Thermal Monitoring and Thermodynamic Modelling of Distribution Transformers

Final report

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Contents

Executive summary

As one of the most promising pathways in the transition period towards the low carbon economy, a large scale implementation of electric vehicles (EVs) is expected in the near future. Concentration of EVs charging in a small area or within a short time will dramatically affect the load, especially the peak load in the distribution network. As a result, distribution transformers are facing hazards of shortened lifetime due to extra loads, and direct failures caused by potential overloads. Considering the large number of distribution transformers and the massive investment involved, the adaptability of the population of distribution transformers under future EV scenarios should be assessed.

In this project, an assessment strategy for the future adaptability of distribution transformer population under EV scenarios is introduced. Assessing the adaptability is to assess the hot-spot temperature, loss-of-life, expected lifetime and failure probability of each individual in the distribution transformer population.

Determination of hot-spot temperature of distribution transformers is essential for the assessment. In order to achieve accurate prediction of hot-spot temperatures under EV scenarios, thermal parameters should be refined for individual distribution transformers so that their thermal characteristics can be reflected more accurately than using the generic values recommended for all distribution transformers in the IEC loading guide. Two methods for the refinement are proposed in this project. One method is to curve-fit hot-spot temperatures measured in the extended heat run test; and the other is to calculate each parameter with developed equations in the loading guide with standard heat run test results.

The assessment strategy is introduced and demonstrated on a group of selected distribution transformers from the population under three EV scenarios, i.e. Business as usual (BAU), High-range and Extreme-range scenarios, which represent 0%, 32% and 58.9% EVs penetration levels respectively. Results show that EVs charging would be less concerned on the acceleration of thermal ageing and the corresponding increment of loss-of-life and reduced lifetime than the direct failure due to bubbling. Since the peak load and hot-spot temperature under EV scenarios would be compensated by low values during the off-peak time of a day, which eventually leads to a moderate thermal ageing. Occasionally, over-ageing would be resulted by overwhelmingly high hot-spot temperatures, and the lifetime would be reduced to an unacceptable level. However, on such occasions, hot-spot temperatures would be high enough to trigger bubbling and cause direct failure of transformers. Therefore, concerns on the short term failure would be prioritised over the reduction of lifetime due to long term thermal ageing.

In terms of the failure probability, results show that no distribution transformers are facing failure risks due to bubbling under BAU scenario. Failure starts under High-range scenario. If transformers possessing a failure probability over 50% are identified as high risk, then 13% of investigated transformers are at high risk under High-range scenario, while it increases to 39% under Extreme-range scenario. Although older transformers tend to have higher failure probabilities, it is found that the failure probability is dominantly controlled by the peak load, other factors such as transformer age and installation conditions are less influential. A threshold peak load of around 1.5 p.u. is observed that distinguishes transformers in high risk from others under Extreme-range scenario. This observation could be applied to assist the asset management under future EV scenario that the peak load of distribution transformers should be restricted below 1.5 p.u. to prevent potential failure due to bubbling.

1. Introduction

1.1 Background

Humanity in the future is threatened by global warming. Therefore, preventing global warming has long been recognised as a driving factor of the global transformation into a low carbon economy. In Europe, the European Council has set a target of reducing Green House Gas (GHG) by 80% to 95% by 2050 compared to 1990, in order to keep the climate change below 2°C [1]. To realise this ambitious objective, all sectors of the economy would require radical changes to reduce their own GHG emissions.

Electric vehicles (EVs) are one of the most promising pathways in the transition period towards the low carbon economy, since they are playing a key role in decarbonising the transport sector, whose overall share of the GHG reduction is anticipated as significant as 21 % by 2050 [2]. However, to achieve that share, three in every four vehicles are expected to be replaced by EVs [2]. To charge their batteries, EVs need to be connected to the electricity grid, where they are equivalent to active loads. As a result, the distribution network will be affected by extra loads due to a large scale of implementation of EVs.

EVs are directly plugged into the distribution network when charging, therefore their impacts are immediate. Firstly, the system stability will be disturbed, and the potential issues have been widely covered by existing researches [3-9] such as voltage drops, voltage unbalances, network losses and current harmonics. Secondly, load levels and load profiles in distribution network will be affected, which is more concerned in this project. Generally, the average load level will be lifted up. What is worse is EVs charging loads are more mobile and uncertain comparing to normal loads due to the randomness of charging behaviours of EV's users. Clustering, i.e. concentration of EVs charging in a small area or within a short time, will dramatically increase the load, especially the peak load, of the local distribution network, and potentially overload its transformers. Consequently, these transformers are facing shortened lifetime due to extra loads and potential failures due to overloads.

In the UK, distribution transformers generally refer to transformers that step down voltages from 11 kV or 6.6 kV to 0.4 kV, and the typical power ratings are ranging from 15 kVA to 2000 kVA [10] (2500 kVA in IEC 60076-7 [11]). Unlike medium or high voltage power transformers, distribution transformers normally do not operate in parallel in low voltage networks. Also, since feeders in the UK are typically configured in a radial fashion, failure of one single distribution transformer will lead to the disconnection of the whole area rooted at it. For a Distribution Network Operator (DNO), this should be prevented when considering the consequent penalties and compensations it has to pay to The Office of Gas and Electricity Markets (OFGEM) and customers [12].

1.2 Statement of problem

The prevailing of low carbon economy may transform the distribution network and reshape its loading scenarios with novel schemes such as EVs. Consequently frequent or excessive loadings will challenge the large and old distribution transformer population more than ever before by increasing the hot-spot temperature, accelerating ageing, shortening lifetimes and even causing direct premature failures. Therefore, in order to minimise customer interruptions and maximise the return on investment, it is a necessity to face the challenge first by researching how the distribution transformer population will be impacted by future EV scenarios. As a status quo, the following facts are urging such a research.

- Large population of old distribution transformers

ENW has a population of more than 30,000 distribution transformers. The wide-ranged age profile of this population is shown in Figure 1.1. More than 40% transformers are older than 40 years. According to calculation results that will be shown later in this report, older transformers tend to have ageing by-products accumulated inside the transformer such as moisture, which will increase the operational risks by lowering the threshold operational temperature that triggers direct failure. Therefore, they are more vulnerable to EV scenarios.

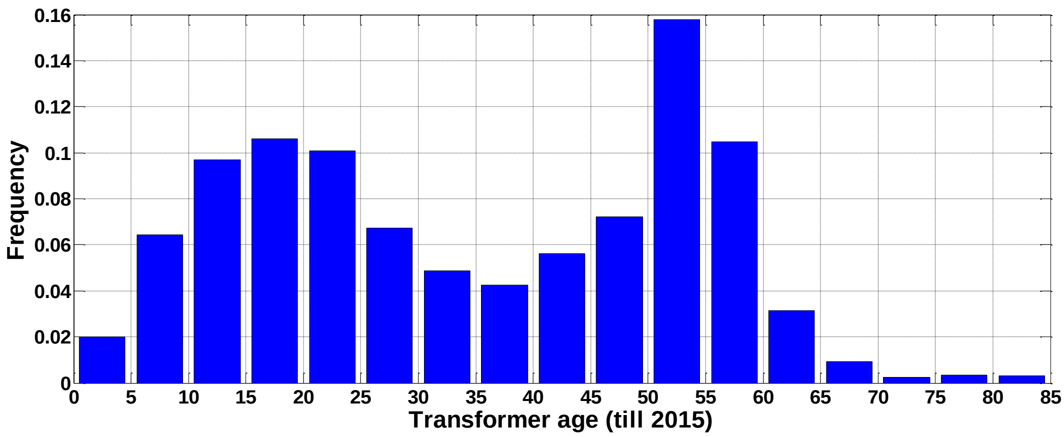

Figure 1.1: Age profile of ENW distribution transformer population

- Diverse variations of designs

Transformer design can be significantly distinguished from manufacturer to manufacturer, since different manufacturers may apply different materials and techniques to meet the specifications. As a result, transformers with different designs will have different responses to same loads. Transformers of the ENW population are designed and produced by more than 240 manufacturers. Figure 1.2 shows compositions of the population in term of manufacturers. Only the top 10 manufacturers are specifically labelled, whose transformers count for 65 % of the whole population. Therefore, in order to take account of design variations, a design-dependent approach should be pursued when assessing the population.

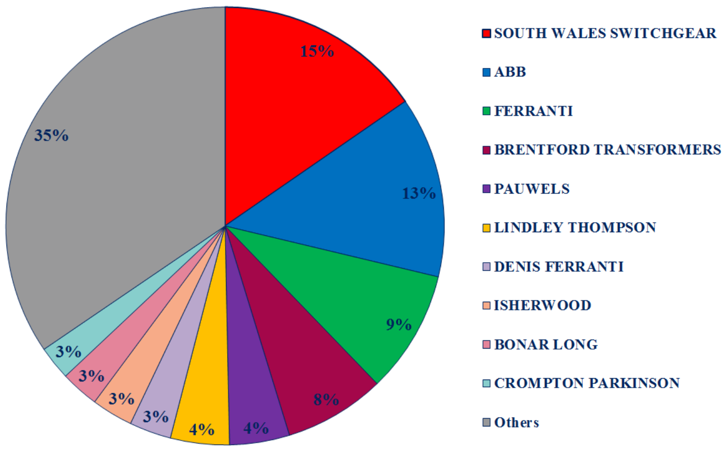

Figure 1.2: Manufacturer composition of ENW distribution transformer population

- Lack of research

Transformer researches have been focused on high voltage power transformers due to their capital-concentrated nature and potential severe post-failure consequences. However, condition monitoring tools and asset management strategies developed for power transformers may not be feasible for a direct transplant onto distribution transformers.

Comparing to high voltage power transformers, distribution transformers are smaller, lighter and manufactured much quicker. They are likely made in different factories, and vapour-phase drying equipment is not generally available [10]. Therefore, the moisture content in paper insulation of a new distribution transformer is normally around 1% while it is 0.5% for power transformers. Also, unlike power transformers, most distribution transformers do not equip the oil conservator and breather, which aim to mitigate moisture ingression from atmosphere to transformer oil and paper. Therefore distribution transformers tend to have relatively higher initial levels and faster accumulation of moisture in paper, which potentially increase failure risks due to breakdown caused by bubbling under high hot-spot temperature induced by high loads.

- Lack of data

Unlike high voltage power transformers that are closely monitored, distribution transformers are more likely to be "fit and forgotten". This is partly due to the inexpensive capital investment and short replacement time; but more importantly it is because past operating experiences have indicated that distribution transformers would work well under current loading conditions since their lifespans are always exceeding the originally expected lifetimes.

However, as aforementioned, under future loading scenarios when low carbon technologies such as EVs are widely implemented, distribution transformers would have to face unprecedented challenges. Under such circumstances, the convention of "fit and forgotten" would consequently result in an embarrassing situation that no data could be found for the research aiming to understand the challenges and to generate solutions. Therefore, alternative approaches such as modelling should be developed to approximate the necessary data for the research with a reasonable accuracy.

To summarise, the distribution transformer population is concerned under future EV scenarios on hazards of reduced lifetime due to the extra loads brought by EVs charging and on hazards of immediate failure caused by breakdown due to bubbling when the hot-spot temperature exceeds the bubbling inception temperature. Therefore, in order to protect the investment and maintain the distribution transformer population in a safe and reliable state, an assessment strategy must be produced for the adaptability under future EV scenarios.

1.3 Objective and methodology of research

This work aims to assess the adaptability of the distribution transformer population of ENW in future EV scenarios. The main objectives are as follows:

1. Define EV scenarios based on projection of EVs penetration in the future, and model EVs charging load in a stochastic manner to reflect the realistic behaviours of EV's users.

2. Refine thermal parameters for individual transformers to reflect their differences in thermal characteristics based on IEC 60076-7 thermal model. Calculate hot-spot temperature, resulting loss-of-life and lifetime for individual transformers with refined thermal parameters under EV scenarios.

3. Model cyclic load and ambient profiles of individual transformers assuming the measured data are not available.

4. Estimate bubbling inception temperature of individual transformers based on their moisture content levels in paper.

5. Estimate failure probabilities of individual transformers if failure occurs due to bubbling once the hot-spot temperature exceeds the bubbling inception temperature.

6. Assess the population in terms of the hot-spot temperature, the resulting loss-of-life and expected lifetime, and failure probabilities under EV scenarios.

Methodologies serving each objective are briefly summarised in Table 1-1.

Table 1-1: Methodologies serving objectives of this project

Background	Objective	Methodologies
Future loading scenarios	1. EV scenarios and charging load	• Stochastic modelling based on existing literature.
Diverse variation of designs	2. (a) Refinement of thermal parameters	• Least Square Estimation fitting with measured hot-spot temperature during extended heat run test. • Calculate each parameter based on extended heat run test results.
	2. (b) Calculate of hot-spot temperature, loss-of-life and lifetime.	• IEC 60076-7 thermal model. • IEC ageing model.
Lack of data	3. (a) Cyclic load modelling	• Modelling based on customer information according to Elexon profiles.
	3. (b) Ambient temperature modelling	• Modelling based on yearly weighted ambient model provided in IEC loading guide. • Historical data of the region from Met Office.
Lack of research	4. Bubbling inception temperature	• Bubbling inception temperature model from literature. • Modelling between moisture in paper and transformer age based on scenario analysis.
	5. Failure probability	• Monte-Carlo simulation.
Aim of project	6. Population assessment	• Statistical analysis. • Results demonstration with a representative group.

2. Strategy assessment strategy for adaptability of distribution transformers under EV scenarios

2.1 Introduction to assessment strategy

In order to assess the adaptability of distribution transformer population, a systematic strategy is proposed in this work. A diagram summarising the strategy is shown in Figure 2.1.

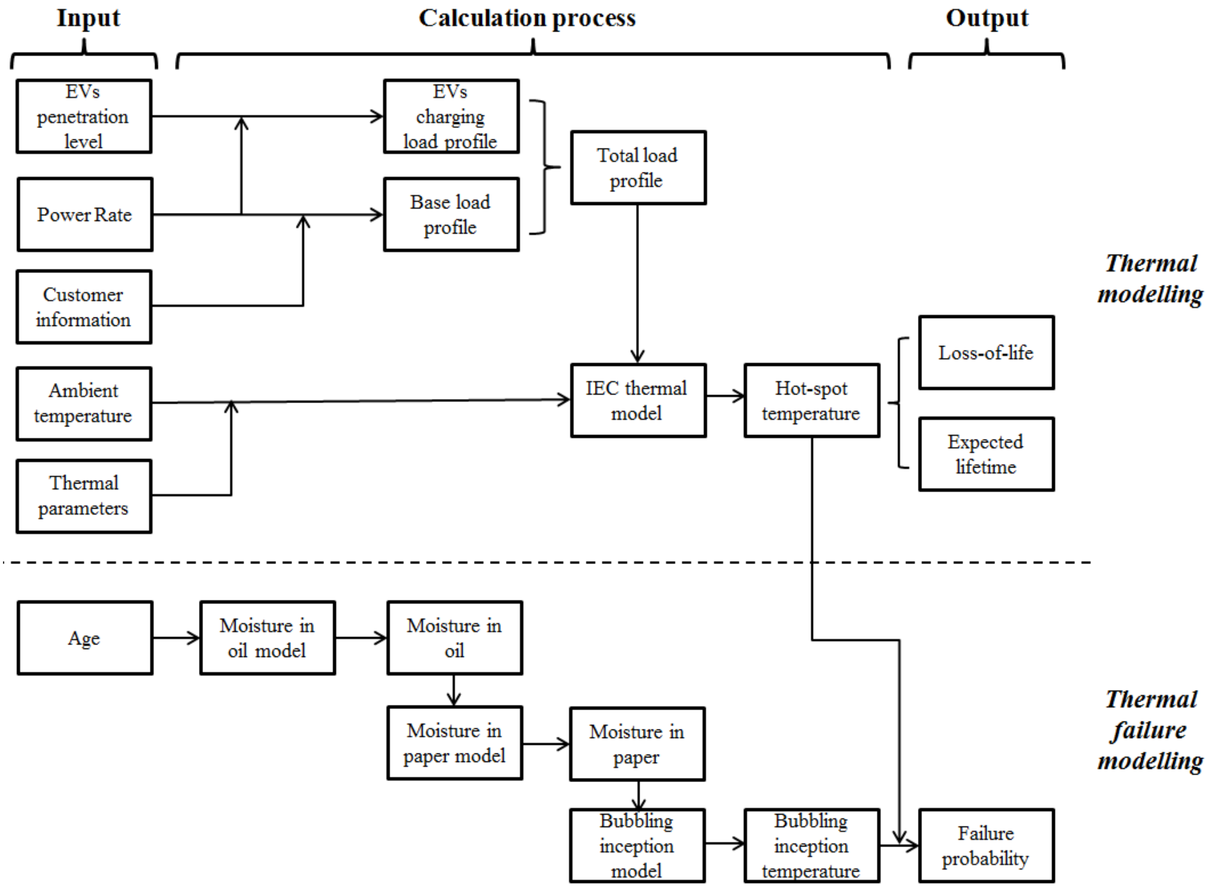

Figure 2.1: Detailed diagram of assessment strategy

The strategy mainly contains two parts, i.e. thermal modelling and thermal failure modelling. Thermal modelling is for the estimation of hot-spot temperatures of individual distribution transformers, which are essential for the calculation of the loss-of-life and lifetime. Hot-spot temperatures are estimated by IEC thermal model, which requires three elements as inputs. The first element is the thermal characteristics element, which indicates the thermal parameters. Ideally, thermal parameters should be refined for individual transformers to reflect the design-dependent thermal characteristics of different transformers. Two methods are proposed in this work to refine thermal parameters. Curve-fitting the measured hot-spot and top-oil temperatures during the extended heat run test is the preferred method since it leads to the most accurate refinement. The other method is to calculate each parameter with data from standard heat run tests.

