ASSESSMENT OF FUTURE ADAPTABILITY OF DISTRIBUTION TRANSFORMER POPULATION UNDER EV SCENARIOS

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<td>A, a</td>
<td>Constants</td>
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<tr>
<td>B, b</td>
<td>Constants</td>
</tr>
<tr>
<td>BAU</td>
<td>Business as usual</td>
</tr>
<tr>
<td>BEV</td>
<td>Battery electric vehicle</td>
</tr>
<tr>
<td>C, c</td>
<td>Constants</td>
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<tr>
<td>CDF</td>
<td>Cumulative distribution function</td>
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<tr>
<td>d</td>
<td>Constant</td>
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<tr>
<td>DjT</td>
<td>Department for Transport</td>
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<tr>
<td>DP</td>
<td>Degree of polymerisation</td>
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<td>E_A</td>
<td>Activation energy</td>
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<td>g</td>
<td>Average winding to oil gradient</td>
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<td>Tensile strength</td>
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<td>V</td>
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LIST OF SYMBOLS AND ABBREVIATIONS

\( W \) Moisture in paper
\( x \) Oil exponent
\( y \) Winding exponent
\( z \) Hot-spot exponent
\( \theta_a \) Ambient temperature
\( \theta_E \) Equivalent ambient temperature
\( \theta_o \) Top-oil temperature
\( \theta_h \) Hot-spot temperature
\( \theta_{ma, \text{max}} \) Monthly average ambient of the hottest month
\( \theta_w \) Average winding temperature
\( \theta_{ya} \) Yearly average ambient temperature
\( \Delta \theta_{\text{ave}} \) Average-oil temperature rise over ambient
\( \Delta \theta_{\text{ave}, \text{rated}} \) Rated average-oil temperature rise over ambient
\( \Delta \theta_b \) Bottom-oil temperature rise over ambient
\( \Delta \theta_{o, \text{surface}} \) Surface measured bottom-oil temperature rise over ambient
\( \Delta \theta_{do - b} \) Duct-oil temperature rise over bottom-oil
\( \Delta \theta_o \) Top-oil temperature rise over ambient
\( \Delta \theta_{oi} \) Initial top-oil temperature rise over ambient
\( \Delta \theta_{or, \text{rated}} \) Rated top-oil temperature rise over ambient
\( \Delta \theta_{o, \text{inside}} \) Inside top-oil temperature rise over ambient
\( \Delta \theta_{o, \text{surface}} \) Surface measured top-oil temperature rise over ambient
\( \Delta \theta_h \) Hot-spot temperature rise over ambient
\( \Delta \theta_{h - do} \) Hot-spot temperature rise over duct-oil
\( \Delta \theta_{hi} \) Initial hot-spot temperature rise over ambient
\( \Delta \theta_{ho} \) Hot-spot temperature rise over top-oil
\( \Delta \theta_{hoi} \) Initial hot-spot temperature rise over top-oil
\( \Delta \theta_{hr} \) Rated hot-spot temperature rise over ambient
\( \Delta \theta_{wr}, \Delta \theta_{w, \text{rated}} \) Rated average winding temperature rise over ambient
\( \tau_o \) Average-oil time constant
\( \tau_{o, \text{top}} \) Top-oil time constant
\( \tau_w \) Winding time constant
\( \mu \) Oil viscosity
\( \Lambda \) Thermal conductance
ABSTRACT

As one of the most promising pathways in the transition period towards the low carbon economy, a large scale implementation of electric vehicles (EV) is expected in the near future. Concentration of EV charging in a small area or within a short time will dramatically affect the load demand profile, 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 thesis, an assessment strategy for the future adaptability of distribution transformer population under EV scenarios is introduced. Assessing the adaptability is to understand the impact of 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 thesis. 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% EV penetration levels respectively. Results show that EV charging would be less concerned on the acceleration of thermal ageing than the direct failure due to breakdown caused by decrease of dielectric strength in an event of bubbling. Since the peak load and hot-spot temperature under EV scenarios only last for a short time and would be compensated by low values during the rest time of a day, which eventually leads to a moderate thermal ageing. Occasionally, severe over-ageing can be caused by extremely high hot-spot temperatures, and the lifetime will be reduced to an unacceptable level. However, on such occasions, hot-spot temperatures would be high enough to trigger bubbling and reduce the dielectric strength of transformer’s insulation system to a level that is incapable of undertaking the voltage stress, which eventually causes breakdown of transformers.

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. 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 scenarios that the peak load of distribution transformers should be restricted below 1.5 p.u. to prevent potential failure due to bubbling.
DECLARATION

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ACKNOWLEDGEMENT

This has been the most enjoyable part to write in this thesis, but I hope this is not the most enjoyable part to read. Sincerely, there is much more worth being cited in this thesis other than the previous statement.

My first gratitude goes to my supervisor Prof. Zhongdong Wang for taking me as her PhD student, for guiding me through four years of research, and for helping me complete PhD degree. Among the massive I have learnt from my supervisor, her professionalism is of the most value to me. No matter where I will be and what I will be doing, professionalism will be my priority pursue.

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My deepest gratefulness is for my parents. I am always indebted to my parents, for being absent when they need me, for wasting their lifetime savings, for being incapable of making them proud. They never understand what I have been doing during PhD, but they have always been supporting me in all ways with their endless unconditional love.

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To my parents and Dr. Wen Yue.
CHAPTER 1 INTRODUCTION

1.1 Background

Humanity 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, which is an economy based on minimal emissions of greenhouse gas (GHG) in various sectors such as transport, energy and agriculture. In Europe, the European Council has set a target of reducing 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 (EV) 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 EV [2]. EV are vehicles propelled by one or more electric motors powered by rechargeable battery packs. EV include electric motorcycles, cars, trains, boats, airplanes etc., but the term “EV” is generally referring to cars, especially passenger cars. Three major groups are categorised as Hybrid Electric Vehicles (HEV), Battery Electric Vehicles (BEV) and Plug-in Hybrid Electric Vehicles (PHEV).

To charge their batteries, EV need to be connected to the electricity grid, where they are equivalent to active loads. As a result, power system networks will be affected from the generation to the distribution side by extra loads due to a large scale of implementation of EV. Investigations [3] show that the generation and transmission systems in the UK will be able to digest the potential EV charging loads, since both of them have sufficient surplus capacity to cope with the projected EV penetration in the near future (as shown in Table 1-1). However, the influence of EV charging on the distribution network is not negligible.
Table 1-1: Projected UK generating capacity, annual demand and demand from EV charging [3]

<table>
<thead>
<tr>
<th>Year</th>
<th>2010</th>
<th>2020</th>
<th>2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generating capacity</td>
<td>79.9GW</td>
<td>100GW</td>
<td>120GW</td>
</tr>
<tr>
<td>Projected annual UK demand</td>
<td>380TWh</td>
<td>360TWh</td>
<td>390TWh</td>
</tr>
<tr>
<td>EV demand</td>
<td>13GWh</td>
<td>3.5TWh</td>
<td>17TWh</td>
</tr>
<tr>
<td></td>
<td>(0.003% of NEP)</td>
<td>(1.0% of NEP)</td>
<td>(4.4% of NEP)</td>
</tr>
</tbody>
</table>

NEP: National Electricity Production

EV, as passenger cars, 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 [4-10] 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 PhD work. Generally, the average load levels will be lifted up. What is worse is EV charging loads are more mobile and uncertain comparing to normal loads due to the randomness of charging behaviours of EV’ users. Clustering, i.e. concentration of EV 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, according to the loading guide [11], transformers can be categorised into two categories, which are distribution transformer and power transformer. Distribution transformers generally refer to transformers that step down voltages from 11 kV or 6.6 kV to 0.4 kV (which was 0.415 kV until January 1995), and the typical power ratings are ranging from 15 kVA to 2000 kVA [12] (2500 kVA in IEC 60076-7 [11]). Power transformers generally refer to transformers with voltage and power rating higher than 11 kV and 2500 kVA. In utilities, transformers may be categorised differently according to their functionalities. For example, apart from distribution transformers, which in utilities also refer to transformers that step down voltage from 11 kV or 6.6 kV to 0.4 kV, there are low voltage transformers (voltage level lower than 3.3 kV), extra high voltage transformers (33 kV) and grid transformers (132 kV).

Unlike medium or high voltage power transformers, distribution transformers normally do not operate in parallel in low voltage networks, since feeders in the UK are typically configured in a radial fashion as illustrated in Figure 1-1. 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. Typically, the unit penalty to a DNO is £6 per customer, plus a further £6 per hour disconnected [13]. Additional compensations of £50 per customer are paid to whom have are continuously disconnected for 18 hours, plus £25 for each succeeding 12 hours [13]. In addition, such disconnections will damage the annual performance of a DNO in the review by OFGEM, and performance against target below average is subject to financial penalties costing millions of pounds [13]. Penalty policies from OFGEM might be updated from time to time, but the message is straightforward that DNOs must spend on maintaining their operations in a safe and reliable state; otherwise pay for the potential consequences.

![Figure 1-1: Illustration of radial distribution network configuration](image)

1.2 Statement of problem

This PhD work aims to assess the adaptability of a large distribution transformer population owned by Electricity North West Ltd. (ENW) in future EV scenarios. Why distribution transformers need to be assessed, and what the adaptability refers to will be the essential parts of the statement of the problem.

1.2.1 Distribution transformers
Distribution transformers are designed based on load levels they will undertake so that they can operate safely to reach the designated lifetime. Firstly, power ratings are selected to ensure the transformer will not operate with more than 80% of rated capacity [14] so as to limit overloading risks. Secondly, temperatures inside the transformer under the rated load is restricted by industrial standards [11, 15] to guarantee its lifetime by limiting the unit loss-of-life. Highest temperature on the winding of a transformer is the key factor to determine its lifetime, since a transformer’s life is dominated by the life of its paper insulation system. Paper insulations get weaker along the time of transformer operation, which is known as paper ageing or transformer ageing. The higher the temperature is, the faster the ageing goes. The weakest point of the paper insulation system locates at the highest temperature along the winding, which is known as the hot-spot temperature and determines the transformer lifetime.

Operating experiences to date suggest that controlling the load and temperature has been successful when considering the fact that distribution transformers in the UK have far exceeded their originally expected lifetimes. For instance, transformers installed in as far back as the 1930s still remain operating in the current network. In addition, DNOs tend to employ “fit and forget” strategy to manage their large distribution transformer population due to their inexpensive capital cost and short replacement time after failure. In summary, it seems that under current loading scenarios, distribution transformers have worked well even though they are “forgotten”.

However, the prevailing of low carbon economy may transform the distribution networks and reshape its loading scenarios with novel schemes such as EV. Consequently frequent or excessive loadings as aforementioned will challenge the large, old and forgotten 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 a return on investment, it is a necessity to face the challenges first by researching how the 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

Taking ENW as an example, it has a population containing more than 30,000 distribution transformers. From a capital cost point of view, in spite of the low cost of each individual
distribution transformer, massive capitals still have to be invested in such a huge population. The wide-ranged age profile of this population is shown in Figure 1-2. More than 40% transformers are older than 40 years, which is possibly due to the major network expansion during 1960s and 1970s. According to calculations made in this thesis, old transformers tend to have ageing by-products accumulated inside the transformer such as moisture, which will increase the operational risks; under the same loads they tend to have higher failure probabilities than their younger peers if the design is the same. Therefore, they are more vulnerable to EV scenarios.

![Figure 1-2: Age profile of ENW distribution transformer population](image)

- Diverse variations of designs

Although the fundamental principle of a transformer has been unchanged since it was first invented more than 100 years ago; materials used, technologies applied and design specifications have been evolving with time. Take thermal specifications as an example, Table 1-2 shows the evolution with time of top-oil temperature rise and average winding temperature rise limitations under rated load for ONAN-cooled transformers (distribution transformers are mostly ONAN-cooled). The increase of temperature rise limitations implies the general growing understanding and confidence in transformer manufacture and operation. It also implies that old transformers tend to be designed more conservatively, in an over-engineered fashion in order to reserve more safety margin for the operation [11].
Table 1-2: Temperature rise limitations for ONAN-cooled transformers

<table>
<thead>
<tr>
<th>Years of standard</th>
<th>Top-oil temperature rise (K)</th>
<th>Average winding temperature rise (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1959 [16]</td>
<td>50</td>
<td>60</td>
</tr>
<tr>
<td>1978 [17]</td>
<td>60 with conservator or sealed; otherwise 55</td>
<td>65</td>
</tr>
<tr>
<td>1997 [18]</td>
<td>60</td>
<td>65</td>
</tr>
<tr>
<td>2011 (current version) [19]</td>
<td>60</td>
<td>65</td>
</tr>
</tbody>
</table>

From another perspective, even following the same specifications, 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 the same loads. Transformers of the ENW population are originally designed and produced by more than 240 manufacturers. Figure 1-3 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. The rest more than 230 manufacturers are aggregated as others. Therefore, in order to take account of design variations due to the wide age range or the diverse manufacturer composition, a design-dependent approach should be pursued when assessing the population.

![Figure 1-3: Manufacturer composition of ENW distribution transformer population](image-url)
• 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 [12]. 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 ingress 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 a devastating phenomenon called bubbling under high hot-spot temperature induced by high loads. When bubbling occurs, free bubbles are released in the transformer liquid insulation, and the dielectric strength of the liquid insulation is therefore significantly reduced.

Concerning the potential failure risks caused by overloading, IEC standard [11] has specified load current and hot-spot temperature limits applicable to loading beyond nameplate rating as shown in Table 1-3. Normal cyclic loading is a type of load which is equivalent to the rated load under rated ambient temperature in term of unit thermal ageing, but has both of over and under rated variations cancelling each other within one cycle [11]. Long-time emergency loading is a type of load resulted from the prolonged outage at system level, therefore it may last for hours or days or even longer [11]. Short-time emergency loading is a type of heavy load originated by occasional transient (normally less than 30 mins) disturbances due to one or more unlikely events [11]. This type of loading is expected to occur rarely, but should be swiftly reduced or the transformer should be disconnected to avoid its failure.
Table 1-3: Loading and temperature limits applicable to loading beyond nameplate rating [11]

<table>
<thead>
<tr>
<th>Type of loading</th>
<th>Limits specifications</th>
<th>Distribution transformer</th>
<th>Large power transformer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal cyclic loading</td>
<td>Load current (p.u.)</td>
<td>1.5</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>Winding hot-spot temperature (°C)</td>
<td>140</td>
<td>140</td>
</tr>
<tr>
<td>Long-time emergency loading</td>
<td>Load current (p.u.)</td>
<td>1.8</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>Winding hot-spot temperature (°C)</td>
<td>140</td>
<td>140</td>
</tr>
<tr>
<td>Short-time emergency loading</td>
<td>Load current (p.u.)</td>
<td>2.0</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>Winding hot-spot temperature (°C)</td>
<td>N/A*</td>
<td>160</td>
</tr>
</tbody>
</table>

*: No limit is set for hot-spot temperature under short-time emergency loading for distribution transformers because it is usually impracticable to control the duration of emergency loading in this case.

According to Table 1-3, imagining a monitoring tool is developed based on these limits; then necessary adjustments must be made if it is made for large power transformers but intended to apply on distribution transformers.

1.2.2 Assessing adaptability in future EV scenarios

Assessing the adaptability of distribution transformer population is to assess the hot-spot temperature, resulting loss-of-life, expected lifetime, and failure probability of each individual transformer of the population, in order to investigate how future EV scenarios will influence the population and to propose replacement plans and management strategies to minimise the potential hazards.

Hot-spot temperature of a transformer determines its unit loss-of-life and expected lifetime; also failure might be triggered if the hot-spot temperature reaches the restricted zone. For individual transformers, hot-spot temperature is determined by three elements, i.e. the load element, transformer thermal characteristic element and environmental element.

