Fasina, L.M. Cipcigan, Low carbon technologies integration in smart low voltage network, in: Proc. - 2017 IEEE 15th Int. Conf. Ind. Informatics, INDIN 2017, 2017, pp. 462–467.
[8] R.O. Oliyide, L.M. Cipcigan, The impacts of electric vehicles and heat pumps load profiles on low voltage distribution networks in Great Britain by 2050, Int. Multidiscipl. Res. J. 11 (2021) 30–45.
[9] R. Guo, S. Meunier, C. Protopapadaki, D. Saelens, A review of European low-voltage distribution networks, Renew. Sustain. Energy Rev. 173 (2023) 113056.
[10] W. Zou, et al., A review on integration of surging plug-in electric vehicles charging in energy-flexible buildings: impacts analysis, collaborative management technologies, and future perspective, Appl Energy 331 (2023) 120393.
[11] A.D. Hilshey, P.D.H. Hines, P. Rezaei, J.R. Dowds, Estimating the impact of electric vehicle smart charging on distribution transformer aging, IEEE Trans. Smart Grid 4 (2) (2013) 905–913.
[12] M.J. Rutherford, V. Yousefzadeh, The Impact of Electric Vehicle Battery Charging On Distribution Transformers, IEEE, 2011.
[13] International Electrotechnical Commission (IEC), “IEC 60076-7:2005-power transformers-Part 7: loading guide for oil-immersed power transformers,” 2005.
[14] IEEE Standards Association, *IEEE guide for loading mineral- oil-immersed transformers and step-voltage regulators*, vol. 2011, no. March. 2012.
[15] E. Baker, S.V. Nese and E. Dursun, “Hybrid condition monitoring system for power transformer fault diagnosis,” *Energies*, 16 no 3, pp. 1151, 2023.
[16] D. Alvaro, R. Moreno, M.E. Orchard, D.S. Kirschen, Cost-benefit analysis of maintenance plans: case study of the power system of a large industrial facility, IEEE Trans. Power Syst. (2022).
[17] S. Nkosi, “Prediction of Planned Outages of a Power Transformer Using Dissolved Gas Analysis and Nonlinear Autoregressive Neural Networks,”, University of Johannesburg, South Africa, 2020.
[18] J. Hu, H. Morais, T. Sousa, S. You, and R. D’hulst, “Integration of electric vehicles into power distribution network with a modified capacity allocation mechanism,” *energies*, 2017.
[19] A.N.M.M. Haque, D.S. Shafiullah, P.H. Nguyen, F.W. Bliek, Real-time congestion management in active distribution network based on dynamic thermal overloading cost, Power Syst. Comput. Conf. (2016) 1–7.
[20] S. Hattersley, “Enhanced Transformer Ratings Tool -Application Guide,”, Manchester, 2015.
[21] A. Abu-Siada, S. Islam, A novel online technique to detect power transformer winding faults, IEEE Trans. Power Deliv. 27 (2) (Apr. 2012) 849–857.
[22] D. Martin, Y. Cui, C. Ekanayake, M. Hui, T. Saha, An updated model to determine the life remaining of transformer insulation, IEEE Trans. Power Deliv. 30 (1) (Feb. 2015) 395–402.
[23] V.A. Primo, B. Garcia, J.C. Burgos, Applicability of nanodielectric fluids to the improvement of transformer insulation properties, in: Proceedings of the 2016 IEEE International Conference on Dielectrics, ICD, 2016, pp. 76–79. 2016, vol. 1,.
[24] L. Yang, S. Gao, B. Deng, J. Zang, W. Sun, E. Hu, Inhibition method for the degradation of oil–paper insulation and corrosive sulphur in a transformer using adsorption treatment, IET Gener. Transm. Distrib. 10 (8) (2016) 1893–1900.
[25] P.W.R. Smith, Z.D. Wang, M. Daghrah, D. Walker, Q. Liu, P. Mavrommatis, Design of experimenal setup to study factors affecting hot spot temperature in disc type winding transformers, in: IET International Conference on Resilience of Transmission and Distribution Networks (RTDN), 2015, p. 29. 2015(6 .)-29 (6 .).
[26] M. Daghrah, Z.D. Wang, Q. Liu, D. Walker, C. Krause, G. Wilson, Experimental investigation of hot spot factor for assessing hot spot temperature in transformers, in: CMD 2016 - International Conference on Condition Monitoring and Diagnosis, 2016, pp. 948–951.
[27] Y. Cui, H. Ma, T. Saha, C. Ekanayake, D. Martin, Moisture-Dependent thermal modelling of power transformer, IEEE Trans. Power Deliv. 31 (5) (Oct. 2016) 2140–2150.
[28] S. Acharya, P.C. Tapre, Life assessment of transformer using thermal models, in: 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS, 2017, pp. 3515–3520.
[29] L. Petkovska, M. Digalovski, G. Cvetkovski, P. Lefley, A novel approach to multi-objective efficiency optimisation for a distribution transformer based on the Taguchi method, in: 2014 International Conference on Electrical Machines (ICEM), 2014, pp. 2228–2234.
[30] National Grid, “Future energy scenarios,” no. July. pp. 1–119, 2017.
[31] Department of Energy and Climate Change (DECC), Digest of United Kingdom Energy Statistics 2015. 2015.
[32] R.O. Oliyide, Load Management of Electric Vehicles and Heat Pumps in Emerging Electricity System -ORCA (cardiff.ac.uk), Cardiff University (UK, 2019.
[33] United Nations framework convention on climate change (UNFCCC), Paris Agreement, no. December. 2015, p. 32.
[34] UK Energy Research Centre, “Electricity user demand profile data.” [Online]. Available: http://data.ukedc.rl.ac.uk/simplebrowse/edc/efficiency/residential/LoadProfile/data. [Accessed: 22-May-2018].
[35] National Grid, “Future Energy Scenarios,” no. July. pp. 1–228, 2015.
[36] UK Met Office, “Archive services - Met Office.” [Online]. Available: https://www.metoffice.gov.uk/learning/library/archive/services. [Accessed: 12-May-2016].
[37] Nord Pool, “N2EX day ahead auction prices - UK table.” [Online]. Available: https://www.nordpoolgroup.com/Market-data1/GB/Auction-prices/UK/Hourly/?view=table. [Accessed: 16-Aug-2018].
[38] Office of Gas and Electricity Market (Ofgem), “Understand your gas and electricity bills.” [Online]. Available: https://www.ofgem.gov.uk/consumers/household-gas-and-electricity-guide/understand-your-gas-and-electricity-bills. [Accessed: 16-Aug-2018].
[39] Frontline Systems Inc., “Analytic Solver® Platform.” [Online]. Available: https://www.solver.com/analytic-solver®-platform. [Accessed: 16-Aug-2018].