The second element is the load element, which will be the total load of the current load plus potential EVs charging load under future EV scenarios. The current load refers to day to day load cycles that distribution transformers are carrying. Measurements would be always preferred if available. Otherwise, Elexon profiles could be used to generate distribution transformer load profiles with information of numbers and types of its customers. As to EVs charging load, considering the random charging behaviours of EVs owners, probabilistic modelling is implemented in order to simulate the randomness of charging power, charging duration and charging start time of individual EVs.

The last element is the environment element, which refers to the ambient temperature and the indoor/outdoor installation of distribution transformers. A yearly weighted average ambient temperature is allowed by IEC loading guide when calculating the hot-spot temperature and loss-of-life with IEC thermal model. It can be derived based on historical ambient data and used for distribution transformers that do not have measured ambient temperatures. Additionally, the enclosure affects distribution transformers in two folds. Firstly, it causes extra temperature rises on the ambient and top-oil rise. Secondly, it protects transformers from rainfall or other precipitation weathers so that the moisture accumulation in indoor transformers tends to be slower than in outdoor ones according to the calculation in this work. Consequently, indoor transformers tend to experience higher operational temperatures but lower moisture content in oil.

Thermal failure modelling is aimed to define and quantify the short term failure probability of distribution transformers under EV scenarios. Immediate failure due to bubbling is identified as the fatal risk in the short term of distribution transformers when the hot-spot temperature exceeds the bubbling inception temperature. Therefore, the failure probability is defined as the probability of the hot-spot temperature exceeding the bubbling inception temperature under EV scenarios.

The hot-spot temperature can be calculated with thermal modelling methods. Oommen's [13] widely accepted model is introduced and applied to calculate the bubbling inception temperature. The model requires three inputs of moisture in paper, gas content in oil and oil depth. The moisture in paper is the dominant factor determining the bubbling inception temperature; therefore it is used as the controlled parameter in the assessment of the population. However, unlike moisture in oil, moisture in paper is difficult to measure due to the practical difficulty in taking samples of insulation paper. Therefore, a method is introduced in this work to estimate the moisture in paper level of distribution transformers with the moisture in oil content based on the equilibrium curve of moisture dynamics between oil and paper. Eventually, in case of that the moisture in oil level is unknown; an empirical model could be built to estimate the moisture in oil content of distribution transformers with the transformer age by curve-fitting the available data collected from previous oil tests.

In summary, based on the diagram shown in Figure 2.1, the assessment strategy requires input data including transformer age and rating, installation condition (indoor/outdoor), customer information (number and type), ambient temperature, thermal parameters and EVs penetration levels (defined by EV scenarios). The final outputs are yearly loss-of-life, expected lifetime and failure probability under defined EV scenarios.

In this chapter, modelling process of each required element of the assessment strategy is introduced, and the strategy is demonstrated on a prototype distribution transformer where the measurements of load and ambient data are available.

2.2 Thermal modelling: determination of hot-spot temperature under EV scenarios

Hot-spot temperature can be regarded as a function of the load factor. However, under the same load profile, different transformers will have different hot-spot temperature profiles due to different thermal characteristics, which are inherently determined by transformer designs. Therefore, parameters of the function should be individual-dependent so that variations of thermal characteristics can be reflected.

IEC 60076-7: 2005 thermal model [11] provides such a set of thermal functions. It is developed based on the thermal diagram as shown in Figure 2.2, where the hot-spot temperature is the sum of ambient temperature, top-oil temperature rise over ambient and hot-spot to top-oil gradient.

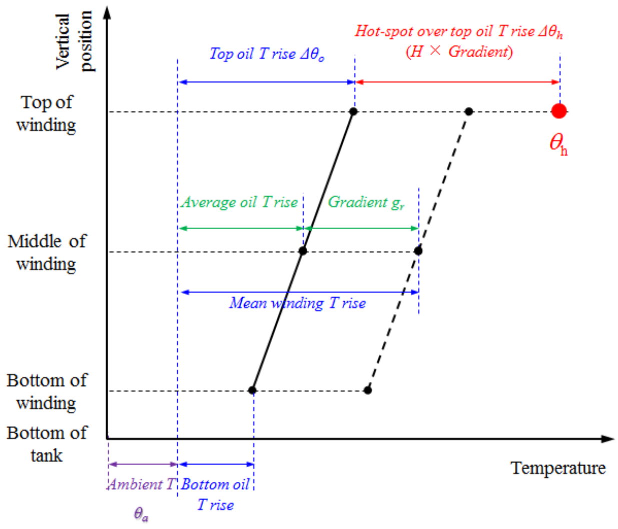

Figure 2.2: Thermal diagram [11]

Since in-service transformers are subject to time varying loads and ambient temperatures, IEC 60076-7: 2005 thermal model estimates hot-spot temperature under arbitrary time-varying load and ambient temperatures. The full set of equations when load increases are shown in Equation (2-1) to (2-5).

$$\theta_h(t) = \theta_a + \Delta\theta_o(t) + \Delta\theta_h(t) \tag{2-1}$$

$$\Delta\theta_o(t) = \Delta\theta_{oi} + \left\{ \Delta\theta_{or} \times \left[\frac{1 + R \times K^2}{1 + R} \right]^x - \Delta\theta_{oi} \right\} \times f_1(t) \tag{2-2}$$

$$\Delta\theta_h(t) = \Delta\theta_{hi} + \left\{ H \times g_r \times K^y - \Delta\theta_{hi} \right\} \times f_2(t) \tag{2-3}$$

where $f_1(t)$ and $f_2(t)$ are

$$f_1(t) = \left(1 - e^{(-t)/(k_{11} \times \tau_o)}\right) \tag{2-4}$$

$$f_2(t) = k_{21} \times \left(1 - e^{(-t)/(k_{22} \times \tau_w)}\right) - (k_{21} - 1) \times \left(1 - e^{(-t)/\left(\tau_o / k_{22}\right)}\right) \tag{2-5}$$

When load decreases, the equation describing hot-spot rise over top-oil, i.e. Equation (2-3), is simplified as

$$\Delta\theta_h(t) = \Delta\theta_{hi} + H \times g_r \times K^y \tag{2-6}$$

Input data required in the model are ambient temperature θ_a and load factor K, and the output is time-varying hot-spot temperature $\theta_h(t)$. Other parameters are thermal parameters that reflect thermal characteristics of a transformer, thus being individual-dependent.

IEC loading guide provides one set of values of thermal parameters for distribution transformers, which are considered conservative and leading to over-estimated hot-spot temperature [14]. In order to obtain more accurate hot-spot temperature by taking consideration of individual differences in designs under EV scenarios, these parameters should be refined for individual transformers. In this work, methods are proposed and validated for refinement of thermal parameters for individual transformers.

2.2.1 Refinement of IEC thermal model parameters for prototype transformer by curve-fitting

When estimating hot-spot temperatures under arbitrary loads with the IEC model, thermal parameters shown in Table 2-1 should be determined for individual transformers for better accuracy. Recommended values for distribution transformers given in the IEC loading guide are also shown in Table 2-1, which are generic values and tend to reach conservative hot-spot temperatures. Two approaches of refining IEC thermal parameters are introduced in this section.

Table 2-1: IEC 60076 thermal model parameters and recommended values given in IEC 60076-7: 2005 [11]

Parameters	$\Delta\theta_{or}$	R	g_r	H	x	y	τ_o	τ_w	k_{11}	k_{21}	k_{22}
Recommended values	60*	9*	16.36*	1.10	0.80	1.60	180	4	1	1	2

*: No recommended values are given in IEC loading guide. These values are derived from guaranteed values seen from distribution transformer specification. When estimating hot-spot temperature for a transformer without any information, these values may be used.

a. Refinement of thermal parameters by curve-fitting

One approach is to curve-fit the measured top-oil and hot-spot temperatures during the extended heat run test with IEC thermal model equations to acquire the best fit thermal parameters.

The estimation process has two steps. The first step is to estimate y, τ_o, τ_w, k_{11}, k_{22} and $H \times g_r$ all together with the hot-spot to top-oil gradient using Equation (2-3) and (2-5). $H \times g_r$ is regarded as one single parameter, since g_r and H are apparently interdependent and no definite value can be determined for one unless the other is known. The second step is to input τ_o obtained from the first step into Equation (2-2) and (2-4) and then estimate x and k_{11}

together with the top-oil temperature measurements using Equation (2-2) and (2-4). The load factor K is an input. The rated load to no-load loss ratio R can be calculated with the rated load and no-load losses given by the nameplate of the transformer and the rated top-oil rise $\Delta\theta_{or}$ is obtained from heat run test results.

Due to the non-linearity of equations subjected to the curve-fitting, it is concerned that the results may be dependent on the initial values. Via sensitivity studies, it is found that parameters k_{11}, k_{22}, τ_o and τ_w are interdependent and no unique values could be determined. However, determinate values are obtained for τ_o / k_{22}, $\tau_w \times k_{22}$ and $\tau_o \times k_{11}$. Thus the conclusion can be drawn that definite values cannot be determined for k_{11}, k_{22}, τ_o and τ_w through curve-fitting unless any of them is known so that others can be calculated based on the estimated results of τ_o / k_{22}, $\tau_w \times k_{22}$ and $\tau_o \times k_{11}$. Besides this conclusion, there are some other observations are made:

- k_{21} is independent on its initial value during the curve-fitting.
- k_{11}, k_{22}, τ_o and τ_w are interdependent. τ_o is proportional to k_{22}; τ_w is reversely proportional to k_{22}; k_{11} is reversely proportional to τ_o.

2.2.2 Refinement of IEC thermal model parameters for prototype transformer by calculating with heat run test data

The curve-fitting approach requires hot-spot temperature measurements during heat run test, which are often unavailable for existing transformers. Therefore, the other approach of refining IEC thermal parameters is proposed to calculate each parameter with standard heat run test results.

In practice, heat run tests can be generally summarised as two regimes, which are conventional and extended heat run test. The main difference is that the conventional test only performs under the rated load, but the extended one performs under three individual loads, which are usually 0.7, 1.0 and 1.25 p.u. representing 50%, 100% and 125% of rated losses. A summary of two regimes of heat run tests is provided in Table 2-2, and so are the obtainable IEC thermal parameters under each heat run test regime. In addition, since the conventional heat run test only provide temperature data under the rated load, the corresponding resultant thermal parameters can therefore only be used for the prediction of time-varying hot-spot temperatures under the rated load. On the other hand, thermal parameters calculated with temperature data obtained during the extended heat run test can be applied to predict time-varying hot-spot temperatures under arbitrary loads.

Table 2-2: Summary of conventional and extended heat run tests

Heat run test regimes	Measured data	Obtainable thermal parameters	Hot-spot temperature that can be calculated accurately
Conventional heat run test	Ambient temperature	Rated top-oil rise; rated average winding to oil gradient; winding time constant; top-oil and average oil time constants	Time-varying hot-spot temperatures under rated load
	Top-oil temperature		
	Bottom-oil temperature		
	Winding resistance		
Extended heat run test	Data above under 0.7, 1.0 and 1.25 loads	Parameters above; oil and winding exponents	Time-varying hot-spot temperatures under arbitrary loads

The process of calculating each parameter with heat run test results are presented as below.

- The rated top-oil rise $\Delta\theta_{o,\,rated}$

$$\Delta\theta_{o,\,rated} = \theta_{o,\,rated} - \theta_a \tag{2-7}$$

- The rated average winding to oil gradient g_r

$$g_r = \Delta\theta_{w,\,rated} - \Delta\theta_{ave,\,rated} \tag{2-8}$$

The winding resistance curve is first converted into the winding temperature curve which is extrapolated to the instant of the transformer shutdown to derive the average winding temperature by either exponential or polynomial function [15].

- The winding time constant τ_w

τ_w can be derived with the measured winding resistance curve. After converting the resistance curve into a temperature curve, τ_w can be obtained by curve-fitting the temperature curve with an exponential function as

$$\theta_{w,\,rated}(t) = \theta_{ave,\,rated} - k \times t + g_r \times e^{-\frac{t}{\tau_w}} \tag{2-9}$$

For transformers with large oil time constants, e.g. oil natural (ON) cooled transformers with relatively low ratings, the average-oil temperature drop may be ignored [15]. In this case, the term $k \times t$ can be ignored.

Polynomial fitting is also used in practice to extrapolate the average winding temperature curve. In this case, τ_w can be obtained by making a tangent of the fitted curve at the instant of transformer shutdown. The crossing point of the tangent and the average-oil temperature line indicates τ_w.

- The top-oil time constant $\tau_{o,top}$

$\tau_{o,top}$ can be obtained by two ways. The first is through curve-fitting the complete temperature rise curve of the top-oil temperature under a constant load with Equation (2-10). This requires the top-oil temperature regularly measured, and also the test load should remain the same for the entire test.

$$\Delta\theta_{o,\,rated}(t) = \Delta\theta_{o,\,ini} + (1 - e^{-t/\tau_{o,top}}) \times (\Delta\theta_{o,\,rated} - \Delta\theta_{o,\,ini}) \tag{2-10}$$

Another method is through an equation given in IEEE loading guide [16],

$$\tau_{o,\,top} = \frac{C \times \Delta\theta_{o.rated} \times 60}{P} \tag{2-11}$$

$$C = 0.132 \times M_A + 0.0882 \times M_T + 0.4 \times M_O \quad \text{(for ONAN cooling)} \tag{2-12}$$

The only required datum from the heat run test is $\Delta\theta_{o,\,rated}$, since the values of P, M_A, and M_O can be obtained on the transformer nameplate.

- The average oil time constant τ_o and thermal constant k_{11}

τ_o and $\tau_{o,top}$ are linked by k_{11}, as

$$k_{11} = \tau_{o,\,top} / \tau_o \tag{2-13}$$

τ_o can be also calculated as

$$\tau_o = \frac{C \times \Delta\theta_{ave,\,rated} \times 60}{P} \tag{2-14}$$

- The oil exponent x

x can be derived based on Equation (2-15).

$$\Delta\theta_o = [\frac{1+R\times K^2}{1+R}]^x \times \Delta\theta_{o,rated} \tag{2-15}$$

To derive x, $\Delta\theta_o / \Delta\theta_{o,rated}$ is calculated and plotted against the value of $\frac{1+R\times K^2}{1+R}$ in a log-log scale. Then the slope of the straight line that best fits all the points can be obtained as *x*.