- Load element

Load element refers to the loading undertaken by the transformer. It is the driving factor, and the hot-spot temperature is generated by combined contributions of no-load and load losses induced by the transformer load. EV scenarios impact this element by increasing load levels, especially peak load levels, to eventually lift the hot-spot temperature.
However, how to define and quantify EV scenarios and how to obtain load data for individual transformers when monitoring data are not available are major challenges. In this PhD work, these challenges are eventually dealt with modelling approaches.

- Transformer thermal characteristic element

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 1-4, where the hot-spot temperature is the sum of ambient temperature, top-oil temperature rise over ambient and hot-spot to top-oil gradient.

![Thermal Diagram](Figure 1-4: Thermal diagram [11])

Assumptions made for the thermal diagram should be noted.
- The oil temperature inside the tank increases linearly from bottom to top.

- The temperature rise of the conductor at any position along the winding increases linearly, parallel to the oil temperature rise. The constant difference between two lines is defined as $gr$, i.e. the average winding to oil gradient.

- The hot-spot temperature rise is higher than the temperature rise of the conductor at the top of the winding. The difference between hot-spot temperature rise and top-oil temperature rise is made equal to $H \times gr$, where $H$ is defined as the hot-spot factor.

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 (1-1) to (1-5).

\[
\begin{align*}
\theta_h(t) &= \theta_o + \Delta \theta_o(t) + \Delta \theta_h(t) \quad (1-1) \\
\Delta \theta_o(t) &= \Delta \theta_{oi} + \left\{ \Delta \theta_{or} \times \left[ \frac{1 + R \times K^2}{1 + R} \right] - \Delta \theta_{oi} \right\} \times f_1(t) \quad (1-2) \\
\Delta \theta_h(t) &= \Delta \theta_{hi} + \left\{ H \times gr \times K^y - \Delta \theta_{hi} \right\} \times f_2(t) \quad (1-3)
\end{align*}
\]

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

\[
\begin{align*}
f_1(t) &= \left(1 - e^{(-t)/(k_{11}\times \tau_o)} \right) \quad (1-4) \\
f_2(t) &= k_{21} \times \left(1 - e^{(-t)/(k_{21}\times \tau_o)} \right) - (k_{21} - 1) \times \left(1 - e^{(-t)/(\tau_o/k_{22})} \right) \quad (1-5)
\end{align*}
\]
When load decreases, the equation describing hot-spot rise over top-oil, i.e. Equation (1-3), is simplified as

$$\Delta \theta_h(t) = \Delta \theta_{hi} + H \times g_r \times K^y$$  \hspace{1cm} (1-6)

Input data required in the model are ambient temperature $\theta_a$ 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 [11]. 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 PhD work, methods are proposed and validated for refinement of thermal parameters for individual transformers.

- Environmental element

Environmental element indicates how the hot-spot temperature of a transformer is affected by its surrounding environment, which refers to ambient temperatures and installation conditions.

The variation of ambient temperature will be copied by hot-spot temperature according to IEC 60076 thermal model. Transformer enclosures, if the transformer is installed indoor, will also affects temperature rises inside the transformer. Extra ambient temperature rise should be considered inside the enclosure. Also, extra top-oil rise is also experienced by the transformer operating in an enclosure, which is around half the value of the extra ambient temperature rise. The extra temperature rise is determined by a few factors such as the ventilation of the enclosure, the number of transformers installed and also the power rating of the transformer [11].

To summarise, the distribution transformer population is concerned under future EV scenarios on hazards of reduced lifetime due to the extra loads brought by EV 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 must be conducted on the future adaptability under future EV scenarios.

**1.3 Objective and methodology of research**

This PhD 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 EV penetration in the future, and model EV charging load in a stochastic manner to reflect the realistic behaviours of EV’s users.

2. Model cyclic load of individual transformers assuming the measured data are not available.

3. 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.

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 1-4.
Table 1-4: Methodologies serving objectives of this thesis

<table>
<thead>
<tr>
<th>Objective</th>
<th>Methodologies</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. EV scenarios and charging load</td>
<td>• Stochastic modelling based on existing literature.</td>
</tr>
<tr>
<td>2. Cyclic load</td>
<td>• Modelling based on customer information according to Elexon profiles.</td>
</tr>
</tbody>
</table>
| 3. (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. |
| 3. (b) Calculate of hot-spot temperature, loss-of-life and lifetime. | • IEC 60076-7 thermal model.  
• IEC ageing model. |
| 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. |
| 6. Population assessment | • Statistical analysis.  
• Results demonstration with a representative group. |

1.4 Outline of thesis

A brief overview of each chapter of this thesis is given as follows:

Chapter 1 Introduction: A general background of the work is provided. Motivation, objectives and general methodologies are also given in this chapter.

Chapter 2 Transformer end-of-life: A literature survey on transformer end-of-life is presented here.

Chapter 3 Transformer thermal performance and EV impacts on distribution transformers: A literature survey on transformer thermal performance and EV impacts on distribution transformers is presented here.

Chapter 4 Assessment of a prototype distribution transformer’s thermal performance under EV scenarios: This chapter demonstrates through an ideal case where a prototype distribution transformer possessing all required datasets is assessed under EV scenarios. Three EV scenarios are defined, which represent no EV penetration, high and extreme EV penetration respectively. Data available for the prototype distribution transformer are briefly introduced, which include nameplate data, extended heat run test data, hot-spot temperature measured during the test and cyclic loading of its daily operation. IEC 60076-7 thermal
model is applied for the hot-spot temperature calculation, where thermal parameters are refined by curve-fitting the measured hot-spot temperature during the extended heat run test. Corresponding loss-of-life and expected lifetime are estimated according to IEC ageing model. Failure probability is defined as the probability of the hot-spot temperature exceeding the bubbling inception temperature, and estimated by Monte-Carlo simulations under EV scenarios.

Chapter 5 Assessment of existing individual distribution transformers under EV scenarios: A majority of existing distribution transformers of the population does not possess all datasets as suggested in Chapter 4. Therefore, some data cannot be obtained as the prototype distribution transformers, and alternative methods are required to derive these data. Firstly, considering existing distribution transformers are more likely to have standard heat run test data than optic fibre measured hot-spot temperature, another method is introduced to derive thermal parameters based on standard heat run test data. Secondly, DNOs do not monitor load data for all distribution transformers, but they often have a database recording numbers of customers connected to each transformer. A load modelling tool, i.e. the Elexon profiles, is introduced to generate yearly load data based on customer information for distribution transformers. Lastly, to take the installation condition into account, extra temperature rises on ambient and top-oil due to enclosure of indoor installed distribution transformers are introduced.

Chapter 6 Assessment of distribution transformer population under EV scenarios: Demographic analysis of the ENW transformer population is first presented in terms of power rating, installation condition, customer composition and oil test data. Assessment of hot-spot temperature, resulting loss-of-life, expected lifetime and failure probability is conducted on a group of representative distribution transformers of the population. Under the no EV scenario, a method is introduced for a quick estimation of loss-of-life of a distribution transformer based on simplified load profiles. Under EV scenarios, the assessment results are investigated for the potential suggestions on the asset management strategy of operating the distribution transformer population into future EV scenarios.

Chapter 7 Conclusion and future work: This chapter draws conclusions of this PhD work and gives recommendations for potential future work.
CHAPTER 2  TRANSFORMER END-OF-LIFE

Transformer end-of-life is defined by CIGRE Working Group A12.18 [20] in three ways as

1. “Strategic end-of-life: the transformer is considered to have unsuitable specifications in its present location and should be replaced.”

2. “Economic end-of-life: the transformer is considered to be replaced as maintaining its operation requires excessive costs.”

3. “Technical end-of-life: the transformer is unable to provide technical function as the electrical energy transferring device and should be replaced.”

Reaching the strategic or economic end-of-life not necessarily means reaching the technical end-of-life, since the transformer would still be able to function if remained in the system. The technical end-of-life is directed associated with the functionality of transformers, and its complete definition is given as

“The point at which a transformer should no longer remain in service because of an actual or potential failure of function which is uneconomic to repair, or because it is no longer sufficiently reliable.”

In this thesis, only the technical end-of-life is discussed, and it is referred as “end-of-life” for simplicity.

2.1 Transformer failure

According to the definition, the transformer life ends when it is removed from service due to the actual or potential failure of its functionality. Transformer failures can be defined and summarised as mechanical failure, dielectric failure and thermal failure according to the mechanism causing the failure. Each failure mechanism is introduced in the following parts. However, thermal failure is of most interest in this literature review. Thermal failure can be further broken down into long-term and short-term failures. Long-term failure is due to the
ageing of insulation cellulose of transformers which reduces the mechanical strength of the paper insulation and eventually causes breakdown when the paper insulation is mechanically worn up. The short-term failure is caused by bubbling triggered by excessive temperature of the hot-spot, which dramatically reduces the dielectric strength of the liquid insulation and eventually causes breakdown. Literature review of transformer end-of-life is organised according to the framework illustrated in Figure 2-1.

The concept of the transformer failure can be illustrated by Figure 2-2 [20, 21], where the failure “occurs when the withstand strength of the transformer with respect to one of these key properties is exceeded by operational stresses”, and the “key properties” refer to the mechanical, dielectric and thermal strength of the transformer [20]. It can be seen that the transformer’s actual withstand strength is declining with the transformer age. Furthermore, each disturbance event the transformer experienced would reduce its withstand strength. A simplification in Figure 2-2 is that the operational stress remains unchanged, but it is more likely to increase with the transformer age due to the growth of the load. The influence of the maintenance is not reflected in the figure, which would reinforce the withstand strength of the transformer and extend its life.
In accordance to the specific function that is associated with the failure, the transformer failure modes can be developed as the mechanical failure, the dielectric failure and the thermal failure [22, 23]. Note such a classification is not necessarily a rigorous taxonomy. Take an instance, transformers under excessive thermal stresses would eventually fail due to breakdown of their insulation systems, thus such failures can be understood as thermal failures or/and dielectric failures at the same time.

### 2.1.1 Mechanical failure

The mechanical failure is normally associated with overcurrents, fault currents caused by short-circuits or inrush currents. Such incidents cause extra leakage flux and induce excessive mechanical forces between components of the mechanical system of transformers such as the clamping, leads support and windings. The consequence would be the displacement of the winding structure. Severe displacement would cause issues such as the collapse of windings or winding supports, buckling of windings and etc. These issues lead to the failure of the solid insulation of transformers and result in transformer failures. Around 10% of transformer failures are due to the replacement of windings caused by short-circuit mechanical stress [24]. Figure 2-3 gives two examples of the bulking of winding and the collapse of winding support.
2.1.2 Dielectric failure

The dielectric failure is the predominant failure mode of transformers, which accounts for 35% to 50% of transformer failures [24]. The dielectric failure is associated with breakdown of transformer insulation systems. It could be triggered by overvoltages such as lightning and switching impulses. It also could be caused by the contamination of the oil, which gradually reduces the dielectric strength [24]. Transformers fail due to oil breakdown when their dielectric strength drops to the point that is no longer capable of withstanding the operational electrical stresses.

2.1.3 Thermal failure

The thermal failure is associated with overheating of transformers. The overheating will accelerate the ageing of the oil and the paper insulation. Ageing of oil could generate water and acids, which accelerate the paper ageing. Also, the insoluble compound such as sludge accumulated during oil ageing could block the oil flow and eventually promote temperature rise in paper insulation and therefore boost its ageing. Ageing in paper insulation would deteriorate its mechanical strength. Localised heating would generate the hot-spot area of the winding, where the hottest temperature inside the transformer is located. The fastest ageing of the paper insulation is found at this point, thus the weakest point of the paper insulation of the transformer. Failure at the weakest point of the paper insulation due to the degradation of its mechanical strength will lead to the electrical breakdown, thus the transformer failure [26]. So the transformer’s ultimate life can be defined by the life of its paper insulation at the weakest point, when the DP drops to 200. The ageing of the insulation is a long-term process.
In the short-term, the overheating of transformers could cause the evolution of gas bubbles, which have a significantly reduced dielectric strength than the liquid or solid insulation, and the breakdown would be triggered if the simultaneous electrical stress exceeds the dielectric strength of gas bubbles.

The key factor affecting the transformer paper ageing and the formation of bubbles is the internal temperature, especially the hot-spot temperature (hottest temperature inside the transformer). For transformers, their internal temperature is determined by the loading. Thus the loadability of transformers is primarily limited by the internal temperature in order to have an acceptable ageing rate of the paper insulation and avoid the bubble formation. Literature reviews of the ageing of transformer paper insulation and the formation of bubbles are presented in this chapter.

### 2.2 Ageing of transformer cellulose insulation

Cellulose materials such as paper and pressboard are basic insulation materials used in transformers [27] (dry-type transformers are not using cellulose insulation, however, they are beyond the scope of this thesis and therefore not discussed). They have been used in transformers ranging from 10 kVA to 1500 MVA since as early as the 1920s [28], and are still the most economic solid insulation by far. Cellulose has never been found pure in nature, but it is the most important composition of plant fibres [27]. More than 95% of cotton fibre is cellulose, and 40 to 55% of the dry weight of wood is cellulose [27]. Therefore, to make cellulose materials for electrical insulation, the most common sources of cellulose are wood pulp and cotton lint. Depending on the purpose of use, different types of cellulose materials such as Kraft paper, cotton paper and pressboard can be made from cellulose pulp.

Cellulose materials are used to provide two purposes in transformers. Firstly, they can act as electrical insulators as inter-turn insulation, inter-disc insulation and inter-winding insulation. Secondly, they are used to provide mechanical support for windings since they have good geometric stability in oil [24].

One disadvantage of cellulose materials is that its ageing process is irreversible. The transformer operation would be affected by the ageing of cellulose insulation. Although it has been confirmed by experiments and field experiences that dielectric strength of cellulose paper are hardly degrading with ageing if there are no mechanically disturbances [29], the
mechanical strength is reducing significantly with ageing, which makes the paper insulation turn brittle and eventually cause breakdown due to mechanical wear [30]. Complex chemical reactions are involved in the degradation of mechanical strength of paper insulation, which are the key element to understand the transformer failure due to the ageing of paper insulation and will be discussed in the following part.

To understand the ageing of cellulose materials, it should be starting from the structure of cellulosics, which is the fundamental composition of cellulose materials. Figure 2-4 shows the structural of cellulose from fibre level down to molecular level.
It is generally accepted that the cellulose is a linear condensation polymer consisting of anhydroglucose joined together by glycosidic bonds [27]. The average number of glycosidic rings in a cellulose macromolecule is known as the Degree of Polymerisation (DP) [27]. DP is applied as a measure of the ageing status of the cellulose [31], where more and more glycosidic rings breaks and the DP value decreases during the ageing. The breaking of glycosidic rings shortens the molecular chain of cellulose, which can be reflected on the physical property of cellulose materials as the decrease of its mechanical strength. Therefore, DP is also a measure of the mechanical strength of cellulose materials.

The other measure of the mechanical strength and the ageing status of cellulose materials is the Tensile Strength (TS), which indicates the maximum tolerance of the exerted physical force it breaks [32]. Comparing to DP, TS is less used when assessing the ageing of cellulose materials in transformers, because it is not easy to measure the TS of the insulating paper of transformers in service due to the difficulty in taking samples [24].

In cellulose materials, a strong correlation has been found between TS and DP. A typical relationship of DP and TS is shown in Figure 2-5, where the tensile index is the ratio of TS \((N/m)\) to the paper’s basis weight \((g/m^2)\). When considering the degradation of one particular cellulose material, the basis weight is a constant. Therefore, the tensile index can be representative to the TS.
Figure 2-5: Correlation between DP and TS for Kraft paper [24, 33]

Since TS and DP are recognised as indicators of the ageing of the paper insulation, the end of life criteria of the paper insulation can be defined by either TS or DP. The transformer’s life ends when its paper insulation fails, so TS and DP can also be used to define the end-of-life criterion of transformers.