- The winding exponent y

y can be derived based on Equation (2-16).

$$g = g_r \times K^y \tag{2-16}$$

To derive y, g/g_r is calculated and plotted against the corresponding load K in a log-log scale. Then the slope of the straight line that best fits all the points can be obtained as y.

Theoretically, in addition to the rated load test, only one non-rated load test is required to derive exponents x and y. However, in order to make the derived exponents more representative, at least one under-load test and one overload test are required in practice.

Three parameters of *H*, k_{21} and k_{22} cannot be derived only with thermocouple measured temperature data during the heat run test, therefore recommended values in IEC loading guide have to be used.

2.2.3 Comparisons between two methods of refining IEC thermal parameters

Two approaches of refining IEC thermal parameters are summarised and compared in Table 2-3. Basically, the curve-fitting method provides better accuracy when predicting hot-spot temperatures under arbitrary loads but it needs the hot-spot temperature measurements which require the installation of optic fibre sensors at the hot-spot location. As an alternative, calculating method can be applied on any transformers that possess results of a standard heat run test.

Table 2-3: A general comparison between two methods for refinement of thermal parameters

Refinement method	Required data	Advantage	Disadvantage
Curve-fitting method	Nameplate information, hot-spot and top-oil temperature measurements	All parameters can be obtained. Better accuracy when predicting hot-spot temperatures.	Require optic fibre sensors for hot-spot temperature measurement.
Calculating method	Nameplate information, measured data of a standard heat run test	Do not require additional data. Can be applied for any transformers as long as the heat run test data are available.	k_{21} and k_{22} cannot be obtained. Poorer accuracy when predicting hot-spot temperatures.

Two approaches are applied on a prototype distribution transformer. Resultant parameters are presented in Table 2-4, where the recommended values of IEC loading guide are also included for the comparison.

Table 2-4: Thermal parameters refined by two methods

Refinement method	$\Delta\theta_{or}$	R	$H \times g_r$	x	y	τ_o	τ_w	k_{11}	k_{21}	k_{22}
Curve-fitting method	56.2	8.67	8.44	0.72	1.08	180	21.7	1.18	2.83	0.91
Calculating method	50.4	8.67	14.5	0.77	2.39	159.6	11.3	1.26	1	2
IEC recommended	60	9	16.36	1.1	0.8	1.60	180	4	1	1

To verify the refined thermal parameters, hot-spot temperatures are calculated with refined parameters under different loadings and compared with measurements.

a. Comparison under heat run test loads

Firstly, hot-spot temperatures calculated with refined thermal parameters are compared with measurements under the load profile of the heat run test, and also hot-spot temperatures calculated with IEC recommended parameters are included in the comparison as shown in Figure 2.3. Error analysis is provided in Table 2-5.

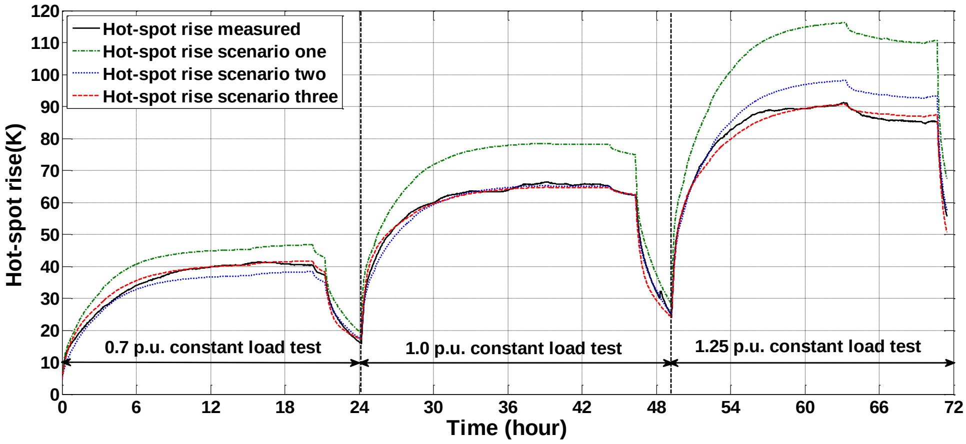

Figure 2.3: Calculated hot-spot temperatures with thermal parameters refined by two methods under heat run test loads

Table 2-5: Error analysis of hot-spot temperatures calculated with thermal parameters refined by two methods under heat run test loads

Refinement method	Maximum error (K)	Mean error (K)
Curve-fitting method	3.53	-0.17
Calculating method	10.25	0.91
IEC recommended	25.87	12.14

Under heat run test load, refined thermal parameters offer better accuracy than IEC recommended parameters by reducing the maximum error from 25.87 to 3.61 K (with curve-fitting method) and 10.25 K (with calculating method), and by almost eliminating the mean error.

b. Comparison under cyclic loads

It may be argued that refined parameters are obtained by curve-fitting the measured data that is then used in this comparison so that good fitting is expected. Therefore, another verification is conducted by comparing calculated and measured hot-spot temperatures under dynamic loads that the prototype transformer is undertaking during its daily operation in a 6.6 kV substation. Same parameters as shown in Table 2-4 are used. The load and ambient profiles of 7 consecutive days in September 2013 are used for the calculation.

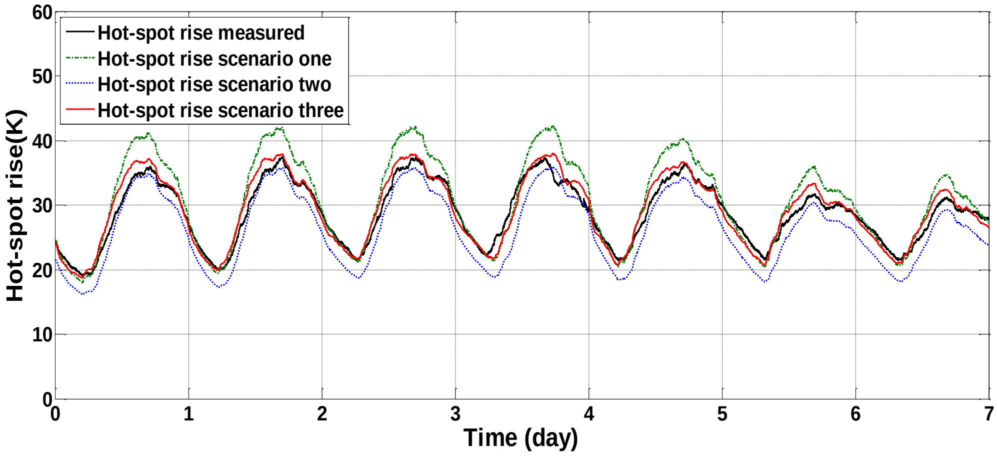

Figure 2.4: Calculated hot-spot temperatures with thermal parameters refined by two methods under cyclic loads

Table 2-6: Error analysis of hot-spot temperatures calculated with thermal parameters refined by two methods under cyclic loads

Refinement method	Maximum error (K)	Mean error (K)
Curve-fitting method	4.16	0.40
Calculating method	-7.40	-2.38
IEC recommended	8.15	3.58

Error analysis in Table 2-6 shows that the maximum error is reduced from 8.15 K to 4.16 K (with curve-fitting method) and -7.40 K (with calculating method) by using refined thermal parameters. In the meantime, the mean error is almost eliminated by using curve-fitted parameters. Therefore, curve-fitted method is preferred to refine thermal parameters when predicting hot-spot temperatures under dynamic loads.

2.3 Thermal failure modelling: determination of failure probability under EV scenarios

EVs charging may cause immediate failure of transformers due to bubbling, which greatly increases the operational risk in the short term perspective. When bubbling happens, dielectric strength of the transformer insulation system is decreased due to the evolution of free gas from the insulation of winding conductor, and breakdown would occur. Bubbling is triggered by temperatures; therefore the bubbling inception temperature is regarded as the critical hot-spot temperature for the transformer to avoid. For example, 140 °C is regulated in IEC loading guide as the hot-spot temperature limit for distribution transformers under normal cyclic loads due to the concerns over bubbling [11].

In order to investigate EVs effects on distribution transformers in the short term, failure probability due to bubbling under EV scenarios is modelled. The failure probability is defined as the probability of the hot-spot temperature exceeding the bubbling inception temperature.

2.3.1 Modelling of bubbling inception temperature

Past researches [13, 17, 18] have shown that bubbling inception temperature is highly dependent on the moisture level of insulation paper of the transformer, and is also affected by the gas content and oil pressure. Oommen [13] proposed and verified a model for the calculation of bubbling inception temperature in transformers as shown in Equation (**2**-**17**),

$$T = 6996.7/(22.454 + 1.4495 \times \ln W - \ln P) - e^{0.473/W} \times (g/30)^{1.585} \tag{2-17}$$

where T is the bubbling inception temperature in K, W is the moisture in paper in % (mass to mass), P is the oil pressure in torr and g is the total gas content in % (volume to volume).

Sensitivity studies have shown that bubbling inception temperature is dominantly controlled by the moisture level in paper, while it is insensitive to the oil pressure and gas content. For example, the bubbling inception temperature is lifted by around 3 K when the oil depth is increased from 1 meter to 3 meters. Effects of gas content is increasing with moisture level; for example, a decrease of over 15 K can be observed for bubbling inception temperature when the gas content changes from 1% to 9% under the moisture in paper content of 10%.

Due to the dominating role that moisture in paper plays in determining the bubbling inception temperature, it is essential to model the moisture content in paper to reflect different transformer conditions.

2.3.2 Modelling of moisture content in paper

It is difficult to sample the insulation paper and measure its moisture content in operational transformers. As an alternative to the direct measurement, equilibrium curves have been developed for the estimation of moisture content of paper with temperature and moisture in oil. Equilibrium curves are developed based on the fact that the moisture distribution in transformer insulation system is at equilibrium state between oil and paper which depends on the temperature [19]. Different equilibrium curves have been developed by several authors [20-23], and Fessler [24] proposed equations of the equilibrium curves which are shown as Equation (**2**-**18**) to (**2**-**21**).

$$C = 2.173\times10^{-7} \times p_v{}^{0.6685} \times e^{4725.6/T} \tag{2-18}$$

$$p_v = PPM / PPM_{sat} \times p_{v,sat} \tag{2-19}$$

$$PPM_{sat} = 10^{(A-B/T)} \tag{2-20}$$

$$p_{v,sat} = \frac{p_c}{760} \times 10^{(\frac{T-T_c}{T})\times(\frac{a+b\times(T_c-T)+c\times(T_c-T)^3}{1+d\times(T_c-T)})} \tag{2-21}$$

where C is the moisture in paper in %; T is the temperature of the equilibrium state in K; PPM is the moisture in oil in ppm; p_v is the partial pressure of water vapour in atm; the subscript *sat* indicates the saturated state; p_c is the critical pressure of water in *mmHg* which is a constant; T_c is the critical temperature of water in K which is a constant; A, B, a, b, c, and d are constants whose value for mineral oil are shown in Table 2-7.

Table 2-7: Constant values in Fessler's equations

A	B	a	b	c	d	p_c	T_c
7.44	1686	3.24	5.86×10^{-3}	1.17×10^{-8}	2.19×10^{-3}	1.66×10^{-5}	647.26

To briefly explain the equations of equilibrium curves, Equation (**2-18**) is proposed by Fessler [24] for the modelling of moisture distribution in mineral oil-paper insulation system under equilibrium state, and it requires the partial pressure of water and temperature on the interface of oil and paper as inputs. The partial pressure of water can be obtained by Equation (**2-19**), and it is proportional to partial pressure in saturation ($p_{v,sat}$) and the relative humidity which can be expressed as the ratio of moisture in oil (PPM) to the water saturation solubility of oil (PPM_{sat}). PPM_{sat} is temperature dependent and can be calculated by Equation (**2-20**), where A and B are constant parameters. $p_{v,sat}$ can be calculated by Equation (**2-21**) which is proposed by Foss in [25].

2.3.3 Modelling of failure probability due to bubbling

With equilibrium curves, moisture in paper can be determined with temperature and moisture in oil under the assumption of equilibrium state. Obtained moisture in paper can then be applied in bubbling inception model to calculate the inception temperature and compare with the hot-spot temperature of the transformer in order to investigate if the transformer will fail. The flow chart shown in Figure 2.5 demonstrates how the failure probability of transformers is modelled under EV scenarios.

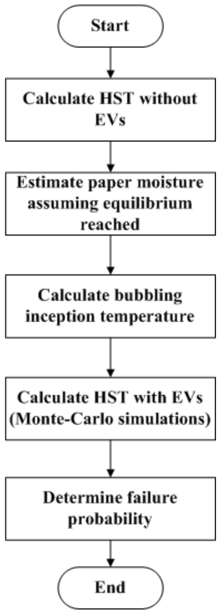

Figure 2.5: Flow chart of modelling failure probability under EV scenarios

However, equilibrium conditions are generally not attained during the operation of transformers due to the variation of load and temperature. Nevertheless, since the time constant of the diffusion of moisture in oil and paper is much larger than the time constant of oil temperature change, the moisture in paper is not varying as significantly as the temperature when the load regularly changes between its peak and valley values in a daily cyclic load. Therefore, it is assumed that equilibrium is achieved under an equivalent temperature which is taken as the average value of the temperature of a day.

Since the hot-spot is the most concerned location in transformers, the oil temperature at the hot-spot location should be used to derive the equivalent temperature under which the equilibrium state is assumed. However, due to the unavailability of the oil temperature adhere to the hot-spot, the hot-spot temperature is used instead.

EVs charging affects mainly the peak hours of a day, and it is assumed that the moisture in paper does not change significantly by EVs charging using the assumption that the charging time is not long enough for the moisture distribution between oil and paper to follow the change of the temperature. Therefore, the moisture level in paper determined with the equilibrium under the average hot-spot temperature of a day is used for the calculation of bubbling inception temperature.

Considering the uncertainties of EVs charging, Monte-Carlo simulations are performed for the calculation of the hot-spot temperatures under EV scenarios, and the results are compared with bubbling inception temperature to determine the failure probability, which is defined as the probability of the hot-spot temperature exceeding the bubbling inception temperature.

2.4 EV scenarios

Department for Transport (DfT) introduced several scenarios to project the EVs uptake up to 2030 in [26], where it assumed the total number of vehicles on road in 2030 in the UK would be 35 million, and depending on different EV scenarios, the total number of EVs (including BEVs and PHEVs) would be as shown in Table 2-8.

Table 2-8: EV scenarios defined by DfT report [26]

Scenarios	Number of EVs (million) in 2030	Penetration level (%) in 2030
Business as usual (BAU)	8.6	8.6
High-range	32.0	32.0
Extreme-range	58.9	58.9

The penetration level is the ratio of the number of EVs to the total number of vehicles in the UK. Three scenarios are introduced in [26] to project the strength of demand of EVs in the UK. Extreme-range scenario is of the worst expected scenario; therefore it is investigated in terms of its impacts on distribution transformers. In addition, two other scenarios are investigated for comparison, which are High-range scenario and Business as usual (BAU) scenario. To simplify the BAU scenario, the EVs penetration level is assumed as 0 %.

BAU scenario, High-range scenario and Extreme-range scenario are going to be investigated to show how distribution transformers will be affected, and the penetration level of three scenarios are 0%, 32% and 58.9% respectively. When modelling the EVs charging load, the number of EVs are determined by multiplying the EVs penetration level with the number of customers connected to the transformer based on the undoubtedly simple assumption that one customer owns one vehicle.

2.4.1 Modelling of EVs Charing load

In order to simulate EVs charging load as realistic as possible, a stochastic approach is utilised, which probabilistically models EVs types, charging power, charging start time and state-of-charge (SOC) transferred to the EVs battery.

a. EVs types

According to the statistics of registered vehicles from DfT by 2015 [27], around 50% of EVs on road are BEVs (17826) and the other 50% are PHEVs (17415), and the most popular models of EVs on road are shown in Table 2-9.

Table 2-9: Most popular EVs models in the UK by 2015 [27]

Models	Market share (%)	Battery type	Battery capacity (kWh)	Max electric range (mile)	BEV / PHEV
Mitsubishi Outlander	34.2	Li-ion	12	34	PHEV
Nissan Leaf	26.4	Li-ion	24	120	BEV
BMW i3	7.0	Li-ion	22	100	BEV
Renault Zoe	5.9	Li-ion	22	130	BEV
Toyota Prius	4.1	Li-ion	4.4	14	PHEV

Considering the dominating shares of the top two EV types, it is assumed in this study that all BEVs are Nissan Leaf and all PHEVs are Mitsubishi Outlander. Therefore, all EVs charged in this study are 50% probability of Nissan Leaf and 50% probability of Mitsubishi Outlander.

Li-ion batteries have a generic charging pattern, which is composed of three stages, i.e. pre-charging, current regulation and voltage regulation stages [28]. The duration of each stage could vary depending on a few factors such as battery models, temperature, battery SOC and charging power. However, detailed modelling of the charging profile of Li-ion batteries is beyond the scope of this work, therefore the charging profile of EVs battery is simplified as a constant value.

b. Charging power

Generally speaking, there are three types of charging in terms of charging power, which are slow charging (up to 3 kW), fast charging (7 to 22 kW) and rapid charging (43 to 50 kW). In residential properties, the maximum allowed power is around 12 kW [29], therefore slow and fast charging are applied for domestic charging. According to statistics of charging points in the UK in 2015, the ratio of fast charging to slow charging points is around 7:3 [30]. In this study, it is assumed that the charging power is 70% probability of 7 kW and 30% probability of 3 kW.

The efficiency of charging is depending on a few factors such as temperature, charging power and energy transferred in a single charge, [31] compares charging efficiency under various conditions and finds the efficiency could vary from 75% to 91%. In this study, the charging efficiency is assumed as 85%.

c. Charging start time

Past researches [29, 32, 33] often model the charging start time based on the traffic data or home arrival time by assuming EVs users start to charge theirs vehicles immediately or one hour after arriving home. The modelling of charging start time can be improved by using data that observed and collected by EVs trials in the UK.

The Technology Strategy Board (TSB) launched the Ultra-Low Carbon Vehicle Demonstrator (ULCVD) programme in 2008, through which 349 EVs were deployed, and data were collected from over 276000 individual trips and 51000 charging events [34-36]. Charging start times were monitored and summarised as shown in Figure 2.6.

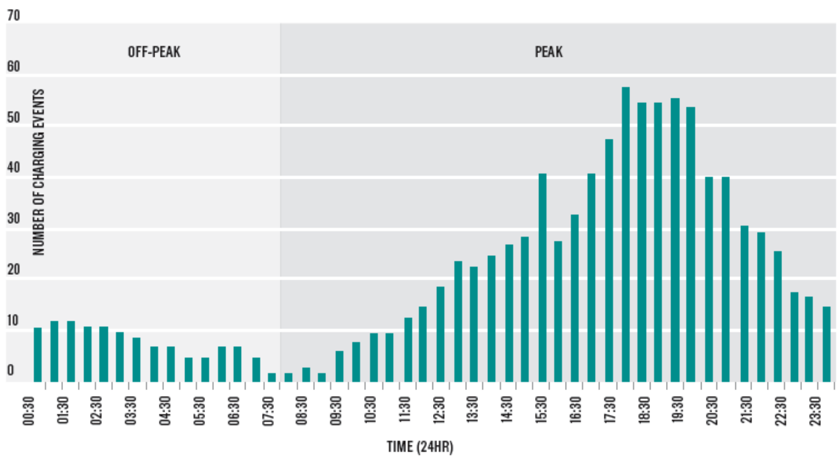

Figure 2.6: Charging start times monitored in Ultra-Low Carbon Vehicle Demonstrator (ULCVD) [35]

According to the monitored data, charging starts through the whole day, but a concentration can be seen during the peak time around 18:30, when people get home from work. As a matter of fact, charging in the morning or afternoon mostly happens in work places or public charging points. Therefore, in this study, in order to simulate the domestic charging, the charging start time is assumed to follow a normal distribution with the mean of 18:30 and the standard deviation of 1 hour.

d. SOC transferred to EVs battery

ULCVD monitored how much SOC was transferred in a single charging event, and Figure 2.7 shows the statistics of the data. The SOC transferred in a single charging event is the difference between the SOC at the end of a charging event and the SOC before it. ULCVD found that most EVs were charged full with the majority of charging events (>70% of all monitored charging events) ending at over 95% SOC [34]. Therefore, in this study, it is assumed that all EVs are charged once a day and they are always charged full.

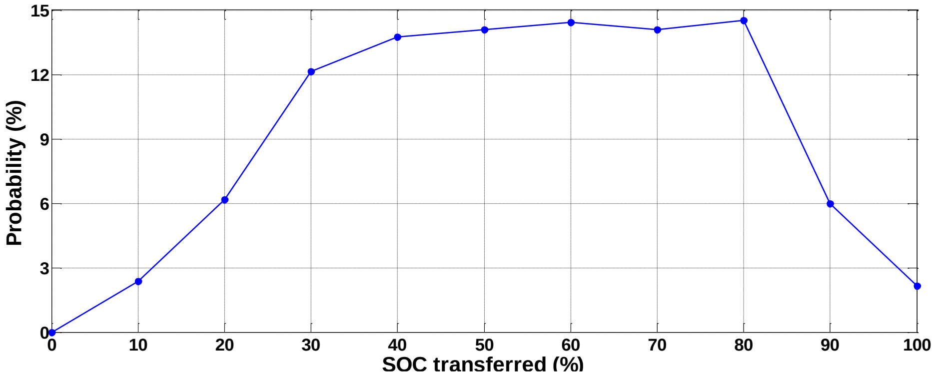

Figure 2.7: SOC transferred in a single charging event [36]

2.5 Case study: assessment of adaptability of a prototype distribution transformer under future EV scenarios

After introducing the assessment strategy and defining EV scenarios, the adaptability of a prototype distribution transformer is assessed under defined EV scenarios as a demonstration.

2.5.1 Assessment of hot-spot temperature, loss-of-life and expected lifetime

Firstly, the hot-spot temperature, loss-of-life and expected lifetime of the prototype distribution transformer under defined EV scenarios are assessed. Due to the uncertainty brought by EVs charging, Monte-Carlo algorithms are applied for the simulation, and the flow chart of the simulation is presented in Figure 2.8. Basically, charging load profiles of individual EVs are generated first with stochastically defined uncertainties including EVs type, charging power, start charging time and SOC transferred. Then the final load profile is created by adding up all individual EVs charging load profiles and the base load profile. The base load profile in this section is from a September day of the substation in which the prototype transformer is installed. The hot-spot temperature is calculated with the refined thermal parameters under the final load profile. The expected lifetime is estimated assuming the load repeats itself for the whole year. This process repeats itself for 5000 times so that 5000 sets of results will be generated. At last statistical analysis is conducted on the results in terms of peak loads, peak hot-spot temperatures and lifetimes.

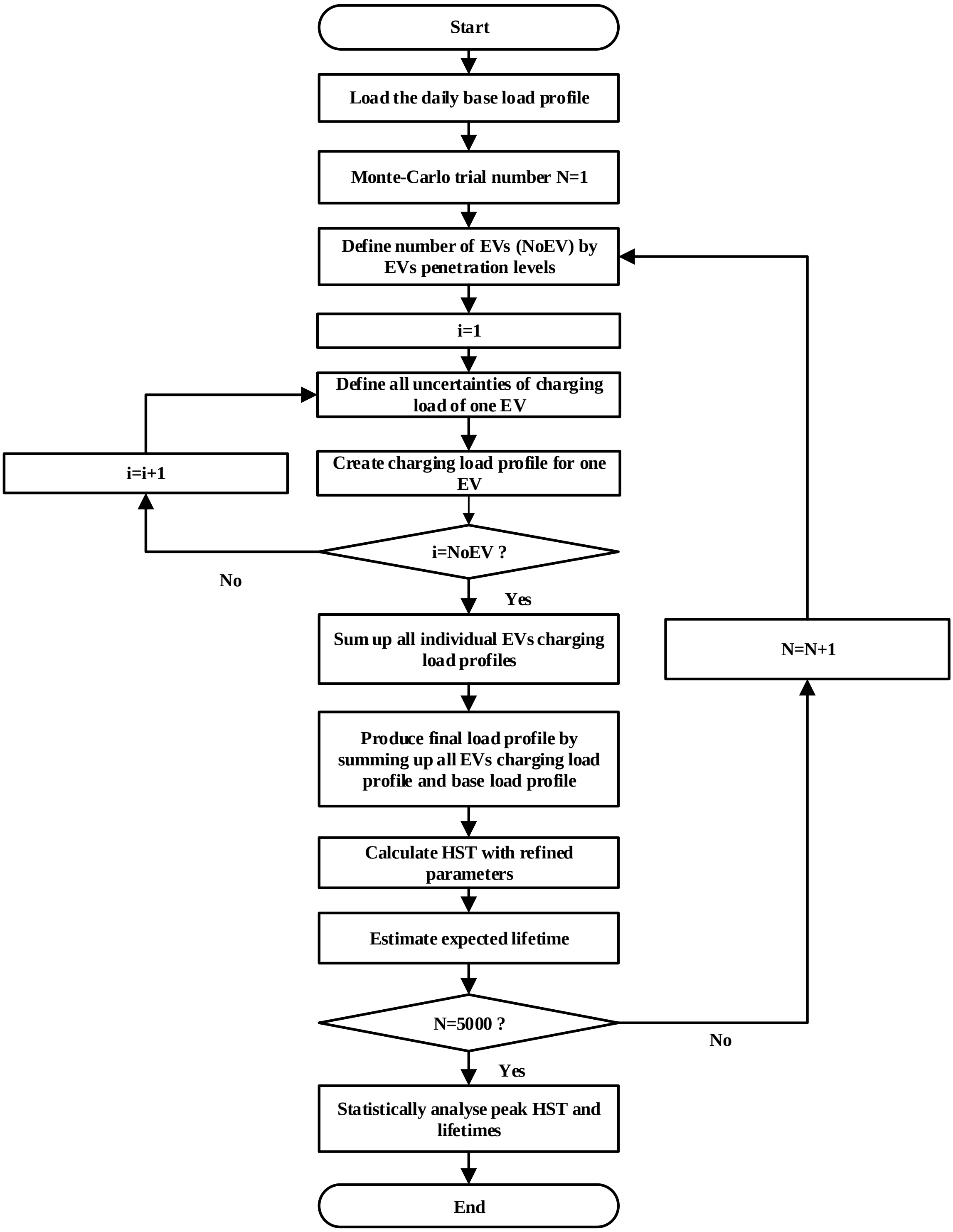

Figure 2.8: Flow chart of Monte-Carlo simulation to determine hot-spot temperature and lifetime of prototype distribution transformer under EV scenarios

The peak load and peak hot-spot temperature are of key concern since they may lead to immediate failure of transformers due to bubbling. Therefore, statistical analysis is conducted to investigate the potential range of peak load and hot-spot temperature as shown in Table 2-10. Table 2-10 presents the peak load and peak hot-spot temperature ranges under three EV scenarios. It is observed that EVs charging load significantly increases the peak load and peak hot-spot temperature. Thermal parameters refined by curve-fitting and calculating methods are applied for the assessment.

Comparing to the BAU scenario, the peak load is increased at least by 39.7% and 93% under High-range and Extreme-range scenarios respectively. The peak hot-spot temperature is increased at least by 23.7% and 55.5% respectively with curve-fitting method. The peak load ranges are almost the same for two refinement methods. In terms of peak hot-spot temperatures, thermal parameters refined by the calculated method lead to underestimated hot-spot temperatures when the load is lower than the rated level; and overestimated hot-spot temperatures during overloads. Therefore, Under BAU scenario, the peak hot-spot temperature of thermal parameters refined by calculating method is lower; but under Extreme-range scenario, when the transformer is heavily overloaded, the peak hot-spot temperature of thermal parameters refined by calculating method is much higher.

Table 2-10: Comparison of peak load and hot-spot temperature ranges under EV scenarios with thermal parameters refined by two methods

EV scenarios	Refinement method	EVs penetration level (%)	Peak load range (p.u.)	Peak hot-spot temperature range (°C)
BAU scenario	Curve-fitting	0	0.73	65.1
	Calculating			60.67
High-range scenario	Curve-fitting	32	[1.02, 1.28]	[80.5, 90.1]
	Calculating		[1.01, 1.29]	[79.2, 92.0]
Extreme-range scenario	Curve-fitting	58.9	[1.41, 1.79]	[101.2, 115.7]
	Calculating		[1.40, 1.78]	[110.2, 135.4]

Figure 2.9 and Figure 2.10 display the CDF plots of peak load and peak hot-spot temperature respectively under High-range and Extreme-range scenarios with two refinement methods.

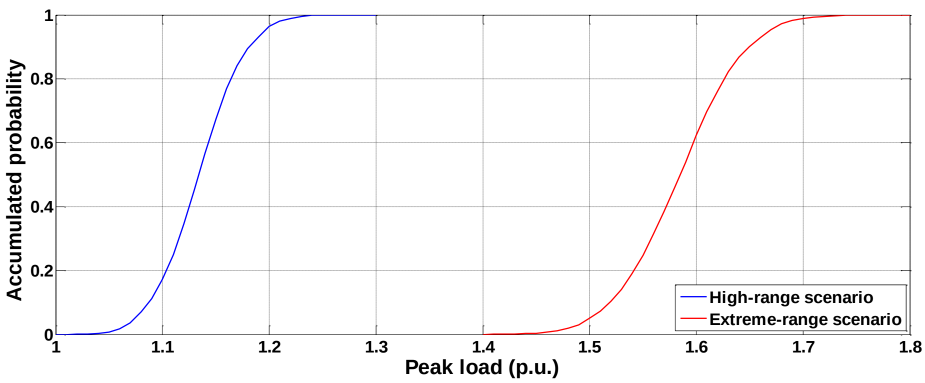

Figure 2.9: CDF of peak loads under EV scenarios

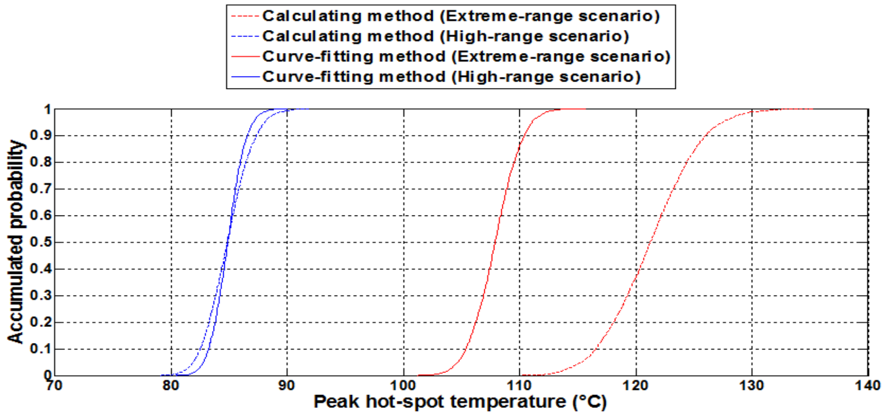

Figure 2.10: Comparison of CDF of hot-spot temperature under EV scenarios with thermal parameters refined by two methods

According to the CDF plots, it can be seen that overloading is guaranteed under both of High-range and Extreme-range scenarios. Especially under Extreme-range scenario, the peak load has over 90% probability to reach the restricted value of 1.5 p.u. given by IEC loading guide for normal cyclic load [11]. From a hot-spot temperature's point of view, the highest hot-spot temperatures that can be reached under High-range scenario are 90.1°C and 92.0°C respectively with curve-fitting and calculating refinement methods, which are lower than the rated hot-spot temperature of 98°C under rated load that is given in the IEC loading guide. It means that under High-range scenario, the transformer is always under-aged, and the expected lifetime will be longer than the value recommended in the loading guide which is assumed under a constant hot-spot temperature of 98°C. However, under Extreme-range scenario, the peak hot-spot temperatures can go up to 115.7 °C and 135.4°C respectively with curve-fitting and calculating refinement methods. It means that during the EVs charging, the transformer ageing will be accelerated. Nevertheless, the daily loss-of-life still could be compensated by the under-ageing during the off-peak time, when the hot-spot temperature is much lower than the rated value of 98°C. Therefore, whether the long term thermal ageing is accelerated or not under Extreme-range scenario cannot be determined solely by the peak hot-spot temperature, but further calculations are required.