**2.2.1 Transformer end-of-life criteria based on DP and TS**

The criterion for transformer end of life by using TS has always been debated. The early consensus of 50% retention of TS was suggested by Montsinger [34], Shroff [35] and McNutt [36]. However, since many transformers with less than 50% TS retention continue operating well, lower values of TS retention have been suggested such as 20% or 25% [37].

New Kraft paper has the DP value in the range between 1000 to 1200 and it will be around 1000 after the factory drying process for transformers [33]. Diverse DP values ranging from 100 to 250 have been used as the end of life criterion [35, 38-40]. Shroff [35] was using 250 in his experiments. Lampe [39] suggested to use the DP value of 200. Fabre and Pichon [40] proposed to use the DP value between 100 and 200. Bozinni [38] suggested to use the DP value between 100 to 150. Now generally, DP of 200 is taken as end of life criterion, which is equivalent to 20% retention of TS and it is accepted as end of life criterion in the IEEE loading guide [37, 41]. Table 2-1 shows the benchmark values of normal insulation life for a well-dried, oxygen-free system which are applied in both of IEEE and IEC loading guides [11, 15].
As shown in Table 2-1, the insulation life is given under certain conditions including moisture level, oxygen level and reference temperature. This is because the ageing of cellulose insulation in transformers is affected by several factors such as water, oxygen, temperature and etc. Influences of these factors on ageing of cellulose insulation are discussed in the following part.

### 2.2.2 Ageing factors of the cellulose insulation

- **Temperature**

Temperature is the driving force of the ageing of cellulose. With the elevation of temperature, the ageing rate is increased, which is generally accepted that the ageing rate doubles for each 6°C increase [11]. Also, with the increase of temperature, different mechanisms are dominating the ageing process, which will be discussed later in the section.

- **Oxygen**

Oxygen in a free-breathing transformer comes from the atmosphere and eventually reaches inside of the tank through breather and oil conservator. The degradation of solid insulation starts with oxygen under a low-water and no-acids environment [33]. Laboratory experiments show that the degradation rate of the solid insulation is less than doubled when the oxygen exits, comparing to the situation that the oxygen is totally excluded [24]. When the oxygen exists, its influence on ageing rate of solid insulation is varying with its concentration in transformer oil, where a higher concentration would yield a higher ageing rate [42]. Experiments show that the rate of degradation of the solid insulation system is five times

---

Table 2-1: Normal insulation life of a well-dried, oxygen-free thermally upgraded insulation system at the reference temperature of 110°C [11, 15]

<table>
<thead>
<tr>
<th>Basis</th>
<th>Normal insulation life</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hours</td>
</tr>
<tr>
<td>50% retained TS</td>
<td>65000</td>
</tr>
<tr>
<td>25% retained TS</td>
<td>135000</td>
</tr>
<tr>
<td>20% retained TS (200 retained DP)</td>
<td>150000</td>
</tr>
<tr>
<td>Distribution transformer</td>
<td>180000</td>
</tr>
</tbody>
</table>
lower if the oxygen level in the transformer oil is below 2000 ppm compared to the free breathing condition where the oxygen level could be 20,000 ppm [43].

- **Water**

Water is recognised as a major factor accelerating cellulose materials ageing, and therefore enormous efforts are made in the industry to process cellulose materials as dry as possible when they are used for transformer insulation due to their hygroscopic nature [21]. Water in operating transformers may come from the atmosphere, and also it can be generated as a by-product of the insulation ageing. [33] estimates that, during the ageing of insulation paper, the water content in paper increases by 0.5 % when the paper’s DP has.

Water is a much more effective factor in accelerating paper ageing comparing to oxygen. Since the presence of water would not only result in accelerated ageing, but also reduce the PD inception voltage [28]. For example, [44] shows that the ageing rate doubles when the water content changes from 0.75% to 2.5%. The rate of degradation of paper with 4 % water content can be 20 times higher than that of dry paper [45]. Figure 2-6 shows the effects of water content in paper on the paper’s DP reduction [46]. It shows that the decrease of DP is proportional to the initial moisture content at the beginning (until month 2), which is followed by a decreased rate of reaction (month 2 to 6). After month 6, the additional moisture ingress is manually introduced to three tests subjects, which results in a rapid decrease of DP until the value of end-of-life.

![Figure 2-6: Influence of water content in paper on its DP reduction](image)

- **Acid**
Acid also acts as an important role in the ageing of cellulose materials. Acid comes from the ageing of paper and oil inside the transformer. The dissociation of acids provides H+ in the system and accelerates the depolymerisation of paper, i.e. the ageing process [33]. It has been found that low molecular weight water-soluble acids are more efficient than the larger hydrophobic acids when catalysing the hydrolysis process [47]. It can be seen from Figure 2-7. The figure shows that the ageing rate is hardly changed by large carboxylic acids like stearic and naphthenic acids, where their DP reduction curves are almost overlapped with the curve representing no acids. On the comparison, other low molecular weight acids significantly accelerate ageing. For example, it takes around 100 hours for the DP to reduce to 400 when Formic acid exits, which is one fourth of the time that is required when no acids present.

![Figure 2-7: Acid influence on reduction of DP from hydrolysis [47]](image)

### 2.2.3 Mechanism of ageing of cellulose insulation

It is commonly accepted that cellulose ageing may be described by three degradation mechanisms which are oxidation, hydrolysis and pyrolysis [27, 33, 35, 36, 48]. In the following part, each mechanism is studied separately. However, in a real transformer, these mechanisms more likely function in a synergetic way [21].

- **Oxidation**
Oxidation is the dominating ageing mechanism when the temperature is below 60°C [24]. During the oxidation, oxygen from air ingress is the oxidising agent. The oxidation starts when the hydroxyl (OH-) groups in cellulose structure are attacked by oxygen, which weakens the glycosidic bond. The ultimate products of oxidation are water, acid and carbon dioxide.

Oxygen is the primary factor during oxidation, and other factors affecting the oxidation include metal ions, which act as catalysts to accelerate the oxidation. Also, oxidation is promoted in an alkaline environment [24].

- **Hydrolysis**

Hydrolysis is the main paper ageing mechanism in transformers, which dominates at a moderate temperature level ranging from 60°C to 150°C [24]. The functioning factors during hydrolysis are water and acid, which are the products of oxidation. Acid provides H+ ions, with the existence of water and H+, the cellulose linkages are hydrolysed and produces more water and carboxylic acids. This process results in the accumulation of water and acids, which further reinforce the hydrolysis. So the hydrolysis is an auto-catalysed process [49]. Other by-products of hydrolysis include furan compounds and carbon oxides.

- **Pyrolysis**

During the pyrolysis, the glycosidic rings are broken directly by thermal destruction without the existence of water and oxygen [24]. Water and gasses like carbon monoxide / carbon dioxide are the products of pyrolysis. Pyrolysis only initialises at a temperature higher than 150°C. Since this temperature is too high that the insulation of transformers barely reaches, pyrolysis is usually ignored when considering the ageing of the cellulose insulation system of an in-service transformer.

As a brief summary, Figure 2-8 provides a comprehensive view of interlinks between affecting factors and mechanisms during the ageing of cellulose materials.
2.2.4 Ageing models of cellulose insulation

As aforementioned, although both of DP and TS can be implemented as indicators of the ageing status of cellulose insulation, DP is a preferred choice due to the difficulty in measuring TS. The ageing of cellulose insulation has been modelled by the reduction of DP values.

Dating back to 1936, Ekenstam [50] found the direct relationship between the reciprocal of DP and the ageing rate of the cellulose as
\[ \ln(1 - \frac{1}{DP_t}) - \ln(1 - \frac{1}{DP_0}) = -k \times t \]  

(2-1)

where \( t \) is the thermal ageing time and \( k \) is the ageing rate. Subscripts \( t \) and \( 0 \) correspond to value at time \( t \) and \( 0 \) respectively.

This relationship has been simplified as Equation (2-2), which has widely been used to describe the kinetics of cellulose insulation due to its simplicity and adequacy.

\[ \frac{1}{DP_t} - \frac{1}{DP_0} = k \times t \]  

(2-2)

In 1947, Dakin [51] proposed a model linking the ageing rate with the temperature by using the Arrhenius equation as

\[ k = A \times e^{-E_\lambda/(R \times \theta)} \]  

(2-3)

where \( k \) is the ageing rate, \( A \) is the pre-exponent factor, \( R \) is the gas constant, \( E_\lambda \) is the activation energy, \( \theta \) is the temperature in Kelvin.

The advantage of the Arrhenius equation is that it links the ageing rate with the temperature, which is the hot-spot temperature when considering the ageing of the cellulose insulation of transformers. It also has been found that values of the pre-exponent factor and the activation energy are different during the different stages of the ageing under various water and oxygen conditions. According to McNutt’s review in 1992 [36] and Emsley’s review in 1994 [48], the \( E_\lambda \) value derived by different researchers varies from 76 to 150 kJ/mol. CIGRE working group A2.24 in 2009 [24] recommends different values of \( E_\lambda \) and \( A \) under different ageing mechanisms as shown in Table 2-2. Pyrolysis is not considered since it only dominates the ageing at high temperatures usually over 150°C, under which the predominant concern would be short-term failure hazard instead of ageing [24].
Table 2-2: Arrhenius equation constants under different oxygen and moisture conditions [24]

<table>
<thead>
<tr>
<th>Ageing mechanism</th>
<th>Oxidation</th>
<th>Hydrolysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paper condition</td>
<td>Dry, oxygen access</td>
<td>1% moisture</td>
</tr>
<tr>
<td>B (kJ/mol)</td>
<td>89</td>
<td>128</td>
</tr>
<tr>
<td>A (hour⁻¹)</td>
<td>4.6 × 10⁵</td>
<td>8.7 × 10¹⁰</td>
</tr>
</tbody>
</table>

A simplified version of the Arrhenius equation is applied for the transformer paper ageing rate in the IEEE loading guide [15]. By setting up a reference temperature of 110°C for thermally upgraded paper, the relative ageing rate is defined and applied in the IEEE loading guide as shown in Equation (2-4).

\[
V = \frac{\text{ageing rate at } \theta_h}{\text{ageing rate at } 110\degree C} = e^{\frac{15000}{110+273} - \frac{15000}{\theta_h+273}}
\]  \hspace{1cm} (2-4)

where \( V \) is the relative ageing rate, \( \theta_h \) is the transformer hot-spot temperature.

The other way to define the insulation paper ageing rate is originated by Montsinger [34] in 1930, who observed the deterioration of mechanical strength of paper insulation doubles for each 5 to 10°C increase in temperature. Actually, the doubling factor is not a constant. It is about 6°C in the temperature range from 90 to 110°C and 8°C for temperature above 120°C [41].

However, people tend to use the doubling factor as a constant and IEC loading guide [11] uses 6°C, which is referred as the “6°C rule”. A relative ageing rate is derived based on the 6°C rule and applied in IEC loading guide. In IEC loading guide, by using 98°C as the reference temperature for Kraft paper, the relative ageing rate can be expressed as Equation (2-5).

\[
V = 2^{\frac{\theta_h-98}{6}}
\]  \hspace{1cm} (2-5)

Since the end-of-life of the paper insulation is also considered as the end-of-life of transformers, the ageing rate of the insulation is also regarded as the ageing rate of the
transformer. So based on the relationship between the transformer ageing rate and the
temperature, the effects of temperature on transformer life depletion can then be quantified by
calculating the loss-of-life. The transformer loss-of-life can be obtained as the integration of
the thermal ageing rate with respect to the thermal ageing time as shown in Equation (2-6).

\[ L = \int_{t_1}^{t_2} V \times dt \quad \text{or} \quad L \approx \sum_{n=1}^{N} V_n \times t_n \quad (2-6) \]

where \( L \) is the transformer loss-of-life, \( V \) is the transformer ageing rate.

### 2.3 Transformer failure risks caused by bubbling

Insulation ageing can be accelerated by the increase of the hot-spot temperature of
transformers. It shortens the transformer life but it is a long term process that would not cause
immediate failure of transformers. In the short-term, heavy loading of the transformer gives a
high and fast temperature rise in the insulation. This could result in the occurrence of
bubbling in the insulation system. Gas bubbles have a much lower dielectric strength than oil
or paper insulation. So bubbles would lead to the significant drop of the dielectric strength of
the insulation system. As a result, breakdown could happen and cause the immediate failure
of the transformer.

#### 2.3.1 Mechanism of formation of bubbles

Three mechanisms have been recognised where gas bubbles could be generated [52].

1. Supersaturation of the oil with a blanket gas
2. Thermal decomposition of cellulose insulation
3. Vaporisation of absorbed moisture in the cellulose

The first mechanism occurs in transformers equipped with a gas blanket oil preservation
system, where the blanket gas is normally the nitrogen. Bubbling would occur when the
transformer is heavily loaded and the load is suddenly removed. Since the transformer tends
to cool quickly after the load is removed, the dropped temperature and the pressure would
force the gas-saturated oil to release the dissolved gas, which forms the gas bubbles [52, 53].
In this mechanism, gas bubbles would be formed in the bulk oil, also is has been reported that some bubbles can be entrapped within the conductor insulation, thus the winding dielectric strength is also reduced [54].

For the other two mechanisms, the involved gas is comprised of water vapour, carbon monoxide, carbon dioxide and water vapour. Carbon monoxide and carbon dioxide are produced during the ageing of cellulose insulation. The water content is partly from the ageing and partly from the releasing of the absorbed moisture from the cellulose insulation. The process of the evolution of bubbles of these two mechanisms can be explained as follows [55].

Initial pores on the surface of the insulation paper can be filled with water vapour and dissolved gases. When the temperature of the insulation paper is rapidly increased under overloading occasions, the pores would expand to contain more water vapour from the paper which is driven out by the high temperature. Eventually, the pores would be large enough to release free gas bubbles [55].

From a physical point of view, the criterion of the formation of bubbles is that the internal pressure of the bubble should overcome the hydrostatic pressure along with the interfacial tension [55]. This criterion can be express as the relationship shown in Equation (2-7).

\[
\text{\textit{P}}_{\text{internal}} > \text{\textit{P}}_{\text{external}} + \text{\textit{P}}_{\text{interfacial tension}}
\]

(2-7)

2.3.2 Investigations on formation of bubbles

In the 1970s, Kaufmann [56] conducted a series of rainfall tests on a new distribution transformers rated 37.5 kVA in order to investigate the operating conditions that result in bubbling. The transformer had thermocouples installed for the measurement of hot-spot and top-oil temperatures. In addition, two observation ports were equipped on the transformer tank in order to observe the bubbles during the test. In the test, the transformer was first constantly loaded for a certain period, and normally the period was long enough for the transformer to be thermally stabilised. Then the rainfall was initialised and maintained for 30 minutes. The rainfall was simulated by water spray. The load was cut off as soon as the rainfall started. Different load levels ranging from 100% to 175% of the rating were applied in the test. Observations made in the test are summarised as follows:
1. Bubbling usually started within 15 to 60 seconds of the start of rainfall and started to taper off after 10 to 15 minutes.

2. The bubble emission was observed mostly at or above the rated load.

3. The intensity of bubbles was dependent on the load level, where more frequency bubble streams were observed under higher loads.

4. Bubbling was observed in a special test, where no rainfall, but a load of 300% of the rated was provided for 30 minutes immediately after the constant 175% constant loadings. In this test, the bubbling was only attributed to the increased heating.