It should be noted that this conclusion may not be representable for other transformers. The rated hot-spot temperature rise is only 65.1 K for the demonstrated transformer, which is much lower than 78 K that is limited by IEC loading guide, hence the thermal design of this transformer is good. For other transformers whose thermal design is not as good as this one, there may be a higher risk to operate under High-range scenario. Therefore the methodology of assessing the thermal performance under EV scenarios introduced here should be applied for individual distribution transformers to investigate their adaptabilities under EV scenarios.

The loss-of-life and expected lifetime is calculated as shown in Table 2-11.

Table 2-11: Comparison of assessment of long term thermal ageing under EV scenarios with thermal parameters refined by two methods

EV scenarios	Refinement method	EVs penetration level (%)	Daily loss-of-life range (p.u.)*	Expected lifetime range (p.u.)+
BAU scenario	Curve-fitting	0	0.009	111
	Calculating		0.005	200
High-range scenario	Curve-fitting	32	[0.025, 0.045]	[22.5, 40]
	Calculating		[0.019, 0.041]	[24.3, 53.2]
Extreme-range scenario	Curve-fitting	58.9	[0.151, 0.476]	[2.1, 6.7]
	Calculating		[0.325, 3.27]	[0.3, 3.1]

*: 1.0 p.u. is under constant 98°C hot-spot temperature according to IEC loading guide [11]
+: The base value is set as 17.12 years.

With curve-fitting refinement method, the daily loss-of-life is increased by a factor as larger as 53 (0.476 compared to 0.009) under Extreme-range scenario, and the expected lifetime is reduced by up to 98% (2.1 compared to 111) with EVs charging. Therefore, from a long-term failure perspective, EVs charging will significantly reduce the thermal life of distribution transformers, and adaptive asset management strategies must be changed to face the upcoming EV scenarios.

Since underestimated hot-spot temperature tend to be obtained under BAU scenario with the calculating method, the loss-of-life is correspondingly underestimated, which leads to an overestimated lifetime. Under overloads, the calculating method tends to give overestimated hot-spot temperatures. Therefore, the resultant loss-of-life is much higher than that of the curve-fitting method, and the resultant lifetime is correspondingly lower under Extreme-range scenario.

2.5.2 Determination of failure probability under EV scenarios

Failure probability is determined for the prototype transformer with two refinement methods under three EV scenarios, i.e. BAU, High-range and Extreme-range EV scenarios. The load and ambient profiles of the day as used in the loss-of-life calculation example are used here. The measured hot-spot temperature of the day ranges from 43.1°C to 64.6°C, and has an average value of 53.8°C. Bubbling inception temperatures are calculated by Equation (2-17), where the gas content used is 9%, and the oil depth used is 1.57 m which is measured from the design diagram of the distribution prototype transformer. The moisture in paper is calculated by Equation (2-18) to Equation (2-21). 53.8°C, the average hot-spot temperature of the day, is used for the calculation of moisture in paper. Various values of moisture in oil are used to reflect different conditions (wetness) of the insulation system. These values are given under the sampling temperature of 20°C, since IEC 60422 [37] suggests to normalise water content under 20°C and gives a guideline to interpret the data for the assessment of the condition of the insulation system. Resultant bubbling inception temperatures are shown in Table 2-12, which also includes the various moisture in oil conditions and resultant moisture in paper values.

To determine the failure probability, the probability of the hot-spot temperature exceeding the bubbling inception temperature is estimated. A simple way is to achieve the failure probability through the CDF of peak hot-spot temperature as the example shown in Figure 2.11 (with curve-fitting refinement method), where the failure probability can be found by the cross point between bubbling inception temperature and the CDF of peak hot-spot temperatures. Therefore, in the example in Figure 2.11, the failure probability under High-range and Extreme-range EV scenarios are found as 0 and 31.5% when the bubbling inception temperature is 108.8°C, which is calculated with a moisture in oil of 17.5 ppm under 20°C by Equations from (**2-17**) to (**2-21**).

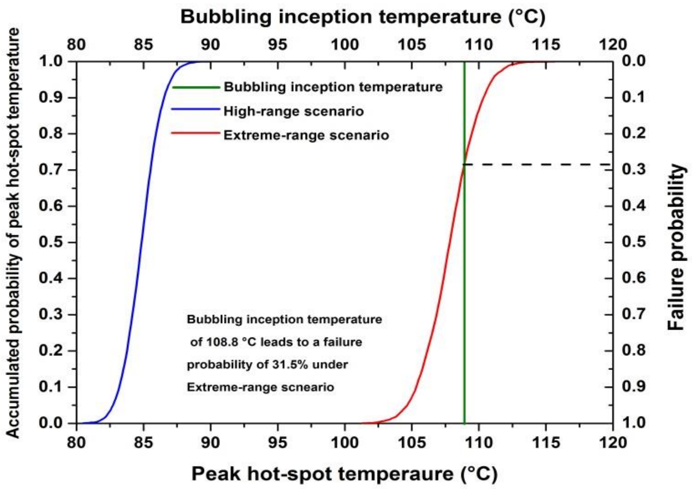

Figure 2.11: Example of determination of failure probability under EV scenarios

Determined results of moisture in paper, bubbling inception temperature and failure probability under three EV scenario are shown in Table 2-12.

Table 2-12: Comparison of assessment of short term failure probability under EV scenarios with thermal parameters refined by two methods

Moisture in oil @ 20 °C (ppm)		2.5	5	10	15	17.5	20	25
Percentage to the saturation (%)		4.5	9.1	18.2	27.3	31.8	36.4	45.5
Conditions according to IEC 60422		Dry	Moderate wet		Wet	Extreme wet		
Moisture in paper (%)		1.54	2.44	3.88	5.09	5.65	6.17	7.17
Bubbling inception temperature (°C)		154.99	137.90	121.80	112.47	108.80	105.48	99.39
		Failure probability (%)						
BAU scenario	Curve-fitting	0	0	0	0	0	0	0
	Calculating	0	0	0	0	0	0	0
High-range scenario	Curve-fitting	0	0	0	0	0	0	0
	Calculating	0	0	0	0	0	0	0
Extreme-range scenario	Curve-fitting	0	0	0	1	31.5	89	>99
	Calculating	0	0	44.3	>99	>99	>99	>99

With curve-fitting refinement method, the prototype distribution transformer only faces failure risks under Extreme-range EV scenario. Also, the failure starts to occur when the insulation is reaching wet status according to IEC 60422. The threshold value of the moisture in oil is 15 ppm @ 20 °C, above which the failure probability increases significantly with the moisture in oil. When the moisture in oil reaches as high as 25 ppm at 20°C, the failure is almost guaranteed under the Extreme-range scenario.

With calculating method, same as the curve-fitting method, no failure risks are faced by the prototype transformer under BAU and High-range scenarios. However, under Extreme-range scenario, since the hot-spot temperature is overestimated during overloads by thermal parameters refined by the calculating method, higher failure probabilities are obtained with the calculating method when the transformer's oil is wetter than 10 ppm @ 20 °C.

However, this conclusion is only applicable for the investigated prototype distribution transformer. For other distribution transformers in the population, the failure probability should be assessed by their own loading condition, thermal performance and wetness status.

2.6 Summary

In this chapter, an assessment strategy is introduced and applied for adaptability of a prototype distribution transformer under EV scenarios in terms of its long term ageing and short term failure risks. The strategy contains two parts, i.e. thermal modelling and thermal failure modelling. Thermal modelling aims to calculate transformer hot-spot temperature, loss-life and lifetime as accurate as possible by refining thermal parameters. Thermal failure model aims to estimate the failure probability due to bubbling under EV scenarios.

Two methods are proposed for the refining of thermal parameters. Comparison of two methods indicates that curve-fitting method is preferred than the calculating method for better accuracy when calculating hot-spot temperature under either heat run test loads or dynamic loads. However, curve-fitting method requires measured hot-spot temperature during heat run test which is often not available for existing distribution transformers.

Failure probability due to bubbling is defined as the probability of hot-spot temperature exceeding bubbling inception temperature. A method of estimating bubbling inception temperature is introduced in this chapter and it requires the moisture in paper as input, which can be estimated by moisture in oil assuming the equilibrium state of moisture between oil and paper is reached during daily operation and EVs charging of distribution transformers.

3. Assessment of distribution transformer population under EV Scenarios

The strategy of assessing adaptability of distribution transformers under EV scenarios is applied on a group of selected transformers from the distribution transformer population of ENW for the demonstration purpose.

Different from the prototype transformer demonstrated in Chapter 2, most existing transformers in the population do not have measured load and ambient profiles. Therefore, alternative modelling approaches to estimate the load and ambient profiles are introduced.

3.1 Load modelling method for operating individual distribution transformers

A load modelling tool is required to construct the load profile of each individual distribution transformer with reasonable accuracy for the hot-spot temperature calculation when the measurements are not available.

In the England, load profiles of electricity customers in the distribution level are defined as eight Profile Classes [38]. Customers in the distribution network are accordingly categorised into eight classes. For each class, nationwide half-hour energy usages have been measured and collected by Elexon. By analysing the data, yearly half-hour load profiles are generated by Elexon for a single customer of each profile class. Considering the seasonality of loads in a year, five sub classes are defined for each profile class, which are spring, summer, high summer, autumn and winter. With Elexon profiles, load profiles of one distribution transformer can be produced by summing up all loads each of which belongs to the eight profile classes. The sub-load profiles can be obtained by multiplying the number of customer and the corresponding Elexon profiles. With the customer number database provided by ENW, yearly half-hour load profiles of any transformers can be modelled by Elexon profiles. Interpolation can be applied to generate the minute-based load profiles for the calculation of hot-spot temperatures.

3.1.1 Accuracy of modelling load profiles with Elexon profiles

Before applying this load modelling approach for the assessment of thermal performance, the accuracy of the approach is investigated by comparing with measured load data of a group of distribution transformers. By comparing with available measured load data, which are half-hour load of 7289 days from 84 distribution transformers, errors of loads modelled by Elexon profiles are statistically analysed, where the results are showing in Table 3-1.

Table 3-1: Error analysis of loads modelled by Elexon profiles of 84 investigated distribution transformers

	Underestimation				**Overestimation**			
Error	<-60%	<-40%	<-20%	<0%	>0%	>20%	>40%	>60%
Percentage of data	11.3%	31.9%	53.9%	76.7%	23.3%	6.9%	<1%	<0.1%

Results show that Elexon profiles tend to underestimate the load data of this group of transformers. Underestimation is observed on 76.7% of compared data, and the error can be as large as -60%. To calibrate the load modelled by Elexon profiles, the mean error instead of the maximum error should be utilised as a conservative indicator to reflect the wide error range. The mean error is observed as -30.6%. Therefore, a calibration factor of 1.3 is introduced in this work when using Elexon profiles to model loads of distribution transformers that do not have recorded load data.

3.2 Modelling of ambient temperature

Ambient temperature is one major environmental factor for the determination of the hot-spot temperature of transformers. Ideally, for dynamic consideration, such as under EV scenarios, actual ambient temperature profiles should be applied when calculating the hot-spot temperature with IEC thermal model. However, actual ambient temperatures are not available for transformers that the surrounding ambient temperatures are not monitored. In this case, a constant equivalent temperature can be taken as ambient temperature according to the IEC loading guide [11].

The equivalent temperature is yearly weighted ambient temperature and is designed as a constant, the fictitious ambient temperature that causes the same ageing as the variable temperature does during the load cycle. It can be derived based on Equation (**3**-**1**) based on the assumption that the real ambient temperature varies sinusoidally during the load cycle [11]. Where θ_E is the equivalent ambient temperature; θ_{ya} is the yearly average temperature and $\theta_{ma,\,max}$ is the monthly average temperature of the hottest month.

$$\theta_E = \theta_{ya} + 0.01 \times [2 \times (\theta_{ma,\,max} - \theta_{ya})]^{1.85} \tag{3-1}$$

3.2.1 Determination of yearly weighted ambient temperature

The value is determined by Equation (**3-1**) with historical monthly ambient temperature data since 1910 in northwest England obtained from Met Office [39].

The yearly average temperature is the mean value of annually averaged ambient temperatures since 1910 in northwest England, which is 12.0 °C. The monthly average temperature of the hottest month is the mean value of temperatures of the hottest month since 1910, and the value is 19.2 °C. Consequently, the weighted ambient temperature is obtained with as 13.4 °C.

3.2.2 Correction of ambient temperature for transformer enclosure

The other factor of the environmental element considered is the transformer enclosure. Since distribution transformers are mainly ONAN cooled, effective air flows are key to the heat dissipation. Therefore, when a distribution transformer is not installed in the open air, the enclosure would weaken the heat dissipation and the transformer would experience extra temperature rises on the ambient temperature and hence rated top-oil rise. Ideally, the value of the extra temperature rise should be determined by tests, however, considering the general unavailability of such tests, IEC loading guide provides values for different types of transformer enclosures as shown in Table 3-2. The extra temperature rise of the rated top-oil temperature rise is half of the increase in the yearly weighted ambient temperature.

Table 3-2: Correction for increase in ambient temperature due to enclosure [11]

Type of enclosure	**Number of transformers installed**	**Correction to be added to weighted ambient temperature (K)**			
		Transformer size (kVA)			
		250	**500**	**750**	**1000**
Underground vaults with natural ventilation	1	11	12	13	14
	2	12	13	14	16
	3	14	17	19	22
Basements and buildings with poor natural ventilation	1	7	8	9	10
	2	8	9	10	12
	3	10	13	15	17
Buildings with good natural ventilation and underground vaults and basement with forced ventilation	1	3	4	5	6
	2	4	5	6	7
	3	6	9	10	13

In this work, when assessing individual transformers of the population, the type of enclosure is unknown for indoor installed transformers. Therefore, it is all assumed that all indoor installed transformers are in basements or buildings with poor natural ventilation.

3.3 Moisture content in oil

Apart from load and ambient profiles for the calculation of hot-spot temperature, moisture in oil is also required for the estimation of bubbling inception temperature, which could be obtained by oil test. However, due to general unavailability of oil test data, only a limited number of transformers have records of oil test information among the whole population. Oil test data of around 2000 transformers in the population are found. The earliest data found are from early 1990s, and the latest data found are from 2012.

By analysing the moisture in oil data, it is expected to find an empirical model to link the moisture in oil with the transformer age, so that it would be possible to estimate the moisture in oil for every transformer of the population with its transformer age when the measured value is not available.

a. Correcting moisture in oil to 20 °C

In order to link the moisture in oil values to the oil aging status, all measured values are corrected to a standard sampling temperature of 20°C which is recommended in IEC 60422 [40] with Equation (**3-2**). Where PPM_{20} is the moisture in oil at 20°C; PPM_T is the moisture in oil under temperature T in °C.

$$PPM_{20} = PPM_T \times 2.24 \times e^{-0.04 \times T} \tag{3-2}$$

In the oil test database, moisture in oil is given in ppm with the date when the oil sample is taken, while the sampling temperature is missing. Since a large number of values are greater than 55 ppm, which is the saturated level of mineral oil under 20°C, it is deduced that the sampling temperature is unlikely 20°C but approximate to the operational oil temperature of the transformer subject to the oil test.

The operational oil temperature of each individual distribution transformer is calculated as the yearly mean top-oil temperature with IEC thermal model and yearly load profiles estimated by Elexon profiles and the corresponding customer information.

One set of generic thermal parameters are applied for the calculation, which are refined based on extended heat run test data of 20 distribution transformers representing the population. Information of 20 distribution transformers is presented in the appendix. The methodology of refining IEC thermal parameters based on extended heat run test data proposed in Chapter 2 is applied for the refinement. 20 sets of thermal parameters are first obtained for 20 representative transformers, and the average value of each parameter is obtained to be eventually used for the calculation of the top-oil temperature of the population. The full set of generic thermal parameters applied for the population for determining the “true” moisture in oil is presented in Table 3-3.

Table 3-3: Refined representative thermal parameters for distribution transformer population

R	$\Delta\theta_{or}$	g_r	H	τ_o	τ_w	x	y	k_{11}	k_{21}	k_{22}
8.7	50.6	16.8	1.1	180	11.4	0.8	1.6	1.1	1	2

Resultant mean yearly top-oil temperatures are presented in Figure 3.1, which shows that all moisture data recorded in the database are sampled over 20°C, so when converted to 20°C with Equation (**3-2**), all moisture values will be reduced after correction.

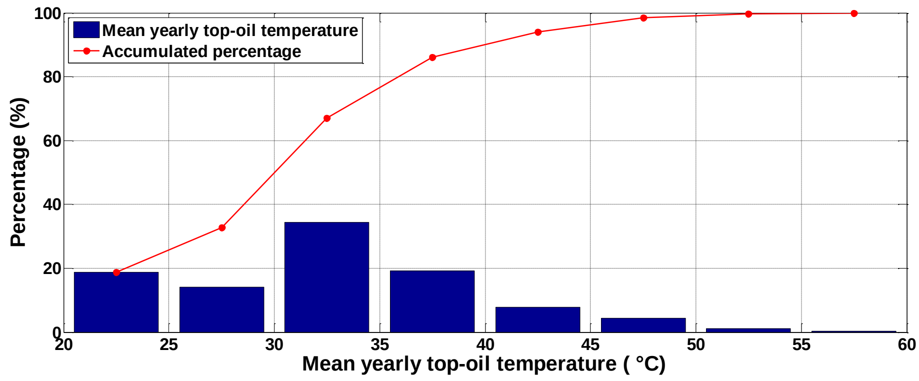

Figure 3.1: Mean yearly top-oil temperature of distribution transformer population calculated with Elexon profiles

The process of accumulation of moisture in transformer oil is complex, which can be affected by many factors such as installation conditions, loading conditions, transformer design and age. By correcting to 20°C with top-oil temperatures calculated by Elexon profile derived yearly loads, the effects of loading conditions are considered to be eliminated. A comparison between original measured moisture in oil values and corrected values is shown in Figure 3.2. It can firstly be seen that corrected values (blue marks) are lower than original values (red dots). Secondly, a clear increasing trend with transformer oil age can be observed on either of the original or the corrected values.

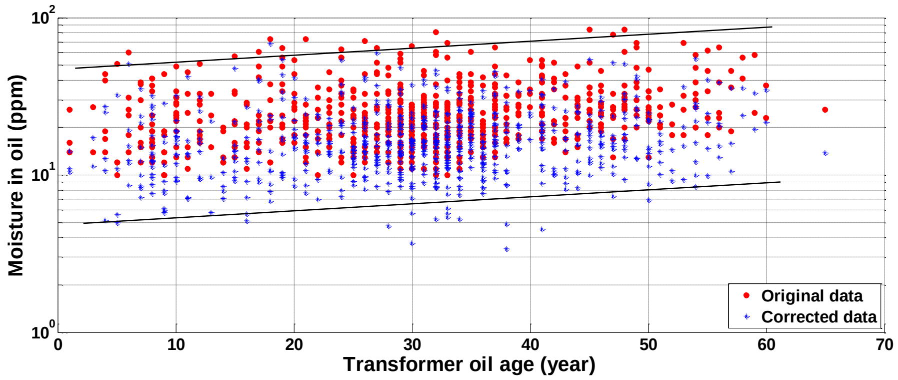

Figure 3.2: Originally measured moisture in oil data and corrected values of distribution transformer population

The corrected moisture values are investigated in terms of installation locations, transformer design and age respectively on the accumulation of moisture in oil.

b. Effects of variation of transformer design

To investigate the effects of transformer design, transformers are grouped in accordance to their manufacturers. Moisture in oil data of transformer from three most popular manufacturers are compared. Due to the distinguished oil age distribution of three manufacturers, transformers within age group of 20 years to 40 years are selected for the comparison. The mean values of moisture in oil data for this age group are 13.5 ppm, 11.7 ppm and 17.7 ppm for Ferranti, Lindley Thompson (LT) and South Wales Switchgear (SWS) transformers respectively.

SWS transformers have highest mean value of moisture in oil for this age group, which indicates SWS's design may be worse and less robust in terms of controlling the moisture accumulation during the transformer ageing. However, due to the limited number of transformers (only 34 transformers contained in this age group for SWS), this conclusion is still suspicious. For the other two manufacturers, 1.8 ppm difference is not significant considering the range of the variation is between 2 ppm to 50 ppm. Therefore, based on the investigation at this stage, no conclusions can be drawn on how the variation of transformer design would affect the moisture accumulation in oil during the transformer ageing.

c. Effects of installation conditions

It is known that transformer enclosure would cause extra rises in the ambient and top-oil temperatures, and how it impacts the moisture accumulation is investigated by comparing the corrected moisture data of indoor and outdoor installed transformers as shown in Figure 3.3. According to the results, outdoor installed transformers tend to have higher moisture in oil values. The average moisture in oil value of outdoor transformers is 9.8 ppm higher than that of indoor transformers.

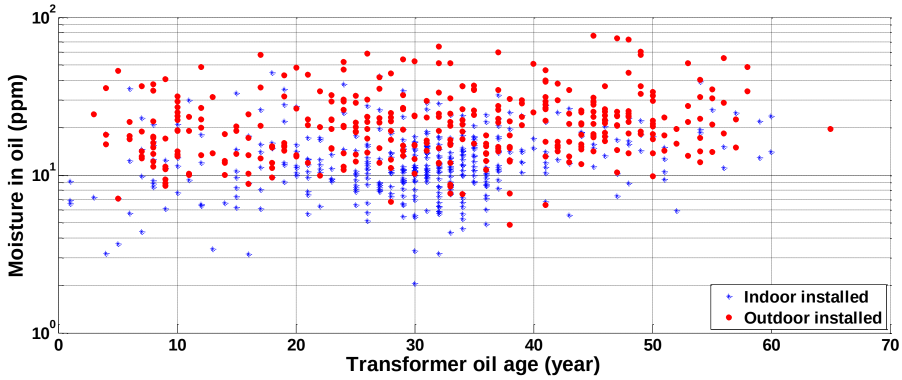

Figure 3.3: Corrected moisture data of indoor and outdoor installed distribution transformers

d. Estimate of moisture in oil with transformer oil age

The purpose of the analysis of moisture in oil data is to build an empirical model to estimate the moisture in oil with transformer oil age for transformers that do not have measured moisture in oil data. Since the previous analysis shows that transformer enclosures impact the moisture accumulation in oil, separate models should be built for indoor and outdoor transformers.

Linear regression is applied to fit the moisture in oil data of indoor and outdoor transformers separately. Intercepts of both fittings are fixed at 5 ppm when the transformer age is 0 in order to reflect the dry condition of the oil in new transformers. The reason of utilising the linear regression instead of non-linear regression is that due to the dispersity of the data, applying a more complexed non-linear equation does not improve the goodness of fitting comparing to applying a simple linear equation. Either of linear or non-linear regression only gives out a goodness of fitting no better than 0.3. Therefore, the simpler linear regression is selected for the fitting.

Fitting of indoor transformers is presented in Figure 3.4. In order to capture the variation of the data along the fitted line, a random variation is defined to follow the normal distribution. The standard variance of the normal distribution is obtained by finding the upper and lower lines in Figure 3.4, which indicates the range that covers 90% of all data. The upper line is the fitted line plus three times of the standard variance, and the lower line is the fitted line minus three times of the standard variance. The standard variance is found by increasing from a small number until the number of data between the upper and lower lines reaches 90% of all data. As a result, the equation to estimate the moisture in oil data of indoor transformers is obtained as Equation (**3-3**), where T is the transformer age; PPM_{in} is the moisture in oil of indoor transformers under age T, and $N(0,3)$ is a normal distribution with mean of 0 ppm and standard variance of 3 ppm.

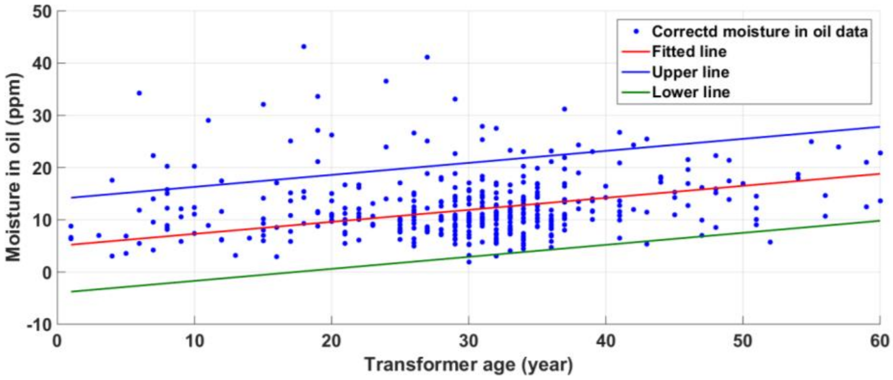

Figure 3.4: Fitting of moisture in oil data of indoor distribution transformers

$$PPM_{in} = 5 + 0.23 \times T + N(0,3) \qquad (3\text{-}3)$$

Similar to indoor transformers, the fitting is conducted to outdoor transformers as shown in Figure 3.5, and the resultant equation is shown as Equation (3-4). Comparing to indoor transformers, the slope of the linear line fitted to outdoor transformers is significantly increased (0.35 ppm/year comparing to 0.23 ppm/year), which indicates the accumulation rate of outdoor transformers is much larger than that of their indoor peers. In addition, the standard variance of outdoor transformers is 5 ppm, while it is 3 ppm of indoor transformers, which indicates the moisture in oil of outdoor transformers are more dispersed and uncertain to predict.

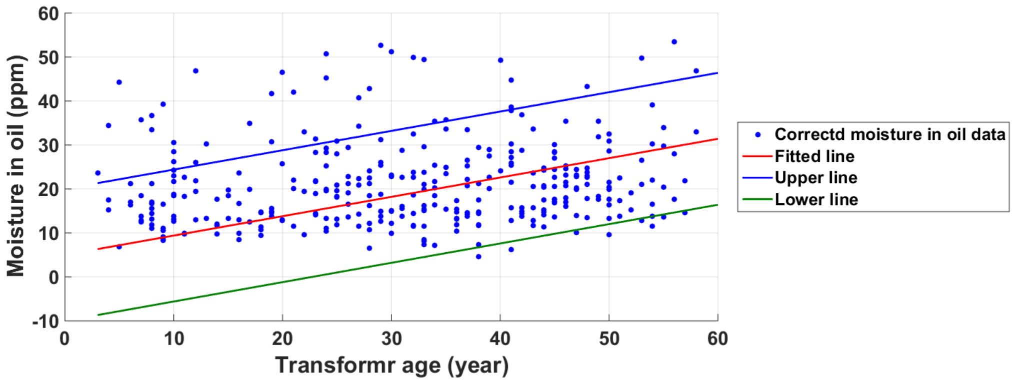

Figure 3.5: Fitting of moisture in oil data of outdoor distribution transformers

$$PPM_{out} = 5 + 0.35 \times T + N(0,5) \qquad (3\text{-}4)$$

With the models derived above, moisture in oil value can be estimated for any distribution transformers in the population by the transformer age. Resultant moisture in oil can be applied for the calculation of moisture in paper and the obtained moisture in paper will be used for the calculation of bubbling inception temperature with the bubbling inception temperature model. Eventually, the bubbling inception temperature will be utilised for the estimation of failure probabilities of distribution transformers under EV scenarios.

Accumulation of moisture in oil is a complex process, and a simple linear equation used for the regression in this stage is only to attempt to fit the measured data of a small group of sampled transformers and to roughly capture the trend. Considering the fitted data are the only available data of the population, the method introduced here is necessary for the prediction of moisture in oil of transformers without measured values in spite of its insufficiency. Potential future work of deriving a more sophisticated model for the prediction of moisture in oil will be extremely beneficial so that the moisture in paper and eventually the failure probability under EV scenarios can be estimated more accurately.

3.4 Assessment of distribution transformer population under EV scenarios

3.4.1 Selection of transformers for demonstration

150 transformers are selected from the population for the demonstration of the assessment strategy. The transformer age is controlled in the selection so that the wide age profile can be covered. Three age groups are defined as 0 to 20, 20 to 40 and 40 to 60 years old transformers. For each age group, 50 transformers are randomly selected from the population. Figure 3.6 shows age and yearly peak load data of the selected transformers. The load of each transformer is calculated with its customer information and Elexon profiles, and the calibration factor of 1.3 is applied.

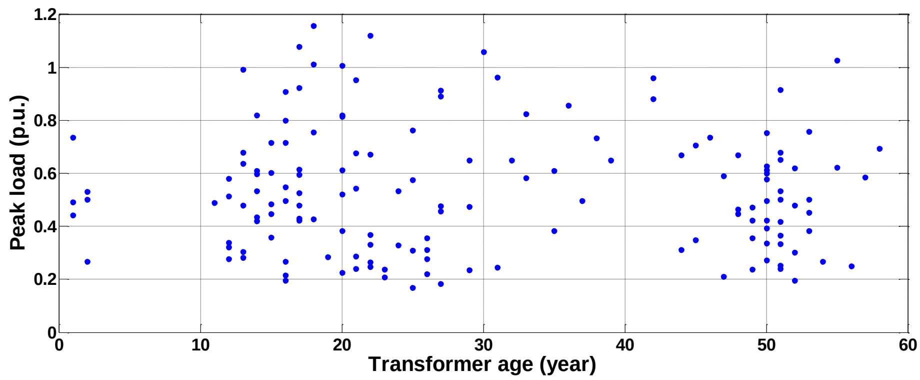

Figure 3.6: Distribution transformers selected for demonstration

3.4.2 Long term risks under EV scenarios

Yearly loss-of-life is calculated for each transformer under three EV scenarios. Firstly, yearly loss-of-life, mean and peak hot-spot temperatures are calculated under BAU scenario as shown in Figure 3.7.

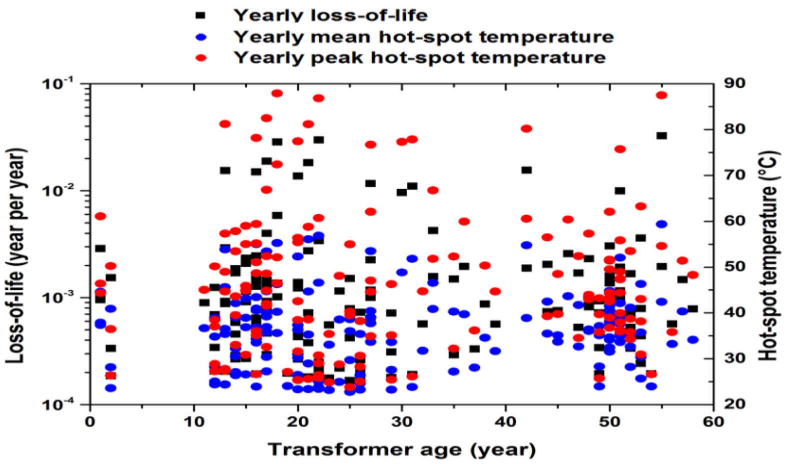

Figure 3.7: Yearly loss-of-life, mean and peak hot-spot temperatures under BAU scenario (No EVs penetration)

According to the IEC ageing model, the loss-of-life is non-linearly associated with the hot-spot temperature, and results show that the mean and peak yearly hot-spot temperatures are well below the 98°C which is the hot-spot temperature under a constant rated load representing a rated loss-of-life. Therefore, the resultant loss-of-life is much lower than the rated value. The unit of the yearly loss-of-life used here is year per year, which means the equivalent years of ageing in a yearly operation. The highest yearly loss-of-life is obtained as 0.03 year per year under the peak and mean hot-spot temperatures of 87.5 °C and 59.3 °C respectively. Statistical analysis of loss-of-life, mean hot-spot temperature and peak hot-spot temperature under BAU scenario are demonstrated in Table 3-4. More than 97% of the transformers have a yearly loss-of-life lower than 0.01 year per year. Mean hot-spot temperatures of 96% transformers are below 50 °C, and peak hot-spot temperatures of 94% transformers are below 70°C.