The rainfall test proves that sudden temperature and pressure drop would trigger the bubbling. Apart from the rainfall test, Kaufmann also conducted a series of impulse and AC tests on full-size transformers or winding coil models in order to investigate how the breakdown voltage is affected by bubbling [56, 57].

The impulse test was conducted on 54 new full-size commercial distribution transformers. 26 out of 54 transformers were subjected to an ageing process leading to a loss-of-life of 50% or more. 4 of the 26 aged transformers were further subjected to a vacuum process in order to remove any gas bubbles entrapped in the winding without significantly diminishing the water content of the system. During the impulse test, all transformers were broken down, and the breakdown voltages were recorded as shown in Table 2-3.

<table>
<thead>
<tr>
<th>Unaged transformers</th>
<th>kV - Crest</th>
<th>Aged transformers</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Not evacuated</td>
<td>After evacuation</td>
<td></td>
</tr>
<tr>
<td>150</td>
<td>110</td>
<td>125</td>
<td></td>
</tr>
<tr>
<td>149</td>
<td>115</td>
<td>136</td>
<td></td>
</tr>
<tr>
<td>160</td>
<td>92</td>
<td>105</td>
<td></td>
</tr>
<tr>
<td>162</td>
<td>106</td>
<td>92</td>
<td></td>
</tr>
<tr>
<td>114</td>
<td>99</td>
<td>115 (averaged value)</td>
<td></td>
</tr>
<tr>
<td>106</td>
<td>103</td>
<td></td>
<td></td>
</tr>
<tr>
<td>127</td>
<td>87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>116</td>
<td>87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>136 (averaged value)</td>
<td>100 (averaged value)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2-3: Comparison of impulse breakdown voltages of tested distribution transformers in [56]
The average breakdown voltage for unaged transformers was 136 kV. For aged transformers, the average breakdown voltages for un-evacuated and evacuated transformers were 115 kV and 100 kV respectively. Based on these results, the author concluded that approximately 42\% \left( \frac{115-100}{136-100} \times 100\% \approx 42\% \right) of the decrease in impulse breakdown strength was attributed to gas bubbles, while the remaining 58\% decline being caused by other factors. However, the test with a result of 92 kV in the “After evacuation” column is potentially suspicious since it is much deviated from other three tests. Based on this observation, assuming 92 kV is an invalid test result, then the conclusion would be modified that about 61\% (instead of 42\%) of the decrease in impulse breakdown strength was attributed to gas bubbles.

The AC test was conducted on winding coil models. Tests on new, gas-free coils showed that at 25°C and 120°C, the breakdown voltages are both 18 kV-rms for between layers and 8 kV-rms for between turns. In addition, results from tests under overload conditions, as seen in Table 2-4, confirmed that the insulation strength decreases substantially while a discharge of bubbles was in progress. However, another series of tests indicated this decrease was temporary. A few samples were overloaded to 300\% and left for 2 hours under rated load. The following breakdown tests gave an average breakdown voltage of 16 kV-rms for between layers, which was the same level before the overload (18 kV-rms). Therefore the dielectric strength would recover to the original level within about two hours after the load dropped back to rated current.

**Table 2-4: AC breakdown voltages of winding coil models during overload [56]**

<table>
<thead>
<tr>
<th>Load current (p.u.)</th>
<th>1.0</th>
<th>1.85</th>
<th>2.25</th>
<th>2.25</th>
<th>2.25</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hot-spot temperature (°C) (as start of test)</td>
<td>124</td>
<td>190</td>
<td>229</td>
<td>226</td>
<td>234</td>
</tr>
<tr>
<td>Bubble activity</td>
<td>None</td>
<td>Continuous</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Breakdown voltage (kV-rms)</td>
<td>Between layers</td>
<td>19</td>
<td>16.5</td>
<td>8</td>
<td>9.5</td>
</tr>
<tr>
<td></td>
<td>Between turns</td>
<td>10.5</td>
<td>7.5</td>
<td>7</td>
<td>6</td>
</tr>
</tbody>
</table>

More AC breakdown tests were conducted for the observation of bubble formation by GE and EPRI on winding models subjected to different loadings and hot-spot temperatures in the 1970s [58]. The temperature range for conductor hot-spot investigations was 25°C to 250 °C, covering both short-circuit and overload conditions. The test was conducted in an oil tank that was maintained at 80°C but was open to the atmosphere. Before high voltage was applied, a 30 minutes heating period was applied to permit the coil temperature to stabilise at the target level. The starting voltage was selected at 50\% of the expected failure voltage. The
voltage was applied in steps held for 1 minute each, where the step varied between 2 kV to 10 kV.

In the test, it was found that gas bubbles were first observed when the hotspot exceeds 140°C. The bubbling was moist intense during the first 15 minutes at each current level and then tended to taper off. This indicates the greatest risk of dielectric failure would occur during a sudden load change. From Figure 2-9, it can be seen that the breakdown strength decreases sharply when the hot-spot temperature is above 150°C, which indicates the occurrence of bubbling and the consequent reduction of dielectric strength of the insulation system. However, due to the lack of data in the dash area, it may be difficult to conclude that how fast the dielectric strength is decreasing with the hot-spot temperature. As shown in Figure 2-10, up to approximately 150°C the decrease in dielectric strength was roughly 5% for every 25°C increase in temperature. Above 150°C, depending on the type of conductors, the dielectric strength showed a sharp drop. Also in Figure 2-10, for wetter cellulose insulation, the sharp reduction of breakdown strength can be seen at temperature as low as 100°C, indicating the aged transformers are more susceptible to bubbling and reduction in dielectric strength.

![Figure 2-9: AC breakdown voltage of winding coil models](image)
AC tests in [58] showed that the evolution of gas bubbles can be triggered by high hot-spot temperatures. But the initiation temperature is strongly affected by the moisture content level. Same conclusions can be found in [28, 52, 55, 59-61].

Apart from the absolute temperature and the moisture level, Koch and Tenbohlen also emphasised the crucial importance of the rate of the hot-spot temperature rise for the bubble emission [59]. For low rise rates (<3K/min), no bubble emission was observed in the test since the water only diffuses into the oil without forming gaseous pores. Figure 2-11 marks the hot-spot temperature gradient that is necessary to release the water in the form of bubbles.

The inception temperature of the bubble formation can also be affected by other factors besides the moisture level. Oommen in [62] found that a static head of oil over the heated
conductor can elevate the temperature for bubble formation by 20 to 25 degrees as shown in Table 2-5.

**Table 2-5: Effect of static head of oil on critical temperature for bubble evolution [62]**

<table>
<thead>
<tr>
<th>Static head (inch)</th>
<th>Critical temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>133</td>
</tr>
<tr>
<td>12</td>
<td>141</td>
</tr>
<tr>
<td>24</td>
<td>146</td>
</tr>
<tr>
<td>36</td>
<td>150</td>
</tr>
<tr>
<td>48</td>
<td>154</td>
</tr>
<tr>
<td>60</td>
<td>157</td>
</tr>
<tr>
<td>72</td>
<td>160</td>
</tr>
</tbody>
</table>

In addition, an initial stabilised load condition can reduce the local moisture concentration around the hot-spot (drying effect) and elevate the bubble inception temperature by 15 to 25 degrees [62] as shown in Table 2-6.

**Table 2-6: Effect of initial stabilised load on critical temperature for bubble evolution [62]**

<table>
<thead>
<tr>
<th>Prior load (p.u.)</th>
<th>Critical temperature range (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>146 – 147</td>
</tr>
<tr>
<td>0.25</td>
<td>149</td>
</tr>
<tr>
<td>0.5</td>
<td>157</td>
</tr>
<tr>
<td>0.75</td>
<td>164 – 154</td>
</tr>
<tr>
<td>1.0</td>
<td>171 – 175</td>
</tr>
</tbody>
</table>

### 2.3.3 Modelling of bubbling inception temperature

Oommen in [55] proposed a model for the calculation of bubbling inception temperature in transformers based on the relationship in Equation (2-7), which reveals that bubbling occurs when the internal pressure when the bubble is forming exceeds the sum of the total external pressure and the interfacial tension. However, the interfacial tension is neglected in Oommen’s model mainly due to the fact that when free bubble is formed inside the transformer, the interfacial tension is small enough to be ignored comparing to the external pressure. Interfacial tension is reversely proportional to the radius of the bubble, and it can be so large to collapse a bubble at its initial stage with a very small radius. Therefore, it is agreed by bubble dynamic experts that a free bubble is not formed in oil, but in a pore of the insulation surface. With the accumulation of water vapour and dissolved gasses inside a pore during overheating of the insulation paper, the pore would expand and eventually be large enough to release its water and gas content as a free bubble.
The internal pressure when a bubble is forming is contributed by water vapour and gases. Oommen’s model first only considered the water vapour and obtained an equation linking the temperature with water vapour pressure as:

\[ T = \frac{6996.7}{(22.454 + 1.4495 \times \ln W - \ln P)} \] (2-8)

where \( T \) is the temperature in K; \( W \) is water content in paper in % and \( P \) is the total pressure in torr.

To take the pressure attributed by gases, an empirical term is added to Equation (2-8) in order to fit the experiment results, and the final form of the model is shown as:

\[ T = \frac{6996.7}{(22.454 + 1.4495 \times \ln W - \ln P)} - e^{0.473/W} \times (G/30)^{1.585} \] (2-9)

where \( G \) is the gas content in %.

To obtain the bubbling inception temperature \( T \) using Equation (2-9), the total pressure \( P \) should be inputted as the total external pressure which should be the sum of atmosphere pressure plus oil pressure.

With Equation (2-9), the bubbling inception temperature is now determined by three parameters, among which the water content in paper is still the dominating factor. Experiments have shown in Figure 2-12 that bubbling inception temperature is hardly affected by gas contents at low moisture levels. Only when moisture value is high, above around 3% according to Figure 2-12, a significant impact can be observed.
Oommen also verified his model by comparing predicted bubbling inception temperatures with observed ones in a series of tests as shown in Figure 2-13, where the largest deviation is 8.6% underestimation in test No. 3. The average error is 4 K, and in percentage is 1.84%. The agreement between the observed and predicted values is good. One potential concern is that the observed values are made in the tests which are conducted on test tanks which are much simpler than a real transformer.

In summary, the transformer life will end when the paper insulation is mechanically worn out due to thermal ageing or when bubbling occurs under high hot-spot temperatures induced by high loads. Thermal ageing and bubbling can be therefore recognised as the long term and
short term thermal risks of transformers. In this thesis, long term and short term thermal risks as described in this chapter are assessed for distribution transformer population.

Hot-spot temperature is the primary factor affecting both of long term and short term thermal risks. Hot-spot temperature indicates the hottest location on the transformer winding, where the weakest point of the paper insulation is located. Thermal ageing rate is non-linearly increasing with the hot-spot temperature, and can be quantified by IEC ageing model with the hot-spot temperature. Bubbling occurs when the critical temperature is reached, which is determined by a few factors including the moisture in paper, gas content and oil pressure. However, the moisture in paper is identified as the dominant factor. In this next chapter, a literature review is presented introducing how the transformer thermal performance, especially the hot-spot temperature is assessed.
The transformer thermal performance can be determined by specifying the average winding temperature rise, hot-spot temperature rise and top-oil temperature rise over ambient [24]. Lower temperature rises indicate better thermal performance.

The thermal performance of transformers can be experimentally assessed by the heat run test, in which the top-oil and the average winding temperature rises are obtained. However, the hot-spot temperature cannot be measured directly during the conventional heat run test. Thus there has been a long-standing desire to have instrumentation available for direct measurement of hot-spot temperatures. Many attempts have been made to develop reliable measuring devices. Optic fibre sensors have been proposed as an approach to the direct measurement of actual transformer winding temperatures and they have been increasingly used since the mid-1980s [63-66].

However, due to the cost restriction, not every transformer can be installed with optic fibre sensors. A modelling approach has been developed to mathematically estimate the hot-spot temperature under arbitrary load profiles. This chapter includes an extensive literature review on experimental and simulation approaches of assessing transformer thermal performance including direct measurement, heat run test and thermal modelling. A brief comparison of three methods is shown in Table 3-1 in terms of requirement, advantage and disadvantage. In addition, the literature review of transformer thermal performance is organised based on the framework shown in Figure 3-1.
Table 3-1: Comparison of three methods of assessing transformer thermal performance

<table>
<thead>
<tr>
<th>Method</th>
<th>Requirement</th>
<th>Advantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct measurement</td>
<td>Optic fibres installed at top-oil and hot-spot locations</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1. Most accurate.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Reliable for monitoring purpose.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1. Cost to install optic fibres.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Not widely available for existing transformers.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3. Hot-spot location must be found.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4. Only for monitoring, unable to predict.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1. Cost to perform.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Not for monitoring nor predicting purposes.</td>
</tr>
<tr>
<td>Thermal modelling</td>
<td>Mathematic model and corresponding input data</td>
<td>1. Depending on model, could be applied for monitoring and predicting purposes under arbitrary loads.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. No cost induced.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1. Accuracy depending on the model and input data.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2. Input data may be not available.</td>
</tr>
</tbody>
</table>

Figure 3-1: Organisation of literature review of transformer thermal performance
3.1 Direct measurement of winding temperatures with optic fibre sensors

3.1.1 Principles and specifications of optic fibre sensors

The principle of the temperature measurement using optic fibre probes is either based on the wavelength change of visible or ultraviolet light with temperatures; or the variation in phosphor fluorescent decay time with temperatures. The temperature-dependent light signal transmits via the optic fibre and reaches the receiver at the other end so that the temperature can be decided by observing the change of the wavelength or the phosphor fluorescent decay time.

Optic fibre sensors used for the measurement of transformer winding temperatures are robust in its working environment with a good accuracy of ±1°C. A large measurement range is provided from -40 to 225 °C, which safely covers the operating temperatures of transformers. Also, experiences have indicated the natural resistance to the electromagnetic noise of optic fibre sensors [67]. The usage of optic fibre sensors is restricted mainly by its cost. It is difficult to justify in terms of costs and returns to install optic fibre sensors for every new transformer. But optic fibre sensors tend to be installed in prototype transformers in order to understand the thermal performance of a group of transformers for which a prototype transformer represents. Another shortage of optic fibre sensors is that they are mechanically fragile and highly vulnerable to physical damages, thus careful installation is required [22].

3.1.2 Installation of optic fibre sensors

Optic fibre sensors are often placed in slots inside the spacers and inserted into windings. The slot must be arranged to position the sensor tip at the measurement location. The spacer should be wedged in windings slowly without damaging the insulation. Figure 3-2 shows a spacer with an optic fibre sensor installed in it.
The number and the location of sensor deployment is the key to the correct measurement of the hot-spot temperature. In order to answer the question that how many optic fibre sensors should be used to detect the real hot-spot, the working group CIGRE WG 12.09 [69] sent the question to different countries. According to the answers received, 2 to 8 sensors would be enough for standard transformers, and 20 to 30 sensors would be enough for prototype transformers. A compromise is necessary between the necessity of inserting a large number of sensors to locate the hot-spot and the additional costs and efforts caused by sensors. The recommendations of the location of the sensors made in [69] is to place the sensors in the uppermost disc or turn, between conductors or in spacers, with the circumferential position varied.

However, although the conductors near the top of the winding experience the maximum leakage flux and highest surrounding temperatures, it has been shown by measurements that the hottest spot might move to lower conductors [11, 68]. Therefore, it is recommended that the sensors should be distributed among top few conductors of a winding [68]. Also it is recommended in [68] that sensors should be installed in different windings, since the real hot-spot location could change from one winding to another when the load current changes [70].

An example is presented here to show how optic fibre sensors are implemented for the measurement of the hot-spot temperature. The example is taken from [68]. 20 optic fibre sensors from Nortech are installed in the 400 MVA 410/120 kV transformer. In both windings, 8 sensors are installed in the three top discs / turns. The sensors are inserted in radial spacers before the spacers are installed in the winding. Locations as well as the
measurements at the end of 1.6 p.u. overload test are shown in Figure 3-3 and Figure 3-4. The numbers are temperature measurements that are taken as temperature rise above the ambient temperature, which is 25.6°C in this context. The measurements also verify that the hottest temperature is between the 3rd and 4th discs from the top, but not on the top disc.

Figure 3-3: Local temperature rises above air temperature in the LV (125 kV) winding at a load of 1.6 p.u. [68]

Figure 3-4: Local temperature rises above air temperature in the HV (410 kV) winding at a load of 1.6 p.u. [68]

As a brief summary, direct measurement is the ideal approach for the determination of hot-spot temperatures of transformers. Optic fibre sensors have been therefore developed and used for the direct measurement of hot-spot temperatures in transformers. In order to identify the real hot-spot on transformer windings, a number of optic fibre sensors should be installed. It is found that the hot-spot is located on the position that is a fewer turns / discs lower than the top. However, due to the cost restriction, only a small number of transformers have optic fibre sensors installed; therefore, alternative methods have been developed to assess the transformer thermal performance.
CHAPTER 3   TRANSFORMER THERMAL PERFORMANCE AND EVS IMPACTS ON DISTRIBUTION TRANSFORMERS

3.2 Heat run test

Heat run test or also known as temperature rise test, is a type test [12]. It is made on a transformer to demonstrate that it complies with specific requirements that are not covered by routine tests. The maximum limit of temperature rises for hot-spot rise and top-oil rise are specified in IEC and IEEE loading guide shown in Table 3-2.

<table>
<thead>
<tr>
<th></th>
<th>IEC (ambient assumed as 20°C)</th>
<th>IEEE (ambient assumed as 30°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top-oil temperature rise</td>
<td>60 K</td>
<td>65 K</td>
</tr>
<tr>
<td>Average winding temperature rise</td>
<td>65 K for ON and OF</td>
<td>65 K</td>
</tr>
<tr>
<td></td>
<td>70 K for OD</td>
<td></td>
</tr>
<tr>
<td>Hot-spot temperature rise</td>
<td>N/A</td>
<td>80 K</td>
</tr>
</tbody>
</table>

The purpose of the heat run test is to establish and measure the stabilised oil and winding temperatures. Traditionally, the top-oil and bottom-oil temperatures are measured by thermocouples. Ideally, the top-oil and bottom-oil temperatures should be measured at the top and bottom locations of the transformer oil. However, in practice, the top-oil temperature is often measured at the surface of the tank or radiator at the top location; or inside the top bulk oil through an oil pocket. The bottom-oil temperature is measured at the surface of the tank or radiator at the bottom location.

3.2.1 Short-circuit method to perform heat run test

Short-circuit method is the most frequently used method to perform heat run test. In the short-circuit method, one winding of the transformer is short-circuited and the power is supplied to the other winding. Normally the test starts with a supplied power equal to the total loss of the transformer under the rated load. The test current at this moment is larger than the rated current in order to provide additional losses equal to the no-load loss. The aim of the total loss supply is to establish the stabilised oil temperature, therefore it should terminated after the rate of the change of top-oil temperature rise has fallen below 1K per hour and has remained for at least 3 hours. The steady-state top-oil and bottom-oil temperature is taken as the average value of the temperature during the last hour.
After the total loss injection, the supplied current is reduced to the rated current in order to provide the load loss only. The load loss injection normally lasts for 1 hour. At the end of the hour, the resistance of the winding is measured, based on which the average winding temperature can be calculated.

### 3.2.2 Heat run test regimes

Practical heat run test regimes can be summarised as the conventional heat run test and the extended heat run test [71, 72]. The schemes of two heat run test regimes are illustrated in Figure 3-5.

![Conventional heat run test](a)

![Extended heat run test](b)

Figure 3-5: Two regimes of heat run test. (a). Conventional heat run test. (b). Extended heat run test

The procedure of the conventional heat run test is introduced in IEC 60076-2 [19] and IEEE C57.12.90 [72]. The conventional heat run test provides temperature information including the ambient, stabilised top-oil, bottom-oil and average winding temperatures.
Occasionally, in order to reduce the duration, the conventional heat run test starts with an accelerated heating process by a load higher than that tested load. The accelerated heating normally lasts for a few hours until the top-oil temperature reaches a level equal to around 70% of the expected stabilised value under the original test load.

To determine dynamic hot-spot temperatures under arbitrary loads, more thermal information is expected and this can be achieved by conducting the extended heat run test. IEEE C57.119 \cite{73} prescribes the extended heat run test, where the heat run test is conducted under three constant loads of 0.7 p.u., 1.0 p.u. and 1.25 p.u. separately. Each constant load test has the same procedure to the conventional heat run test, but with a different load level.

### 3.2.3 Measurements taken in heat run test

#### a. Ambient temperature measurement

Ambient temperature is taken as the temperature of surrounding air of the transformer subject to heat run test. At least three thermocouples should be placed uniformly around the transformer at a level about halfway up the cooling surfaces and distributed around the tank around two meters away. The averaged value of three thermocouples is used as the ambient temperature for the test.

#### b. Top-oil and bottom-oil temperature measurement

The top-oil temperature is conventionally measured at the bulk of oil above the winding or at the inlet of the cooling equipment. Top-oil temperature measurement at different locations could be different. As an example, Susa \cite{74} placed thermocouples at different locations to measure the top-oil temperatures in a 2.5 MVA transformer. The locations can be seen in Figure 3-6, where T1, T2, T3, T4 are top-oil thermocouples and B1, B2, B3 are bottom-oil thermocouples. T1 is placed 50 mm under the tank, right above the central line of the active part. T2 is inserted in oil pockets at each end of the tank, the distance from the tank wall to the centre of the pocket pipe is about 30 mm. T3 is on the outside surface of the tank, attached to the central line of the long side of the tank wall. T4 is in winding oil duct outlet, right in the centre of the duct. Temperatures measured by top-oil thermocouples at the end of a 515-min-long (so that the oil temperature is stabilised) 1.0 p.u. constant load are presented in Table 3-3.
According to Table 3-3, the top-oil temperature yields different values at different locations, due to the various oil circulation paths formed in the transformer tank. The lowest temperature is measured by T2, in the oil pocket. The highest is measured by T4, in the winding oil duct outlet. The difference is as large as 12.9 K.

The transformer bottom-oil temperature is identified with the temperature of the liquid returning from the cooling equipment to the tank. It shall be determined by sensors placed at the outlet of radiators, which is normally locate in the lower part of the tank, at the same horizontal level with the winding bottom. The average-oil temperature is the average value of the top-oil and bottom-oil temperatures.

c. Average winding temperature

The average winding temperature is determined based on the relationship between temperature and resistance of copper or aluminium (winding conductor material). The resistance increases with the temperature since the change of resistance is proportional to the change of temperature. When determining the average winding temperature, the winding resistance is measured immediately after the power supply is turn off in the heat run test. The
measured resistance dropping curve is converted into the temperature dropping curve with equations below for copper (Equation (3-1)) or aluminium (Equation (3-2)).

\[
\theta_t = \frac{R_t}{R_a} \times (235 + \theta_a) - 235 \tag{3-1}
\]

\[
\theta_t = \frac{R_t}{R_a} \times (225 + \theta_a) - 225 \tag{3-2}
\]

where \( \theta_a \) is the ambient temperature and \( R_a \) is the reference resistance measured at ambient temperature. \( R_t \) and \( \theta_t \) are winding resistance and average winding temperature at time \( t \).

The temperature dropping curve is then extrapolated to the instant of transformer shutdown to obtain the average winding temperature during the supply of the rated load losses.

Guidance for the procedure is provided in IEC 60076-2 [19, 75]. Compared to the previous version (IEC 60076-2:1997 [75]), significant improvements have been made on the latest version (IEC 60076-2: 2011 [19]), which are briefly summarised here.

1. The time gap between the transformer shutdown and the first valid measure point recommended. It is 2 mins for transformers < 100 MVA; 3 mins for transformers from 100 MVA to up to 500 MVA; 4 mins for transformers \( \geq 500 \) MVA.

2. The total duration of the measurement is clarified, which is 20 mins for medium size transformers and up to 30 mins for large transformers.

3. A numerical method for the extrapolation of the cooling down curve is provided to replace the previous graphical method.

Although the procedure is detailed in IEC 60076-2 [19], cautions still need to be paid on some points that are essential to the correct determination of the average winding temperatures [22].

1. Precision of the resistance measurement should be guaranteed.

2. Careful measurement of the cold winding resistance is essential.
3. Fans and pumps should be left running during the determination of the cooling curve. Understand heat run test is essential in this PhD work. For existing transformers, assessment of thermal performance via direct measurement of top-oil and hot-spot temperatures is rarely possible since optic fibres are rarely installed. As a comparison, heat run test results are more obtainable, thus they are of significant importance on the assessment of thermal performance of existing transformers, and also on providing data that are potentially required for thermal modelling.

### 3.3 Transformer thermal modelling

Apart from the direct measurement or heat run test as aforementioned, thermal modelling is an alternative approach to determine the internal temperatures including the hot-spot temperature of transformers. A category of thermal models [74, 76-85] based on the thermoelectric analogy have been developed for the determination of the hot-spot temperature under overloading and dynamic loading.

#### 3.3.1 Thermoelectric analogy modelling

The analogy between thermal and electrical process is presented in Table 3-4. The thermal resistance and capacitance are defined as the ability of the material to resist and store heat respectively.

<table>
<thead>
<tr>
<th>Thermal</th>
<th>Electrical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generated heat</td>
<td>( q )</td>
</tr>
<tr>
<td>Temperature</td>
<td>( \theta )</td>
</tr>
<tr>
<td>Resistance</td>
<td>( R_{th} )</td>
</tr>
<tr>
<td>Capacitance</td>
<td>( C_{th} )</td>
</tr>
</tbody>
</table>

A brief summary of thermoelectric modelling literature is given in Table 3-5.
Selected work from the literature review is introduced in this section to demonstrate how thermal modelling is developed and the status quo.

Swift [76] was a pioneer who developed a thermal model based on thermoelectric analogy. The overall circuit model is displayed in Figure 3-7.

Swift modelled the transformer total loss as the heat source for top-oil and hot-spot. The thermal resistance and capacitance were modelled as lumped values. Considering the non-linear nature of the heat convention between oil and air, a general non-linear model was applied as presented in Equation (3-3), where $R_{th}$ is the thermal resistance, $q$ is the power losses corresponding to the heat source, and $n$ is an empirical value. The better the heat convention is, the closer to 1 $n$ should be.

$$\theta = R_{th} \times q^n$$  \hspace{1cm} (3-3)
Then the oil temperature model is derived from the oil thermal circuit as Equation (3-4).

\[
\frac{1 + R \times q^n}{1 + R} \times \Delta \theta_{ow}^n = \tau_o \times \frac{d\theta_o}{dt} + (\theta_o - \theta_a)^n
\]  

(3-4)

where \( R \) is load loss to no-load loss ratio, \( K \) is load factor. The subscripts \( o \), \( or \) and \( a \) correspond to oil temperature, oil temperature at rated load and ambient temperature respectively. \( \tau \) is the time constant, which is the product of thermal resistance and capacitance.

Swift then verified his oil temperature model in [77] on a 250 MVA power transformer under a cyclic load, where the maximum error is 1 °C when fitting his model to the measurement. But he did not continue to derive hot-spot model equations based on the thermal circuit.

Based on Swift’s work, Susa [74, 82-85] and Nordman [68, 90] developed a series of new models predicting the temperature of top oil and hot-spot. Susa was focusing on improve the modelling of non-linear thermal resistance. Nordman improved Swift’s model by modelling the overshoot phenomenon of hot-spot rise over top oil as a combined effect of hot-spot rise and top-oil rise. Both of hot-spot rise and top-oil rise are modelled in an exponential manner with different time constants. The hot-spot rise has a small time constant (e.g. 4 min) therefore it responds swiftly to the load change. The top-oil rise is lagging to the hot-spot rise due to its large time constant (e.g. 180 min). The hot-spot is first heated by total losses of transformer, and the top-oil is absorbing heat from the hot-spot. Thus the temperature difference between hot-spot and top-oil will increase until the total losses are not sufficient to provide energy required by both of hot-spot and top-oil rises, and then the temperature difference will decrease and the overshoot occurs.

\[ \text{a. Susa’s models} \]

In Swift’s model, thermal characteristics of transformer oil are assumed constant, in other words, temperature-independent. However, it is over-simplified to neglect the temperature-dependency of the thermal characteristics of transformer oil. So Susa introduced a new model in [84] to reflect the temperature-dependent thermal characteristics of transformer oil by modelling the thermal resistance as non-linear.
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According to heat transfer theories, the thermal resistance is inversely proportional to the heat transfer coefficient.

$$R_{th} = \frac{1}{h \times A} \tag{3-5}$$

where $R_{th}$ is the thermal resistance, $h$ is the heat transfer coefficient, and $A$ is the area of heat transfer.

The heat transfer coefficient can be expressed in a complex function involving transformer oil temperature and many oil thermal properties such as density, specific heat, thermal conductivity, coefficient of thermal cubic expansion and viscosity. These oil thermal properties are varying with temperature at different extents. It is presented in Table 3-6.

<table>
<thead>
<tr>
<th>Temperature $\theta$, °C</th>
<th>Density $\rho$, kg/m$^3$</th>
<th>Specific heat capacity $c_{th}$, J/(kg·°C)</th>
<th>Thermal conductivity $k$, W/(m·°C)</th>
<th>Coefficient of thermal cubic expansion $\beta$, 1/°C</th>
<th>Viscosity $\mu$, kg/(m·s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-15</td>
<td>896.885</td>
<td>1900</td>
<td>0.1262</td>
<td>8.6x10$^{-4}$</td>
<td>0.0694</td>
</tr>
<tr>
<td>-5</td>
<td>890.295</td>
<td>1940</td>
<td>0.1247</td>
<td>8.6x10$^{-4}$</td>
<td>0.0463</td>
</tr>
<tr>
<td>5</td>
<td>883.705</td>
<td>1980</td>
<td>0.1232</td>
<td>8.6x10$^{-4}$</td>
<td>0.0318</td>
</tr>
<tr>
<td>15</td>
<td>877.115</td>
<td>2020</td>
<td>0.1217</td>
<td>8.6x10$^{-4}$</td>
<td>0.0224</td>
</tr>
<tr>
<td>25</td>
<td>870.525</td>
<td>2060</td>
<td>0.1201</td>
<td>8.6x10$^{-4}$</td>
<td>0.0162</td>
</tr>
<tr>
<td>35</td>
<td>863.935</td>
<td>2100</td>
<td>0.1186</td>
<td>8.6x10$^{-4}$</td>
<td>0.0119</td>
</tr>
<tr>
<td>45</td>
<td>857.345</td>
<td>2140</td>
<td>0.1171</td>
<td>8.6x10$^{-4}$</td>
<td>0.0089</td>
</tr>
<tr>
<td>55</td>
<td>850.755</td>
<td>2180</td>
<td>0.1156</td>
<td>8.6x10$^{-4}$</td>
<td>0.0068</td>
</tr>
<tr>
<td>65</td>
<td>844.165</td>
<td>2220</td>
<td>0.1140</td>
<td>8.6x10$^{-4}$</td>
<td>0.0053</td>
</tr>
<tr>
<td>75</td>
<td>837.575</td>
<td>2260</td>
<td>0.1125</td>
<td>8.6x10$^{-4}$</td>
<td>0.0042</td>
</tr>
<tr>
<td>85</td>
<td>830.985</td>
<td>2300</td>
<td>0.1110</td>
<td>8.6x10$^{-4}$</td>
<td>0.0033</td>
</tr>
<tr>
<td>100</td>
<td>821.100</td>
<td>2360</td>
<td>0.1087</td>
<td>8.6x10$^{-4}$</td>
<td>0.0024</td>
</tr>
</tbody>
</table>

It is indicated that the variation of viscosity with temperature is much higher than others. Thus all oil parameters except the viscosity are replaced by a constant. Then the heat transfer coefficient can be expressed as:

$$h = C \times \left( \frac{\Delta \theta_o}{\mu} \right)^n \tag{3-6}$$

where $h$ is the heat transfer coefficient, $\mu$ is the viscosity, $C$ is the constant replacing all other oil parameters. $\Delta \theta_o$ is the change of oil temperature and $n$ is an empirical constant. The viscosity dependency on temperature is given by Equation (3-7).
The temperature-dependent thermal resistance expressions can be obtained by combining Equation (3-5), (3-6) and (3-7). Put the obtained expression into Swift’s model in Equation (3-4), Susa’s improved oil temperature model is obtained. By following the same principles, the hot-spot temperature model is also obtained. Equations of both models are presented below.

\[
\frac{1 + R \times K^2}{1 + R} \times \mu_{p,u.} n \times \Delta \theta_{or} = \mu_{p,u.} n \times \tau_{or} \times \frac{d\theta_{o}}{dt} + \frac{(\theta_{o} - \theta_{a})^{1+n}}{\Delta \theta_{or}^n}
\]

\[
K^2 \times P_{p,u.} \times \mu_{p,u.} n \times \Delta \theta_{hr} = \mu_{p,u.} n \times \tau_{wr} \times \frac{d\theta_{h}}{dt} + \frac{(\theta_{h} - \theta_{o})^{1+n}}{\Delta \theta_{hr}^n}
\]

where \( K \) is the load factor, \( R \) is load loss to no load loss. \( n \) is an empirical constant. The same empirical constant \( n \) is also appearing in Equation (3-3) and (3-4). \( \theta \) and \( \tau \) are temperature and time constant. The subscripts \( o, h \) and \( r \) correspond to the values of oil, hot-spot and under rated load respectively. Equation (3-8) is for calculation of top-oil temperatures; and Equation (3-9) is to calculate hot-spot temperature, which requires the top-oil temperature as an input.