Table 3-4: Statistical analysis on loss-of-life, mean hot-spot temperature and peak hot-spot temperature under BAU scenario

Loss-of-life (year per year)	**[0.0001, 0.001)**	**[0.001, 0.01)**	**[0.01, 0.1)**
Percentage (%)	56.7	36	7.3
Mean hot-spot temperature (°C)	[20, 50)	[50, 70)	[70, 90)
Percentage (%)	96	4	0

Peak hot-spot temperature (°C)	[20, 50)	[50, 70)	[70, 90)
Percentage (%)	67.3	26.7	6

The lifetime of a transformer will be increased by a factor equal to the reciprocal of its yearly loss-of-life comparing to the expected lifetime of a constantly rated loaded transformer. Assuming the lifetime of a constantly rated load distribution transformer is 17.12 years according to IEC loading guide [11], the expected lifetimes of the group of transformers will be as large as over 100 years. In this case, the value itself is practically meaningless, however, it indicates that these transformers will not fail due to the long term thermal ageing under current loading conditions before they are replaced or fail due to other causes.

To investigate the loss-of-life under High-range and Extreme-range EV scenarios, Monte-Carlo simulations are conducted so that the randomness of EVs charging load is taken into account. Results of the load, hot-spot temperature and loss-of-life from all repetitions are averaged and outputted as the final results for each transformer. A statistical analysis of yearly RMS and peak loads under three EV scenarios is presented in Table 3-5, which shows the percentages of transformers in different load ranges.

Table 3-5: Statistical analysis of yearly RMS and peak loads under three EV scenarios

RMS load (p.u.)	**[0, 0.3)**	**[0.3, 0.6)**	**[0.6, 0.9)**
BAU scenario	46%	51.3%	2.7%
High-range scenario	34.7%	59.3%	6%
Extreme-range scenario	28.7%	56%	15.3%
Peak load (p.u.)	**[0, 1.0)**	**[1.0, 2.0)**	**[2.0, 3.0)**
BAU scenario	98%	2%	0
High-range scenario	58%	41.3%	0.7%
Extreme-range scenario	30%	57.3%	12.7%

The number of overloaded transformers is increasing with the penetration of EVs. Under BAU scenario, only 2% transformers are overloaded, while under High-range and Extreme-range scenarios, the percentage increases to 42% and 70% respectively. Furthermore, 12.7% transformers are extremely overloaded under Extreme-range scenario, where peak load exceeds 2.0 p.u. Depending on the penetration level, the peak load can be doubled or tripled. However, as to the yearly RMS load, since the huge peak load is compensated by the low valley load values during a day, the increase of RMS load caused by EVs charging load is relatively less than the peak load. For 150 demonstrated distribution transformers, the peak load increases by

77 % and 146% in average under High-range and Extreme-range EV scenarios respectively; and as a comparison, the yearly RMS load only increases by 16% and 33%.

A statistical analysis of yearly mean and peak hot-spot temperatures under three EV scenarios is presented in Table 3-6. It can be seen the peak hot-spot temperature is significantly influenced by EVs penetration. Under BAU scenario, the highest peak hot-spot temperature is 87.5°C, and the majority of transformers (85.3%) are operating below 60°C. Under High-range scenario, more than half of all transformers have peak hot-spot temperature higher than 60°C, and there are 4% transformers having peak hot-spot temperatures over 120°C, which might trigger a potential failure. Under Extreme-range scenario, as much as 27.3% transformers have peak hot-spot temperatures over 120°C.

Table 3-6: Statistical analysis of yearly mean and peak hot-spot temperatures under three EV scenarios

Mean hot-spot temperature (°C)	**[6, 40)**	**[40, 60)**	**[60, 80)**
BAU scenario	76%	24%	0
High-range scenario	61.3%	37.3%	1.4%
Extreme-range scenario	48.7%	47.3%	4%

Peak hot-spot temperature (°C)	**[0, 60)**	**[60, 120)**	**[120, 180)**	**[180, 240)**
BAU scenario	85.3%	14.7%	0	0
High-range scenario	43.3%	52.7%	4%	0
Extreme-range scenario	20.7%	52%	24%	3.3%

For 150 demonstrated distribution transformers, the peak hot-spot temperature increases by 47% and 100% in average under High-range and Extreme-range EV scenarios respectively; and as a comparison, the yearly average value only increases by 6% and 13%. Results show that even the peak hot-spot temperature can go up to 230°C according to the calculation; the highest yearly mean value is only as large as 72°C. Since the peak temperature only lasts for few hours during a day, it may contribute less to the yearly loss-of-life than the mean temperature. Therefore, the dominant value will be the yearly mean hot-spot temperature in terms of yearly loss-of-life, and EVs charging only poses a limited impact on it. Consequently, the yearly loss-of-life is only limited affected by the EVs penetration, as shown in Figure 3.8.

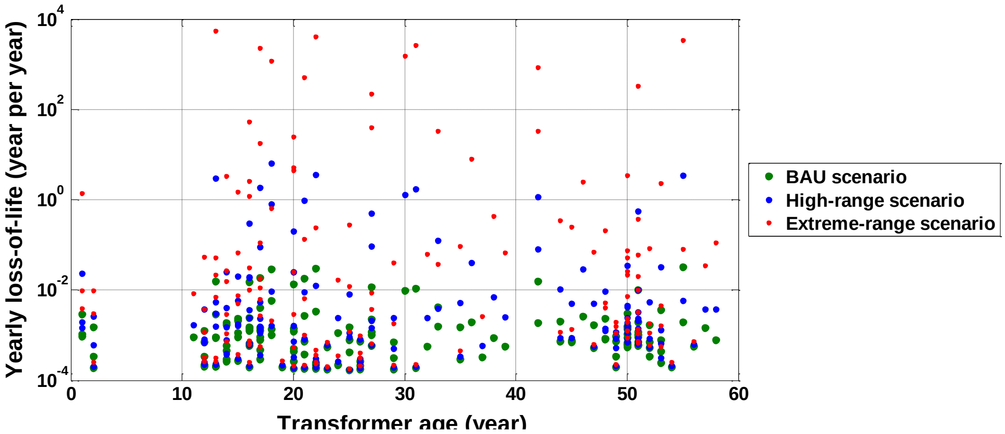

Figure 3.8: Yearly loss-of-life under three EV scenarios

Table 3-7: Statistical analysis of yearly loss-of-life under three EV scenarios

Loss-of-life (year per year)	[0.0001, 0.01)	[0.01, 0.1)	[0.1,1)	[1,10)	[10, 100)	[100, 10000)
BAU scenario	92.7%	7.3%	0	0	0	0
High-range scenario	78.7%	11.3%	4.7%	5.3%	0	0
Extreme-range scenario	54%	19.3%	7.3%	6%	4%	8%

A statistical analysis on the loss-of-life under three scenarios is displayed in Table 3-7. The majority of investigated distribution transformers is not over-aged even under Extreme-range EV scenario. Under High-range EV scenario, only 8 out of 150 transformers (5.3%) have a yearly loss-of-life larger than the rated value. Under Extreme-range EV scenario, the number is 27 out of 150 transformers (18%). The reason is that despite of the huge peak load and peak hot-spot temperatures, the yearly loss-of-life is very much compensated by the off-peak time, when the load and hot-spot temperature are much lower than the peak time.

Further investigations in Figure 3.9 show that all of these over-aged transformers are possessing peak hot-spot temperatures over 130 °C. Under such high values of hot-spot temperature, the top concern will be the short term failure instead of long term thermal ageing.

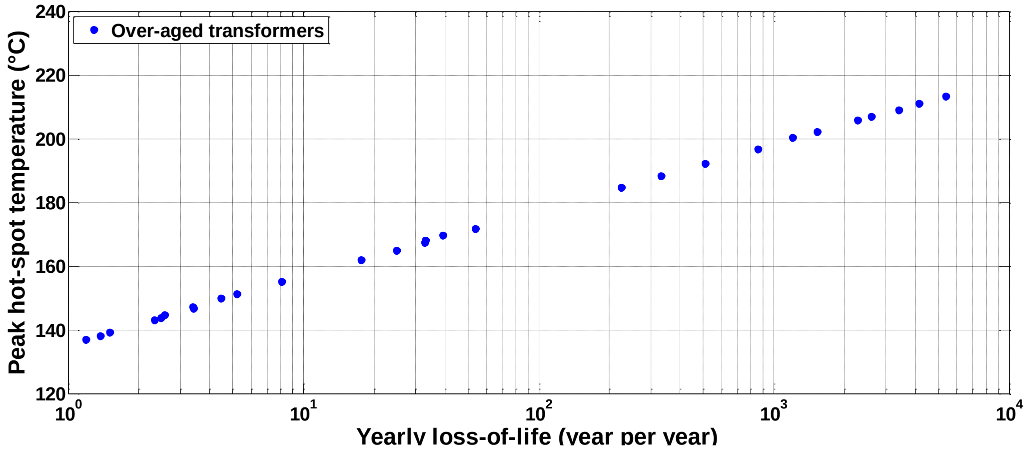

Figure 3.9: Peak hot-spot temperatures of over-aged distribution transformers

Therefore, it might be concluded that EVs charging would be less concerned on the acceleration of thermal ageing and the reduction of transformer lifetime than the immediate failure due to bubbling, since the peak load and hot-spot temperature will be compensated by the low values during the off-peak time and eventually lead to a moderate ageing even under high EVs penetration such as Extreme-range EV scenario.

3.4.3 Short term risks under EV scenarios

Short term risks of distribution transformers under EV scenarios are essentially due to bubbling. According to the assessment strategy proposed, the bubbling inception temperature is dominantly determined by the moisture in paper insulation, which is derived by the moisture in oil of the transformer. Figure 3.10 shows the moisture levels respectively in oil and paper which are derived by the models introduced in Chapter 2. In accordance to the moisture in oil model, i.e. Equation (**3-3**) and (**3-4**), apart from the linear increase with age, a random variation is considered. Therefore, for each transformer, different values of moisture in oil are generated for each repetition during the Monte-Carlo simulation. In addition, since the transformer age is the only input data for estimation of moisture in oil or paper, same values of moisture in oil or paper are applied for the same distribution transformer under different EV scenarios in one simulation. The data plotted are mean values from all repetitions of simulations of each transformer.

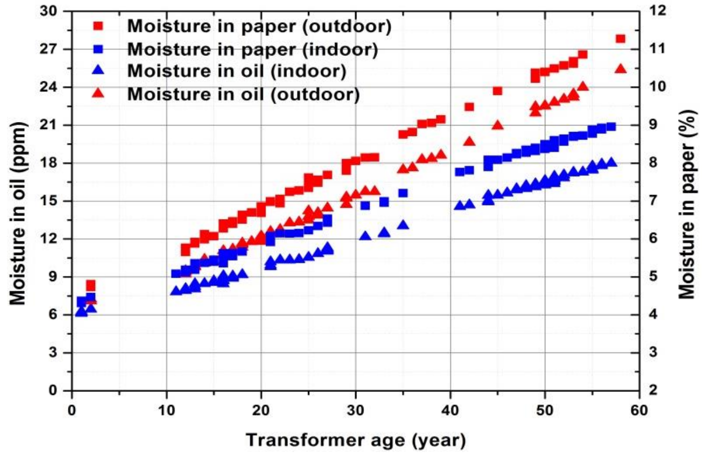

Figure 3.10: Moisture in oil and paper of selected transformers

Results in Figure 3.10 show that a noticeable deviation can be observed between indoor and outdoor transformers in terms of either moisture in oil or paper. The derivation is increasing with the transformer age. For transformers over 50 years old, the deviation could be as large as 7 ppm and 2.5 % for moisture in oil and paper respectively. These significant deviations imply that outdoor transformers tend to have lower bubbling inception temperatures, which is indeed observed in the following analysis.

Based on the derived moisture in paper, the bubbling inception temperature is calculated and compared with the peak hot-spot temperature as shown in Figure 3.11. Since the hot-spot temperatures of each repetition during the Monte-Carlo simulation are different due to the randomness of EVs charging load, the data plotted are mean values of all repetitions of each transformer.

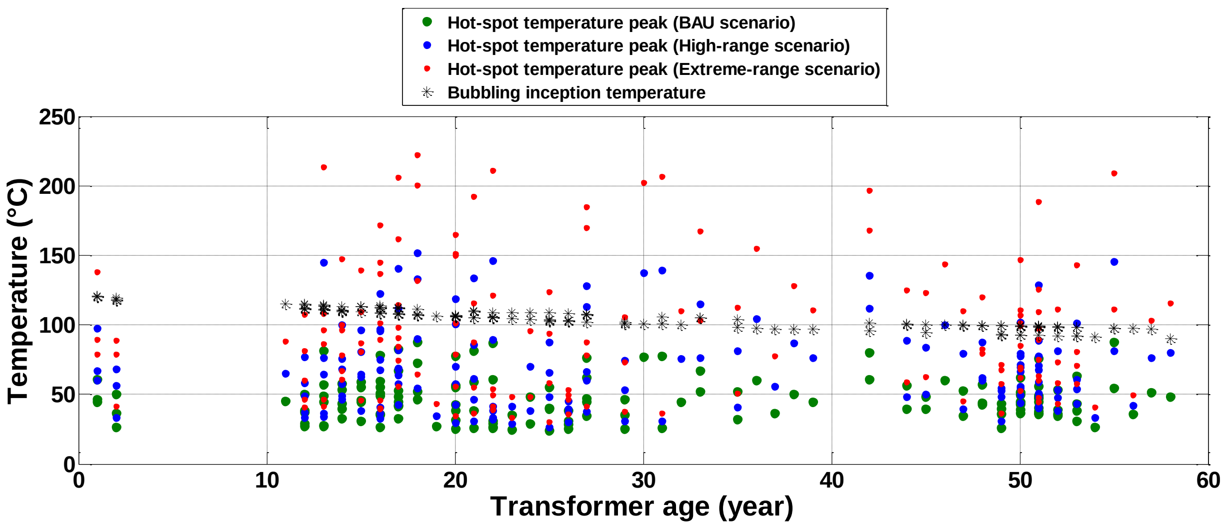

Figure 3.11: Peak hot-spot temperatures and bubbling inception temperatures under three EV scenarios

Bubbling inception temperatures are decreasing with the transformer age due to the accumulation of moisture in paper. For young transformers, the bubbling inception temperature is around 120°C, while for transformers over 50 years old, it can be lower than 100°C. In addition, similar to the moisture in paper, a deviation between indoor and outdoor transformers is observed, which are increasing with the transformer age, and could be over 7 °C lower for outdoor transformers when the age goes beyond 50 years. However, considering that indoor transformers could have higher temperature rises due to the enclosure, which would trade off the effects of lower bubbling inception temperatures in terms of the bubbling formation, it is still unclarified to claim how the potential failure probability would be influenced by the installation condition of distribution transformers.

The failure occurs when the peak hot-spot temperature exceeds the bubbling inception temperature. The failure probability is calculated for each distribution transformer as the ratio of number of simulations that failure occurs to the total number of repetitions during the Monte-Carlo simulations under three EV scenarios. Results are shown in Figure 3.12.