In this model, the same empirical constant \( n \) is used for both of top oil and hot-spot models. Susa later improved this model by introducing different empirical constants in oil and hot-spot models in [82], which are referred as \( n \) and \( m \) respectively. Then in [83], similar models were developed on bottom-oil and hot-spot models. Also different values of the empirical constant were proposed for transformers with different cooling types. The developed models have been verified on 5 transformers with the power ratings varying from 2.5 MVA to 650 MVA.

b. Nordman’s models
Swift only gave a top oil model in [76]. It was later used as the top oil model in Nordman’s model [90]. As to the hot-spot model, Nordman developed a model for the hot-spot rise over top oil based on thermoelectric analogy.

When modelling the hot-spot rise over top oil, it is accepted that the stabilised value can be expressed as \( H \times g_r \times K^y \). Where \( H \) is the hot-spot factor, \( g_r \) is the average winding to oil gradient at rated load. \( K \) is the load factor and \( y \) is winding exponent.

The transient model of hot-spot rise over top oil is expressed as:

\[
\Delta \theta_{ho} = H \times g_r \times K^y \times f_2(t) \tag{3-10}
\]

\[
f_2(t) = k_{21} \times (1 - e^{-\frac{t}{(k_{22}\tau_o)}}) - (k_{21} - 1) \times (1 - e^{-\frac{t}{(\tau_o/k_{22})}}) \tag{3-11}
\]

where \( k_{21} \) and \( k_{22} \) are thermal constants, \( \tau_o \) and \( \tau_w \) are oil and winding time constants.

\( H \times g_r \times K^y \) in Equation (3-10) stands for the stabilised value of hot-spot rise over top-oil under load K. \( f_2(t) \) describes the relative increase of hot-spot rise over top oil based on the unit of the steady state value. It is modelled in such a way due to the observation that it always takes some time before the oil circulation has adapted its flow speed to correspond to the increased load level [68].

In other words, during a short period immediately after the load rises, the hot-spot temperature increases fast to respond to the load rise while the oil temperature is still not reacting. This consequently leads to a swift rise of hot-spot rise over top oil at the beginning time. The rise rate is mainly depending on the winding time constant. This period is normally short than 1 hour. In \( f_2(t) \), this period is described by the term of \( k_{21} \times (1 - e^{-\frac{t}{(k_{22}\tau_w)}}) \).

After this period, the oil temperature starts to increase to respond to the load rise while the hot-spot temperature almost finishes increasing. Therefore the hot-spot rise over top oil starts to drop from a peak value and converge gradually to the steady state value. The speed of
change at this stage is therefore dominated by the oil time constant. In \( f_2(t) \), this stage is described by the term of \( (k_{21} - 1) \times (1 - e^{-\frac{t}{\tau_{22}k_{22}}}) \).

\( k_{21} \) indicates the peak value \( f_2(t) \). \( k_{22} \) describes the oil temperature’s effects on oil and winding time constants. When the oil temperature increases, the oil flows faster and the speed of heat transfer between winding and oil also increases. In other words, it becomes easier for the winding to dissipate heat and the oil to absorb heat. Consequently, the growth of oil temperature gets faster but the increase of the winding temperature turns slower. Equivalently the oil time constant decreases but the winding time constant increases. The values of \( k_{21} \) and \( k_{22} \) cannot be obtained by experimental approaches, but they can be numerically obtained through curve fitting with the measurement hot-spot rise over top oil [63]. Alternatively, recommended values are provided in [90] for transformers with different cooling types. Nordman’s model has eventually been accepted by IEC loading guide in 2005, and is often referred as IEC (60076) thermal model.

c. Other models

In Swift’s model, the thermal resistance and capacitance are not appearing in the final form of the equations since they are represented as the time constant. For thermoelectric analogous models, it is not always the case. Tang [78, 79] and Radakovic [80, 81] investigated the non-linearity of thermal resistance by directly modelling the thermal conductance as follows:

\[
\Lambda = A \times \Delta \theta^n
\]  

(3-12)

Where \( \Lambda \) is the thermal conductance, \( A \) and \( n \) are constants to be determined. \( \Delta \theta \) is the related temperature change.

Tang only worked on the top oil model and applied genetic algorithm to determine the values of \( A \) and \( n \). Radakovic worked on both of oil and hot-spot models. He also developed a method to determine the values of \( A \) and \( n \) with short-circuit heat run test results [91]. The method requires measurements of input power losses, top oil temperature and hot-spot temperature. The heat run test should be conducted with more than one input power loss. With each input loss, the duration should be long enough for the top oil temperature to
stabilise. Since the thermal conductance can be expressed as the ratio of input power loss to the corresponding temperature change ($\Delta \theta$), it can be calculated based on the measured values of power loss and temperature change. With more than one input power losses, at least two points of thermal conductance against temperature change can be obtained so that the values of $A$ and $n$ can be obtained by curve fitting. Radakovic’s hot-spot model was later verified on a 630 MVA power transformer in [80] but the error observed was as large as 7.5 K.

3.3.2 IEC and IEEE loading guide thermal models

a. Thermal models in previous loading guide

Thermal models provided in the previous IEC loading guide (IEC 354:1991 [92]) and IEEE loading guide (IEEE C57.91:1995 [41]) assume that the hot-spot temperature is composed of the ambient temperature, top-oil temperature rise and hot-spot rise over top-oil.

The difference between IEC 354 and IEEE C57.91 is the modelling of hot-spot rise over top-oil. In IEC 354 it is modelled as the product of hot-spot factor and average winding to oil gradient. In IEEE C57.91 instead of using the hot-spot factor, the hot-spot rise over top-oil temperature is directly used in the modelling.

Under transient state, both models in IEC 354 and IEEE C57.91 assumes that either the top oil temperature rise or the hot-spot rise over top oil changes exponentially with time when load changes as shown in Equation (3-13). The subscripts $t$, $i$ and $u$ correspond to the value at time $t$, initial value and ultimate value respectively. However, the suitability of such modelling of hot-spot temperature is increasingly questioned due to the significance of dynamic loading and overloading, since significant underestimation is observed when using this model to predict the hot-spot temperature during dynamic loading and overloading [68].

$$\theta_i = \theta_i + (\theta_u - \theta_i) \times (1 - e^{-\frac{t}{\tau}})$$ (3-13)

b. Improvement of loading guide models

During the last twenty years optic fibre sensors have been used by many researchers such as Pierce [70, 89, 93], Nordman [68, 90], Radakovic [80, 81, 94] and Susa [74, 82, 83, 85, 95,
in order to obtain as accurate as possible values for transformer temperatures. It was then found that the hot-spot temperature calculation method given in previous IEEE [41] and IEC [92] loading guides would yield significantly low values during dynamic load conditions, especially in the case of a short-term emergency load [68]. In [68] the hot-spot temperature was measured after a 20-minute long overload of 2.5 p.u. following a preload of 0.3 p.u. The measured value is 156°C while the values calculated by thermal models in [41] and [92] are 93°C and 85°C. The underestimation is caused by that the calculated hot-spot temperature based on [41] and [92] is following an exponential rise which is too slow during the first hour after the load increase compared to the actual rise of hot-spot temperature [68].

Aubin [87, 88] and Pierce [70, 89, 93] were the first pioneers who attempted to improve the loading guide’s model. They observed the overshoot phenomenon of the hot-spot rise over top oil. To avoid directly modelling the overshoot, the hot-spot temperature calculation methods were obtained based on the bottom-oil temperature. The modelling equations from Pierce in [89] have been presented as a more complex approach for dynamic hot-spot temperature calculation in IEEE loading guide Annex G [41], which is often referred as IEEE Annex G model.

\subsection*{b.1. IEEE Annex G model}

The general equation to calculate the hot-spot temperature in IEEE Annex G model is presented in Equation (3-14).

\[ \theta_h = \theta_a + \Delta \theta_b + \Delta \theta_{do-b} + \Delta \theta_{h-do} \] (3-14)

where $\theta$ with subscripts of $h$, $a$, $b$, $do-b$ and $h-do$ respectively refer to the hot-spot temperature, ambient temperature, bottom-oil temperature rise over ambient, duct oil temperature rise over bottom-oil and hot-spot temperature rise over duct oil.

For each component of the hot-spot temperature in the equation above, the heat contributing to the temperature rise is calculated by subtracting the dissipated heat from the generated heat. Then basic heat transfer theory is applied to calculate the temperature change corresponding to the heat.
IEEE Annex G model considers the temperature-dependent variation of transformer load losses and the oil viscosity, which makes it more accurate but complex to predict the hot-spot temperature. However, in IEC 354 model and previously mentioned IEEE model (which is always referred as IEEE Clause 7 model), the effects of load loss variation and oil viscosity are considered to cancel each other. Thus neither of them is modelled in IEC 354 and IEEE Clause 7 models.

b.1. IEC 60076-7: 2005 model

As an improvement, IEC 354 model was replaced by Nordman’s model [68, 90] in IEC loading guide 60076-7 in 2005, which is now known as IEC 60076 model. A comparison between IEC 60076 model and IEEE Annex G model made in [90] shows that both models provide reasonable accuracy in hot-spot temperature prediction while the former tend to overestimate and the later tend to under-estimate. However, IEC 60076 model is simpler to use since it only requires ambient temperature and load profiles as input. For comparison, IEEE Annex G model requires extra input data that are difficult to acquire such as rated hot-spot rise and hot-spot location. The simplicity and accuracy make IEC 60076 model one of the most widely used thermal models, and therefore, it is applied in this PhD work for the assessment of thermal performance of transformer population in future EV scenarios.

Apart from input data, IEC 60076 model requires a set of parameters to reflect the thermal characteristics of individual transformers, which are known as thermal parameters. IEC loading guide [11] provides recommended values of thermal parameters for transformers of various ratings and cooling types as shown in Figure 3-8, which are considered as conservative values since overestimated hot-spot temperature would be obtained with recommended values in order to lower the operational risk by providing sufficient margins [63].
A calculation example given in the loading guide shows that an overestimation of hot-spot temperature as larger as 7 K can be resulted in by IEC 60076 model with recommended thermal parameters during overloading. According to the “6 °C” ageing rule, ageing rate resulted from estimated hot-spot temperature will be more than doubled than the actual value, which will eventually lead to a much under-estimated lifetime estimation.

Accuracy of IEC 60076 model can be improved further by refining thermal parameters for individual transformers or for a group of transformers with similar thermal design, since transformer thermal characteristics are design dependent. This PhD work has also endeavoured to propose and validate methodologies of refinement of IEC 60076 model thermal parameters.

### 3.4 EV impacts on distribution transformers

Thermal performance of distribution transformers is concerned under future loading scenarios with a large scale of EV implementation. EV charging would bring extra loads onto these distribution transformers and therefore shorten their lifetimes and even cause premature failures. Extensive endeavours have been made by researchers to simulate the potential impacts that EV charging would bring on distribution networks.

Based on literature review on EV, the academic researches of EV carried out within UK are summarised in Table 3-7.
### Table 3-7: Academic research of EV in UK

<table>
<thead>
<tr>
<th>University &amp; Main researchers</th>
<th>Details</th>
</tr>
</thead>
</table>
| **University of Manchester**  | • Impacts of G2V (grid to vehicle) and V2G (vehicle to grid) on the loading of UK electricity network are investigated.  
• Resultant loads are simulated under diverse EV scenarios by varying the penetration level and charging behaviours of EV customers. It is concluded that a significant investment in UK electrical networks will be required if BEV are the preferred route for the transportation in UK. |
| Nigel Schofield, Mike Barnes [97] | **University of Strathclyde**  | • Research efforts in [98-102] mainly focus on V2G technology.  
• EV are driven for about 5% of the time, thus in 95% of the time they can provide secondary function as responsive load [100, 101].  
• V2G services could help with voltage control, load management in the distribution network [98, 99].  
• Results shows that V2G services have only a minor impact on the network in terms of distribution system losses and voltage regulation but the vehicle owner’s costs are roughly halved and the total recharge energy is reduced significantly [98]. |
| David Infield, Andrew Cruden, [98-102] [103, 104] | • Researches in [103, 104] focus on the optimisation of EV battery efficiency and the improvement of the battery model for the power flow simulations of EV.  
• Improved model is specifically for lead-acid battery. |
| **Glasgow Caledonian University**  | • Research efforts mainly focus on the modelling of EV charging load [105-107, 109], and also extra ageing/wear cost of EV battery due to V2G service is studied [108, 110].  
• An optimisation model of EV charging load is proposed to flatten the pre-known load profile [105]. The concept is to use optimisation program to minimise the variation between the instantaneous loading and the mean daily loading.  
• Study on V2G service’s impact on wear cost of EV battery shows that V2G service is not economic for lead-acid and NiMH batteries in UK since the cost due to extra battery degradation outweighs the benefits of V2G service. Meanwhile it points out Li-ion battery can be used for V2G service thus the authors suggest future research should focus on Li-ion batteries [108]. |
| Chengke Zhou [105-110] | **Cardiff University**  | • Research efforts mainly focus on the EV’s impact on the whole distribution network.  
• Concerns over EV’s impacts on the distribution network are summarised as follows: voltage drop, transformer thermal limits, LV cable thermal limits, Network losses, voltage unbalance, under-frequency and current harmonics.  
• Researches cover all impacts except the under-frequency and current harmonics.  
• Case studies are conducted by penetrating EV in the distribution network model to observe the impact on the whole network as well as individual elements [4-7, 111].  
• [7] is a journal paper and it gives a case study on a residential UK generic network with assumed EV penetration level in UK for the year 2030. It provides a comprehensive overview of EV’s impact on the distribution network on aspects of voltage interference, load elevation, thermal aspect of transformers/cables and the power flow losses. |
| Nick Jenkins [4-8, 111] | **Imperial College London**  | • [112] proposes a novel electricity pricing mechanism for the participation of EV in the electricity market. |
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| Goran Strbac [112] Tim C. Green [113, 114] | • Researches in [113, 114] focus on the optimisation of EV management so as to minimise the energy losses and maximise the economic benefits.
• The optimisation of EV management is achieved by implementing OLTC (off-load tap changer) in electrical networks so that the power losses can be controlled by voltages. The EV management problem is actually converted into an OPF (optimal power flow) problem, and it is solved by OPF programming [113]. |

| University of Bath Miles A. Redfern [115-118] | • Research efforts mainly focus on the investigation of EV charging scenarios and their impacts on the electrical system.
• In [115, 116], case studies compare the uncontrolled charging, deferred charging and smart charging. In smart charging the peak load is controlled best which is slightly higher than the original peak.
• The best overall loading profile is achieved by implementing V2G service, which can reduce the peak demand from the network.
• [117, 118] give a conceptual overview of EV on the aspects of their environmental, economic and social benefits and their interdependent relationship with smart grid. |

| University of Birmingham Xiaoping Zhang [119] | • A method to model the EV charging load for probabilistic power flow calculation is proposed.
• This work is different from the work in Glasgow Caledonian University (GCU). GCU is working on EV charging modelling to optimise the overall loading profile, while this paper's model is for probabilistic power flow calculation.
• This model takes the randomness of charging behaviours into account but assumed that no controlled charging strategy is applied. |

Selected work from the literature review is elaborated in this section in order to show how EV charging load is modelled and how EV charging would affect distribution transformers.