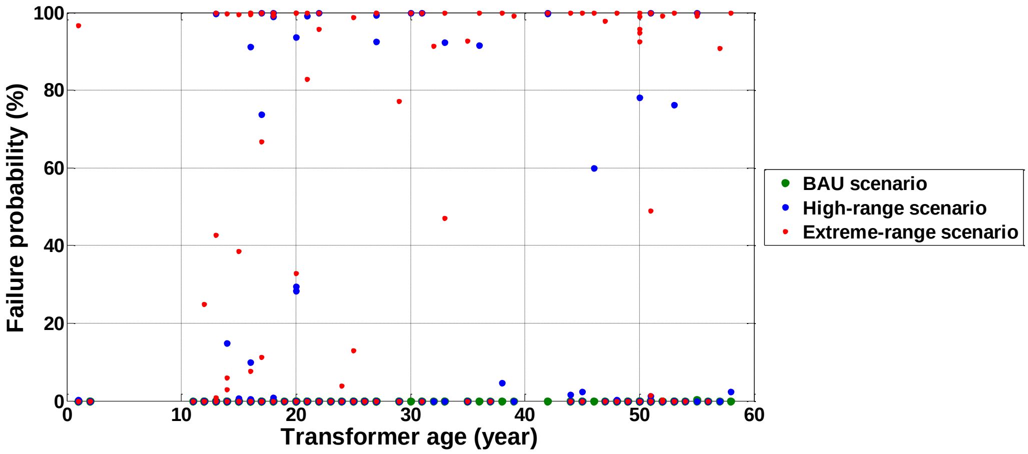

Figure 3.12: Failure probability under three EV scenarios

Under BAU scenario, when no EVs are implemented, no transformers are exposed to the risk of failure. Failures start in the High-range EV scenario, where 32% of customers are owning and charging EVs. If it is defined as “high risk” when a transformer is facing a failure probability of over 50%, then the number of transformers in high risk under each EV scenario is presented in Table 3-8.

Table 3-8: Number of transformers with failure probability over 50%

EV scenarios		BAU scenario		High-range scenario		Extreme-range scenario	
Indoor/outdoor installation		Indoor	Outdoor	Indoor	Outdoor	Indoor	Outdoor
Age group	0 – 20 years	0	0	2	4	6	7
	20 – 40 years	0	0	4	5	7	12
	40 – 60 years	0	0	6	1	15	6
	Total	0	0	11	10	28	25

Under High-range EV scenario, only 21 out of 150 transformers are in high risk, which is 14%. While under Extreme-range EV scenario, where the EVs penetration level increases to 58.9%, 53 transformers are facing high risks, which are 35.4% of the demonstration group.

In terms of age, according to Table 3-8, for indoor transformers, older transformers tend to have more high risk ones. However for outdoor transformers, the oldest group, i.e. age 40 to 60, has fewest high risk transformers. Therefore, solely based on results in Table 3-8, it may not be able to claim a clear relationship between failure probability and transformer age.

Another factor impacting the transformer failure probability is the peak load, which is investigated in Figure 3.13, where the peak loads of high risk and low risk transformers under Extreme-range EV scenario are compared.

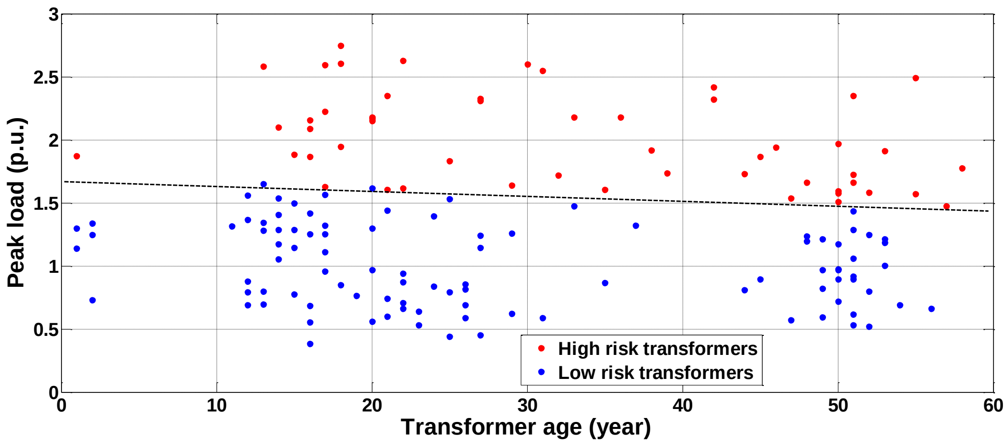

Figure 3.13: Comparison of peak loads between high risk transformers and low risk transformers under Extreme-range scenario

A boundary line as shown in Figure 3.13 can be explicitly identified to distinguish individuals with high or low risks, above which the transformer is in high risk, and otherwise it is in low risk. Therefore, the peak load can be identified as the dominant factor of the failure probability of a distribution transformer under EV scenarios. Furthermore, based on the comparison, it is possible to define an empirical threshold value of the peak load so that the EVs penetration level can be controlled to assure a lower peak load and to guarantee the transformer to operate in low risk regime. In this demonstration, the threshold value of the peak load can be roughly found as 1.5 p.u.

Apart from the age and peak load, the last possible factor affecting the failure probability is installation location, i.e. indoor / outdoor installation. According to Table 3-8, more indoor transformers are observed as high risk. However, there are more indoor transformers in the selected group of transformers. In terms of percentage, under High-range scenario, 13.8% (11 out of 80) indoor transformers are in high risk; and 14.3% (10 out of 70) outdoor transformers are in high risk. Under Extreme-range scenario, percentages get even closer for indoor / outdoor transformers. The percentage is 35% (28 out of 80) for indoor transformers, and 35.7% (25 out of 70) for outdoor transformers. As a result, it is difficult to claim if transformer enclosure is an essential factor causing higher failure probabilities.

In summary, investigations of failure probabilities of the demonstrative transformers under EV scenarios show that no failure risks are faced under BAU scenario. Under High-range scenario, around 14% of investigated distribution transformers will be in high risk; and this percentage will increase to 35.4% under Extreme-range scenario. The failure probability is affected by three factors including transformer age, peak load and installation condition. The peak load is found as the dominant factor. Under Extreme-range scenario, a threshold value of around 1.5 p.u. of the peak load is found, above which distribution transformers in high risk are distinguished.

3.5 Summary

The assessment strategy is applied on a group of demonstrative distribution transformers randomly selected from the population. In case of the unavailability of load and ambient profiles, modelling approaches are introduced to estimate the load and ambient profiles for the calculation of hot-spot temperature.
Results show that EVs charging would be less concerned on the acceleration of thermal ageing and the reduction of transformer lifetime than failure caused by bubbling, since the peak load and hot-spot temperature will be compensated by the low values during the off-peak time and eventually lead to a moderate ageing even under the high EVs penetration such as Extreme-range scenario.

In terms of short time risks, firstly, no transformers are facing failure risks due to bubbling under current conditions (BAU scenario). Around 14% of demonstrative transformers are observed as high risk transformers, which have a failure probability over 50%, under High-range EV scenario. The percentage increases to 35.4% when it turns to Extreme-range scenario. Although older transformers tend to have higher failure probabilities, it is found that the failure probability is dominantly controlled by the peak load, other factors such as transformer age and installation conditions are relatively less influential. An empirical threshold value of around 1.5 p.u. peak load is observed under Extreme-range scenario, above which the transformer would be in high risk with a failure probability over 50%, otherwise it would be in low risk.

4. Conclusions

A systematic assessment strategy for the future adaptability of distribution transformers under EV scenarios is introduced. With the assessment strategy, risks of operating distribution transformers into future EV scenarios are assessed by various quantified indicators including the load, hot-spot temperature, loss-of-life, expected lifetime and failure probability. With these indicators, asset management strategy of the distribution transformer population could be developed accordingly. For example, EVs penetration level should be controlled for transformers with high failure probability; otherwise these transformers should be closely monitored or replaced to avoid failure and disconnection of their downstream customers. The required input data for the strategy are simple and generally accessible, which include IEC thermal model parameters, transformer information such as age, power rating, installation condition and customer information, transformer operation information such as ambient temperature and the interested EVs penetration levels. In case of unavailability of some required input data, alternative modelling approaches have been introduced for approximate estimation. Therefore, with the proposed assessment strategy, a tool in Matlab is developed for ENW to assess their distribution transformers under anticipated EVs penetration level of interest.

In addition, main contributions and findings of this work are summarised below.

4.1 Main contributions

Main contributions of this work are summarised as follows:

- Introducing and demonstrating an assessment strategy for the adaptability of distribution transformer population under EV scenarios
- Proposing and verifying two methods of refining IEC thermal model parameters for distribution transformers
- Modelling of EVs charging load in a probabilistic manner with realistic data collected by EVs trials in UK
- Defining and modelling the short term failure probability of distribution transformers under EV scenarios
- Modelling of moisture in paper using equilibrium curves of moisture dynamics between oil and paper in distribution transformers

4.2 Main findings

Main findings of this work are summarised as follows:

- Refinement of IEC thermal model parameters

Curve-fitting hot-spot and top-oil temperatures measured during the extended heat run test is introduced and verified in this work as the ideal approach to refine the IEC thermal model parameters for distribution transformers. In order to obtain the most accurate values for thermal parameters, curve-fitting should be applied on the hot-spot temperatures measured during the entire duration of the extended heat run test including the cooling intervals between each two consecutive tests. Otherwise less accurate thermal parameters would be resulted, and the accuracy of the prediction of hot-spot temperature can be deteriorated. However, in the standard heat run test procedure [41], temperature measurements during the cooling periods are not mentioned and discussed. Therefore, it is recommended that temperature measurements of cooling periods during a heat run test should be at least discussed and provided as an option in the standard procedure.

- Applying the assessment strategy on a selected group of transformers under three EV scenarios

The assessment strategy is demonstrated on a group of 150 distribution transformers randomly selected from the population by controlling the transformer age. Three EV scenarios, i.e. BAU, High-range and Extreme-range scenarios, are investigated, which represent no EVs penetration, 32% penetration and 58.9% penetration respectively.

When EVs are plugged in, the peak load is increased significantly while the yearly RMS load is much less affected. Depending on the penetration level, the peak load can be doubled or tripled. However, as to the yearly RMS load, since the huge peak load is compensated by the low valley load values during a day, the increased of RMS load caused by EVs charging load is relatively less than the peak load. For 150 demonstrated distribution transformers, the peak load increases by 77% and 146% in average under High-range and Extreme-range EV scenarios respectively; and as a comparison, the yearly RMS load only increases by 16% and 33%.

Similar to the load, when EVs charging occurs, the peak value of the hot-spot temperature is drastically lifted while the yearly average value is only moderately increased. For 150 demonstrated distribution transformers, the peak hot-spot temperature increases by 47% and

100% in average under High-range and Extreme-range scenarios respectively; and as a comparison, the yearly average value only increases by 6% and 13%. Results show that even the peak hot-spot temperature goes up to 230°C under Extreme-range scenario, the yearly average value is only 72°C.

Effects of the increased hot-spot temperatures on the thermal ageing are limited by the duration of the EVs charging. Results show that despite of the high hot-spot temperatures during the peak time (when EVs charging occurs), the yearly loss-of-life is very much compensated by the off-peak time. Thermal ageing of most transformers are not accelerated over an assumed constantly rated loaded transformer under High-range or Extreme-range scenarios. Under High-range scenario, only 8 out of 150 transformers (5.3%) have a yearly loss-of-life over the rated value. Under Extreme-range scenario, the number is 27 out of 150 transformers (18%). In addition, all the over-aged transformers possess peak loads higher than 1.8 p.u. and peak hot-spot temperatures over 130 °C. Under such high values of load and hot-spot temperature, the top concern would be the short term failure instead of long term thermal ageing. Therefore, it might be concluded that EVs charging would be less concerned on the acceleration of thermal ageing and the reduction of transformer lifetime than direct failure due to bubbling, since the peak load and hot-spot temperature will be compensated by the low values during the off-peak time and eventually lead to a moderate ageing even under the high EVs penetration such as Extreme-range scenario.

Short term failure is defined as transformer breakdown due to bubbling. By comparing the peak hot-spot temperatures and the bubbling inception temperatures through Monte-Carlo simulations under EV scenarios, it is found that no transformer is facing any failure hazards under BAU scenario due to the low load and hot-spot temperature. Under High-range scenario, failure starts to occur. If transformers with a failure probability over 50% are considered as high risk, then 14% of transformers are in high risk under High-range scenario, while 35.4% of transformers are in high risk under Extreme-range scenario. Several factors are investigated in terms of theirs impacts on the failure probability such as transformer age, installation condition and load. Age is affecting the failure probability through moisture in oil. The older the transformer is, the more the moisture in oil accumulates and the lower the bubbling inception temperature tends to be. Results show that the bubbling inception temperature ranges from 120.4 °C of a 1 year old transformer to 89.9 °C of a 58 years old transformer. However, by comparing the number of transformers in high risk of various age groups, no definite relationship is observed between transformer age and failure probability.

In terms of the installation condition, similar percentages of indoor / outdoor transformers are observed as high risk under High-range and Extreme-range scenario. Therefore, it is difficult to claim outdoor installation is an essential factor causing higher failure probabilities.

The peak load is found as the most significant factor affecting the failure probability. Take the Extreme-range scenario as an example, an explicit threshold value in peak load can be identified that distinguishes distribution transformers in high risk (failure probability over 50%) from others regardless of age and installation condition, and the value is around 1.5 p.u. Therefore, the peak load can be identified as the dominant factor of the failure probability of distribution transformers under EV scenarios.

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Appendix: Thermal parameters derived by heat run test data of 20 distribution transformers representing population

Index	Power rating (kVA)	Voltage rating (kV)	R	$\Delta\theta_{or}$ (K)	g_r (K)	H*	τ_o* (min)	τ_w (min)	x*	y*	k_{11}	k_{21}*	k_{22}*
1	315	6.27	8.76	45.1	14.3	1.1	180	13.0	0.8	1.6	1.12	1	2
2	500	10.45	8.56	47.5	8.5	1.1	180	14.0	0.8	1.6	1.16	1	2
3	1000	10.45	9.03	56.5	14.8	1.1	180	15.0	0.8	1.6	1.17	1	2
4	315	6.6	8.25	49.1	20.3	1.1	180	10.4	0.8	1.6	1.11	1	2
5	500	6.6	8.55	49.2	17.4	1.1	180	9.1	0.8	1.6	1.14	1	2
6	1000	6.6	8.55	48.5	22.8	1.1	180	6.8	0.8	1.6	1.16	1	2
7	315	6.6	8.20	49.8	20.8	1.1	180	10.3	0.8	1.6	1.15	1	2
8	1000	6.6	8.69	50.9	13.4	1.1	180	11.2	0.8	1.6	1.13	1	2
9	315	11	8.79	49.6	19.5	1.1	180	9.4	0.8	1.6	1.12	1	2
10	500	11	8.24	48.6	20.5	1.1	180	9.9	0.8	1.6	1.15	1	2
11	315	11	8.85	50.2	19.4	1.1	180	8.4	0.8	1.6	1.18	1	2
12	1000	11	9.07	50.3	18	1.1	180	8.7	0.8	1.6	1.13	1	2
13	315	6.6	8.52	50.4	10.6	1.1	180	5.6	0.8	1.6	0.97	1	2
14	1000	11	9.22	51.8	11	1.1	180	16.0	0.8	1.6	1.05	1	2
15	800	6.6	9.00	52	17	1.1	180	9.4	0.8	1.6	1.09	1	2
16	800	11	9.21	49.5	21.9	1.1	180	12.5	0.8	1.6	1.20	1	2
17	500	6.6	8.24	53.6	13.8	1.1	180	11.5	0.8	1.6	1.11	1	2
18	315	11	8.63	52.7	13.5	1.1	180	10.4	0.8	1.6	1.11	1	2
19	1000	6.6	9.40	54.7	14.5	1.1	180	28.6	0.8	1.6	1.11	1	2
20	500	11	8.49	52.3	24.4	1.1	180	8.2	0.8	1.6	1.31	1	2

*: Generic values recommended in IEC loading guide are applied, since required data for the derivation are not available.