3.4.1 EV charging load modelling

Restricted by the rareness of data collected in the daily operation of power systems, researches have been dominated by simulating the charging load of EV to investigate the impacts brought by EV charging to distribution networks.

Generally, EV charging load can be modelled in two approaches, i.e. deterministic modelling and probabilistic modelling.

a. Deterministic modelling

Deterministic modelling is a rather simple way of simulating the charging load of EV. Researchers [4, 9, 97, 109, 114, 120-126] have widely applied it for preliminary studies or worst-case investigations. It considers EV charging load as an aggregated load which omits the randomness of charging behaviours of EV users. It is usually assumed that all EV
batteries are charging simultaneously from zero to full energy with a fixed charging profile which regulates the power and duration required for charging.

Depending on the start charging time, two schemes are often referred as uncontrolled and controlled charging [4, 9, 109, 120, 121, 123, 125, 126]. Uncontrolled charging reflects the worst-case scenario and assumes all EV are charging during the peak time of the day, where the extra load from EV charging overlaps with the peak load of the original load profile, and therefore generates higher peak loads and boosts overloading risks.

Controlled charging is proved to be an effective solution to mitigate the impacts of EV charging by shifting EV charging load onto off-peak time of the day [4, 9, 109, 120, 121, 123, 125, 126]. Tariff strategies have been proposed in realistic operations in order to promote off-peak charging such as the cost of off-peak charging is 9% per kWh compared to peak charging [9].

Apart from controlled charging, smart charging is introduced as a result from optimisation of the controlled charging scheme [109, 120, 123, 127, 128]. The idea of smart charging is to split EV charging load as individual schedules and fill into off-peak time of the day in order to make the load profile more uniform and ideally it can be achieved through communication between power grid and EV users. As an example, a scheme is introduced by implementing distribution Transformers Load Monitoring (TLM) and Adaptive Charging Unit (ACU) [128]. TLM is a device installed at the low voltage side of transformers to collect the real-time loading information and transmit the data to ACU wirelessly. ACU is a microcontroller based device equipped at the customer end. ACU analyses the load data and manages the charging schemes of EV.

As an example, a study is conducted based on distribution network of 100 customers in [120]. A winter daily loading profile is used as a base load for calculation, and different charging methods are applied on it as shown in Figure 3-9. Uncontrolled charging, controlled charging and smart charging are set as the charging schemes and an assumption of 20 % EV penetration is set for the calculation. Under uncontrolled charging, the charging started from around 6:00 p.m.; controlled charging from 1 a.m. and smart charging time is controlled based on the monitored load information. It is observed that under uncontrolled charging, the maximum demand could increase up to 36 %. Under controlled charging, the maximum demand reduces considerably and under smart charging, the loading profile is more uniform.
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compared to the controlled charging. However, in order to achieve the smart charging, necessary hardware should be installed on the charging point to communicate with the power grid so that the charging would be initialised during the off-peak time to fill up the valley period of the cyclic load. This would generate extra cost to the customer and in addition, the charging time of EV would be increased which would deteriorate the charging experiences of EV customers.

![Figure 3-9: Loading profiles under different charging schemes [120]](image)

b. Probabilistic modelling

In order to accurately model EV charging load, the randomness of charging behaviours of EV users must be considered. The probabilistic modelling approach is therefore applied by many researchers [6, 7, 105-107, 109, 119] since statistic patterns have been observed on people’s driving behaviours, based on which charging behaviours might be predicted. A methodology proposed in [105-107, 109] is explained here. Figure 3-10 outlines of the structure on how to model EV charging load. Two preliminary assumptions are made. One is that each customer only owns one EV. The other is that customers only charge their EV at home.
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1. Modelling of charging power

Maximum power is restricted by the charger and the charging mode on which it is built. In the residential areas in the UK, mode 1 and mode 2 are most likely installed considering only household-type of socket is required and the maximum current allowed in households is typically 60 A due to the fuse installed [105, 129]. In addition, mode 1 charging will not be used in the UK due to safety concerns [130]. Therefore, it is reasonable to assume all EV are charging under mode 2 with a maximum power of around 7 kW.

Charging profiles defines the relationship between SOC and power required by the battery during the charging, and they are dependent on battery types. In Chengke’s method [106], two types of battery are considered which are Li-ion and Lead-acid batteries. Also it is assumed EV population is consisted of 60% of Li-ion batteries and 40% of Lead-acid batteries. Charging profiles of these two types of batteries are shown in Figure 3-11. However, according to statistics of UK vehicle licensing registration [131], Li-ion batteries have been dominating the EV market. Chengke’s model [106] can therefore be updated by only considering Li-ion batteries.

Figure 3-10: Outline structure of modelling EV charging [106]
2. Modelling of charging duration

With charging profiles determined, the charging duration only depends on the SOC and the initial and final instant of charging. It is assumed that all EV are charged to full capacity once the charging starts, which makes the final SOC 100%. It is a reasonable assumption considering the sufficient time for charging before the EV are used in the next day, and also the remaining energy is often far beyond zero when charging.

The initial SOC is modelled in a probabilistic way. It is modelled based on an assumption that all EV are fully charged before they are used in a day. Therefore, the initial SOC for charging will be the remaining SOC after a day’s drive, and the consumed SOC depends on the driving distance of the day. The daily mileage of a private vehicle owner shows a lognormal distributed pattern according to the transport statistics of the Department for Transport in the UK. The mean and standard deviation of the distribution are therefore obtained by estimation.

Given the daily travel distance, the initial SOC for charging is calculated as
Where \( E_i \) is the initial SOC for charging, \( d \) is the daily distance travelled which is modelled in a lognormal way, \( dr \) is the maximum range of the EV and it is assumed as 80 miles.

According to Equation (3-15), a linear relationship is assumed for distance travelled and SOC consumed in Chengke’s model [106]. It is a simplification, and for more accurate modelling, a nonlinear relationship may be applied as shown in Table 3-8 [132].

<table>
<thead>
<tr>
<th>Distance travelled (mile)</th>
<th>0 – 20</th>
<th>20 – 40</th>
<th>40 – 60</th>
<th>60 – 80</th>
<th>80 – 100</th>
<th>100 – 125</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy consumption (% SOC / mile)</td>
<td>1.7</td>
<td>1.3</td>
<td>1.1</td>
<td>1.1</td>
<td>1</td>
<td>0.8</td>
</tr>
</tbody>
</table>

3. Modelling of start charging time

The start time of charging is the most controllable factor, thus it can be modelled in various approaches. Three models of start charging time are provided and compared in Chengke’s model [106] by adopting various electricity rate plans as shown in Figure 3-12.

- Uncontrolled charging

Transport statistics of home arrival time of private vehicle customers reveals a peak at around 6 p.m. By assuming all EV start to charge once arrived at home and the electricity rate is
CHAPTER 3  TRANSFORMER THERMAL PERFORMANCE AND EVS IMPACTS ON DISTRIBUTION TRANSFORMERS

fixed throughout the day, the probability distribution of start charging time is modelled as uniform distribution as

\[
p_{\text{uncontrolled}} = \begin{cases} 
1.0 & t = 18 \\ 
0 & t = \text{other times} 
\end{cases} \quad (1 \leq t \leq 24) 
\]  

(3-16)

- Controlled charging

Time-of-use electricity rate structure is adopted. All EV are assumed to charge during the off-peak time between 21:00 to 7:00 of the next day in order to take advantage of the lower electricity price. Therefore, a uniform discrete distribution of the start charging time is applied.

\[
p_{\text{controlled}} = \begin{cases} 
0.33 & t = 21, 22, 23 \\ 
0 & t = \text{other times} 
\end{cases} \quad (1 \leq t \leq 24) 
\]  

(3-17)

- Smart charging

For smart charging, it is assumed that the real-time electricity price is adopted and the start charging time is affected by the electricity rate distribution and also the home arrival distribution. Distribution of start charging time is taken as the reciprocal of the product of home arrival distribution and the price distribution of a day. It is found that the resultant distribution is roughly bell-shaped and therefore it is modelled by a Gaussian distribution as shown in Figure 3-13.

![Figure 3-13: Probability distribution of start charging time](106)

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With charging power, duration and start charging time modelled, charging load of individual EV can be modelled. The overall charging load can be resulted by summing up loads of multiple individual EV.

In this PhD work, a probabilistic model is constructed for EV charging load. It is based on Chengke’s method [106] introduced here but upgraded for more accurate modelling.

3.4.2 EV impacts on distribution transformers

a. EV impacts on distribution network

The influence of EV charging on the distribution network is non-negligible. Extensive researches have been done studying this [4-10]. As an example, a comprehensive summary of the potential effects of EV charging on British distribution network can be found in [4, 7].

Basically, EV charging will disturb the system stability of the distribution network by introducing harmonics or causing voltage drops. In addition, EV charging also introduces extra loads onto the distribution load profile. The effects can be summarised as follows:

- Voltage drop:

EV penetration is going to affect the voltage profile of distribution network by absorbing active power from the network, which would result in a voltage drop. The voltage drop can be calculated based on Equation (3-18).

\[ \Delta V = \frac{P \times R + X \times Q}{V} \]  

(3-18)

Where \( \Delta V \) is the voltage change; \( P \) is the power flow through the cable; \( Q \) is the reactive power flow through the cable; \( R \) is the resistance of the cable; \( X \) is the reactance of the cable; \( V \) is the voltage at the end of the cable.

In the UK, the allowed variation of voltage is specified within +10% and -6% from the nominal single phase voltage of 230 V [7], therefore, the EV penetration should be limited so that the voltage excursion is not exceeding the statutory range. Simulation study in [7] shows that the statutory limit would be violated when the penetration level is beyond 33% on a representative 96 customers LV feeder.
CHAPTER 3 TRANSFORMER THERMAL PERFORMANCE AND EVS IMPACTS ON DISTRIBUTION TRANSFORMERS

- Network losses

The Penetration of EV imposes for additional network losses. A number of factors such as the location, duration and amount of EV penetration will be affecting the energy loss in the cable impedances.

In the UK, around 5% of total energy supplied to distribution customers is network losses [5]. However, it would be preferred to minimise the network losses. Simulations in [5, 7] show that the network losses are increasing with the EV penetration level. Also, the increase is getting faster when the EV penetration level is growing.

- Voltage unbalance

Geographically dispersed EV, along with single-phase connected EV are likely to raise voltage unbalance issue.

- Current harmonics

The battery chargers of EV are likely to introduce harmonics to the distribution network.

- Overloading of cables and transformers

Cables and transformer are always designed to work close to the rated load. The EV charging will probably add a new peak to the load profile of the distribution network and lead to the overloading of cables and transformers.

b. EV impacts on distribution transformers

There is a concern on transformers thermal performance due to the extra loading introduced by the EV charging. Several studies have been conducted on examining the effect of EV charging on the hot-spot temperature and the loss-of-life transformers [122-125]. Generally, the calculation of hot-spot temperature and loss-of-life could be carried out according to Figure 3-14. The inputs are the baseline loading profile and the additional loading by EV charging. The sum of two inputs gives the overall loading profile which is fed into the transformer thermal model for the estimation of the hot-spot temperature. Ambient temperatures and transformers specifications are fed also as inputs. The loss-of-life is calculated with the hot-spot temperature. Either IEC or IEEE thermal model is used in the literatures. [122, 123] used IEC 60076-7 model [11]. [124] used IEEE Clause 7 model [41].
[125] is using IEEE Annex G model [41]. However, the accuracy of the thermal model is not discussed in any of the literatures.

As an example, a study is carried out on estimating the hot-spot temperature and loss-of-life of a 30 kVA ONAN distribution transformer under uncontrolled charging and smart charging in [123]. One thing to note is that the investigation is conducted on an US system, where the transformers are probably shell type instead of core type. However, from thermal modelling point of view, thermal model applied in [123] is applicable in either shell type or core type transformers. Under uncontrolled charging scenario, it is found that there are 2 peaks in the loading profile. Under the smart charging, there is no peak observed from the calculation. Under uncontrolled charging, the hot-spot temperature exceeds the limit of 120 °C, while under smart charging; the hot-spot temperature is well below 100 °C. The daily loss-of-life under uncontrolled charging is around 7 times of that under smart charging.

### Table 3-9: Example of hot-spot temperature and loss-of-life under Uncontrolled and Smart Charging in [123]

<table>
<thead>
<tr>
<th>Charging scenario</th>
<th>Hot-spot temperature (°C)</th>
<th>Daily loss-of-life (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No EV charging</td>
<td>91</td>
<td>90</td>
</tr>
<tr>
<td>Uncontrolled charging</td>
<td>127</td>
<td>1771</td>
</tr>
<tr>
<td>Smart charging</td>
<td>97</td>
<td>272</td>
</tr>
</tbody>
</table>

As a summary, extra loads caused by EV charging is concerned, since they will accelerate the thermal ageing of distribution transformers and reduce their lifetimes. Moreover, potential overloads will lead to an increased hot-spot temperature that could violate the acceptable limits and cause potential failures. In the next chapters, as inspired by the literature review presented in this chapter, methodologies to assess the load, hot-spot temperature, loss-of-life,
expected lifetime and failure probability of a distribution transformer population are introduced and demonstrated.
To assess the adaptability of a distribution transformer population under EV scenarios, the long term and short term impacts should be considered on each individual. In the long term, the ageing is accelerated by increased hot-spot temperatures and consequently the expected lifetime is reduced and the planned replacement point would be advanced which impairs the return of investment. In the short term, direct failures are of concern when the hot-spot temperature increases high enough to reach the restricted zone that triggers bubbling and leads to breakdown. Therefore, the hot-spot temperatures, the expected lifetime and failure probability due to bubbling should be evaluated for individual transformers under various EV penetration levels. In this chapter, various models are proposed for the assessment of hot-spot temperature, lifetime and failure probability of distribution transformers under anticipated future EV scenarios.

In order to investigate into a population of distribution transformers, prototype transformers from different manufacturers are ordered by ENW to represent their own peers from the same manufacturer. A prototype product is normally built to test the design or process and to be replicated by the manufacturer. Results of investigations on a prototype product can therefore be applied on the product family that shares the same design.

Comparing to directly studying existing transformers in the population, it is much advantageous to study the prototype ones, since monitoring devices such as optic fibre sensors can be installed at the manufacture stage and extended heat run tests can be conducted before they are put into commission. Sufficient data can thus be obtained for a thorough assessment of the thermal characteristics, which helps the prediction of the thermal performance under future EV scenarios. In this chapter, methodologies for the ideal case are presented and demonstrated on a prototype distribution transformer when having sufficient data to assess its future adaptability.
4.1 Introduction to assessment strategy

The framework of the proposed strategy is illustrated in Figure 4-1. The refined thermal parameters, load profile and ambient temperature are required inputs. The hot-spot temperature, expected lifetime and failure probability under EV scenarios are ultimately concerned. The hot-spot temperature plays an essential role among the three, as it leads to the expected lifetime calculated by the IEC ageing model. It also determines if the transformer fails or not should it exceed the bubbling inception temperature, where the failure in this thesis is specifically defined as transformer breakdown due to bubble formation 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.

![Figure 4-1: Framework of assessment strategy for adaptability of distribution transformers under EV scenarios](image)

Generally, the transformer hot-spot temperature is determined by three elements, i.e. transformer thermal characteristics, loading and environmental elements. When calculating the hot-spot temperature with the IEC thermal model, these elements can thus be identified as thermal model parameters, load profiles under EV scenarios and ambient temperature profiles. Load profiles are produced by summing up the current load and the EV charging load.
As a complete systematic tool for assessment of individual distribution transformers under EV scenarios, a methodology of refining IEC thermal model parameters for individual transformers is firstly proposed and verified which leads to more accurate estimation of the hot-spot temperature than applying the generic values recommended in the current loading guide. Secondly, a model of EV charging load is introduced based on literature but upgraded with up-to-date UK EV trial data in order to better simulate the charging behaviours of EV users. Lastly, a failure probability model is introduced to evaluate the probability of failure due to bubbling under EV scenarios, which is consisted of a bubbling temperature inception model and a moisture in paper model.

### 4.2 Determination of hot-spot temperature under EV scenarios

Transformer thermal models are provided by IEC and IEEE loading guides for the estimation of transformer hot-spot temperatures. The latest versions of loading guides are IEC 60076-7 : 2005 [11] and IEEE C57.91 : 2011 [133]. For simplicity, the thermal model in IEC loading guide is referred as “IEC model” in this thesis. IEC model is selected in this PhD work for the estimation of hot-spot temperature under EV scenarios.

Apart from input data of load profile and ambient temperature profile, thermal parameters are required in IEC model, which reflect transformer thermal characteristics. Generic values are recommended in the IEC loading guide [11] for distribution transformers. However, in order to achieve more accurate estimation of the hot-spot temperature, thermal parameters of individual transformers should be identified which reflect its design-dependent thermal characteristics, and these parameters are called “refined” parameters in the PhD work. A method is therefore proposed for the refinement of IEC model thermal parameters, and it is demonstrated and verified with a prototype distribution transformer. Before explaining the method, the prototype distribution transformer is briefly introduced.

#### 4.2.1 Prototype distribution transformer

Basic information of the prototype distribution transformer is summarised in Table 4-1.
CHAPTER 4 ASSESSMENT OF A PROTOTYPE DISTRIBUTION TRANSFORMER’S THERMAL PERFORMANCE UNDER EVS SCENARIOS

Table 4-1: Basic information of prototype distribution transformer

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturer</td>
<td>Schneider</td>
</tr>
<tr>
<td>Power rating (kVA)</td>
<td>1000</td>
</tr>
<tr>
<td>Voltage level (kV)</td>
<td>6.6/0.433</td>
</tr>
<tr>
<td>Cooling type</td>
<td>ONAN</td>
</tr>
<tr>
<td>Guaranteed total losses (W)</td>
<td>10000</td>
</tr>
<tr>
<td>Actual total losses (W)</td>
<td>9965</td>
</tr>
<tr>
<td>Guaranteed load losses (W)</td>
<td>9000</td>
</tr>
<tr>
<td>Actual load losses (W)</td>
<td>8934</td>
</tr>
<tr>
<td>Guaranteed no-load losses (W)</td>
<td>1000</td>
</tr>
<tr>
<td>Actual no-load losses (W)</td>
<td>1031</td>
</tr>
<tr>
<td>Guaranteed average winding temperature rise (K)</td>
<td>65</td>
</tr>
<tr>
<td>Actual average winding temperature rise (K) (LV / HV)</td>
<td>52.3 / 49.3</td>
</tr>
<tr>
<td>Guaranteed top-oil temperature rise (K)</td>
<td>60</td>
</tr>
<tr>
<td>Actual top-oil temperature rise (K)</td>
<td>50.4</td>
</tr>
<tr>
<td>Winding types (LV / HV)</td>
<td>Layer type / Spiral layer type</td>
</tr>
<tr>
<td>Radiator arrangement</td>
<td>Banked radiator</td>
</tr>
<tr>
<td>Number of Radiators</td>
<td>Three</td>
</tr>
<tr>
<td>Total mass (kg)</td>
<td>3550</td>
</tr>
<tr>
<td>Core &amp; winding mass (kg)</td>
<td>1845</td>
</tr>
<tr>
<td>Oil volume (L)</td>
<td>950</td>
</tr>
</tbody>
</table>

All route tests are conducted on the transformer, where the load and no-load losses are measured. Measured values for losses are different from guaranteed values since 10% deviation is allowed. Average winding and top-oil temperature rises are measured during the heat run test.

Three banked radiators are installed for the purpose of heat dissipation, two of which are installed close to A phase and the other one is installed close to C phase. The unsymmetrical arrangement of radiators makes the temperature of C phase winding higher than the temperature of A phase winding.

The extended heat run test was performed on the transformer and the test scheme is shown in Table 4-2.
Table 4-2: Test schemes of extended heat run test performed on investigated prototype distribution transformer

<table>
<thead>
<tr>
<th>Test load</th>
<th>Test process</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7 p.u.</td>
<td>20.25h @ total loss</td>
</tr>
<tr>
<td></td>
<td>1h @ load loss</td>
</tr>
<tr>
<td>1.00 p.u.</td>
<td>20h @ total loss</td>
</tr>
<tr>
<td></td>
<td>2h @ load loss</td>
</tr>
<tr>
<td>1.25 p.u.</td>
<td>20.5h @ total loss</td>
</tr>
<tr>
<td></td>
<td>1h @ load loss</td>
</tr>
</tbody>
</table>

Traditionally, thermocouples are applied during the heat run test for the measurement of oil temperatures. For this prototype transformer, apart from thermocouples, optic fibre sensors are also installed to measure the oil and hot-spot temperatures. A total of 12 optic fibre sensors are installed in the transformer to measure the temperature on a minute base and the installation locations are summarised in Table 4-3.

Table 4-3: Summary of installation of optic fibre sensors and their locations in investigated prototype distribution transformer

<table>
<thead>
<tr>
<th>Hot-spot temperature</th>
<th>Sensors</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>4 sensors at LV &amp; HV windings of B &amp; C phases</td>
<td></td>
</tr>
<tr>
<td></td>
<td>On winding outmost surface, 50 mm below the top</td>
<td></td>
</tr>
<tr>
<td>Top-oil temperature</td>
<td>Sensors</td>
<td>Location</td>
</tr>
<tr>
<td></td>
<td>4 sensors at top of LV &amp; HV windings of B &amp; C phases</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 sensor at inlet of radiator near to C phase</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Within oil duct, 50 mm below the top</td>
<td></td>
</tr>
<tr>
<td>Bottom-oil temperature</td>
<td>Sensors</td>
<td>Location</td>
</tr>
<tr>
<td></td>
<td>2 sensors at bottom of B &amp; C phases</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 sensor at outlet of radiator near to C phase</td>
<td></td>
</tr>
<tr>
<td></td>
<td>In LV winding oil duct, 2 mm above the bottom</td>
<td></td>
</tr>
</tbody>
</table>

Top-oil and bottom-oil temperatures are measured at different locations. Sensors at inlet/outlet of radiator near to C phase are set to measure mixed top-oil/bottom-oil temperatures. Sensors inside oil ducts of windings are set to measure top and bottom oil duct temperatures. The hot-spot temperature is measured 50 mm below the top of the winding, since the hot-spot is normally located not the top but a few turns below the top [11]. Installation locations are illustrated in Figure 4-2 and Figure 4-3 to help understand the installation of optic fibre sensors in the prototype transformer.
Stabilised temperatures are measured at the end of total losses, which include both of no-load and load losses. Measured values of each load under the extended heat run test at different locations are presented in Figure 4-4.
CHAPTER 4  ASSESSMENT OF A PROTOTYPE DISTRIBUTION TRANSFORMER’S THERMAL PERFORMANCE UNDER EVS SCENARIOS

The highest temperature in the transformer is always observed on the hot-spot of B phase LV winding, which is the weakest point to potentially cause thermal failures under EV scenarios. Therefore, the hot-spot temperature of B phase LV winding is the most concerned temperature of the transformer and should be estimated under EV scenarios.

Top-oil temperatures are measured at two locations; one is in the mixed oil above the winding, and the other is in the winding oil duct. Generally speaking, temperature in the oil duct of the winding is more representative to the adjacent winding temperature than the mixed oil temperature above the winding, and depending on cooling types, it can be up to 15 K higher than the mixed oil temperature [11]. Either temperature can be used for the calculation of hot-spot temperature by the IEC thermal model. In practice, the temperature in the mix oil above winding is usually measured by a thermocouple in the oil pocket, instead of installing sensors to measure the temperature in the oil duct. Therefore, the term “top-oil temperature” is often referring to the mixed oil temperature above the winding, which is the top-oil temperature measured near to radiator inlet in this context, and it is applied in the remaining part of the thesis and also when utilising the IEC thermal model.

The hot-spot temperature of B phase LV winding and the top-oil temperature measured during the whole heat run test are shown in Figure 4-5. These data will be used for the
refinement of IEC thermal model parameters in this chapter. The hot-spot and top-oil temperatures are measured during the entire process of the extended heat run test, and even transformer cooling periods between two consecutive tests are covered which are not required by the standard procedure. However, it will be proven in the following section that temperatures measured during the cooling periods are of the same importance in order to refine the thermal parameters for the most accurate prediction of the hot-spot temperature under dynamic loads.

The corresponding load profile is presented in Figure 4-6. Test under each load contains three stages, i.e. the total losses stage, load losses stage and the cooling stage. Take 0.7 p.u. test in Figure 4-6 as an example, the total losses stage lasts from the start to around hour 19; the load losses stage is between hour 19 and 20; and it is followed by the cooling stage until hour 24 when the next test start. Ideally, during the total losses stage of each test, the load should be constantly maintained at the required level. In practice, the load is maintained by regular manual adjustments of the load current. However, when the test lasts overnight, the load current is not adjusted until the next morning; this is why a sudden drop is observed between hour 60 and hour 66. The load profile in Figure 4-6 reflects the real load undertaken by the transformer during the test, and it will also be used for the refinement of IEC thermal model parameters.

![Figure 4-5: Hot-spot (B phase LV winding), top-oil and ambient temperatures measured during extended heat run test of investigated prototype distribution transformer](image-url)
The transformer is later installed in a substation after the factory test, and all optic fibre sensors are remaining within the tank to monitor the transformer in operation. Daily load profiles and temperature data have been recorded, and which are eventually used to verify the refined thermal parameters.

### 4.2.2 Refinement of IEC thermal model parameters for prototype transformer

When estimating hot-spot temperatures under arbitrary loads with the IEC model, the exact values of thermal parameters shown in Table 4-4 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 4-4, which are generic values and tend to reach conservative hot-spot temperatures.

#### Table 4-4: IEC 60076 thermal model parameters and recommended values given in IEC 60076-7: 2005 [11]

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$\Delta \theta_{tr}$</th>
<th>$R$</th>
<th>$g_r$</th>
<th>$H$</th>
<th>$x$</th>
<th>$y$</th>
<th>$\tau_o$</th>
<th>$\tau_w$</th>
<th>$k_{11}$</th>
<th>$k_{21}$</th>
<th>$k_{22}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recommended values</td>
<td>60*</td>
<td>9*</td>
<td>16.36*</td>
<td>1.10</td>
<td>0.80</td>
<td>1.60</td>
<td>180</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

*: 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.

One approach to refine IEC thermal model parameters is introduced here. The methodology 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.

#### a. Curve-fitting method
Least squares method is applied for the curve-fitting. Unknown variables in a model can be optimised by minimising the sum of squared residuals, which are the difference between each observed value and the fitted value. The principle of the least square method can be expressed in Equation (4-1).

\[
\text{minimise } \sum_{i=1}^{N} [y_i - f_i(x_1, x_2, ..., x_n)]^2
\]  

(4-1)

where \(N\) is the number of observed data; \(y_i\) is the \(i\)-th observed data; \(f_i\) is the \(i\)-th fitted data; \(x_1, x_2, ..., x_n\) are unknown variables to be fitted.

To determine the goodness of fitting, the coefficient of determination, i.e. \(R^2\), is applied, which is defined as Equation (4-2).

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} [y_i - f_i(x_1, x_2, ..., x_n)]^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}
\]  

(4-2)

where \(N\) is the number of observed data; \(y_i\) is the \(i\)-th observed data; \(\bar{y}\) is the mean of the observed data; \(f_i\) is the \(i\)-th fitted data; \(x_1, x_2, ..., x_n\) are unknown variables to be fitted.

When the least squares method is applied, the numerator in Equation (4-2) is minimised, therefore the closer \(R^2\) is to 1, the better the fitting is. However, \(R^2\) is a relative indicator, and there are no definite values of \(R^2\) to determine if a model can fit the observed data. For the same set of data being fitted, \(R^2\) can be applied as a criterion to compare the goodness of fitting of different models or different parameters of the same model.

b. Refinement of thermal parameters by curve-fitting

The estimation process has two steps. The first step is to estimate \(v, \tau_{o}, \tau_{w}, k_{11}, k_{22}\) and \(H \times g_r\) all together with the hot-spot to top-oil gradient using Equation (4-3). \(H \times g_r\) 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 $\tau_o$ obtained from the first step into Equation (4-4) and then estimate $x$ and $k_{11}$ together
with the top-oil temperature measurements using Equation (4-4). 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.

$$\Delta \theta_{ho}(t) = (H \times g_r \times K^y - \Delta \theta_{hoi}) \times (k_{21} \times (1 - e^{-\frac{t}{(k_{22} \times T_o)}}) - (k_{21} - 1) \times (1 - e^{-\frac{t}{(T_o \times k_{22})}}))$$

(4-3)

$$\Delta \theta_o(t) = \Delta \theta_{oi} + \left\{ \Delta \theta_{oi} \times \left[ \frac{1 + R \times K^2}{1 + R} \right]^x - \Delta \theta_{oi} \times (1 - e^{(-t)/(k_{11} \times T_o)}) \right\}$$

(4-4)

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. Thus each curve-fitting process is repeated for
10,000 times with randomly generated initial values, so that the results’ dependency on initial
values is examined.

The flow chart of the curve-fitting process is displayed in Figure 4-7.
Figure 4-7: Flow chart of curve-fitting process to determine IEC thermal model parameters

Curve-fitting process shown in Figure 4-7 is conducted on the temperature data (as shown in Figure 4-5) measured during the extended heat run test with corresponding load profile (as shown in Figure 4-6). \( \Delta \theta_{or} \) is directly obtained from top-oil temperature measurement, which is the steady-state value measured at the end of total losses stage during 1.0 p.u. test and is 56.2 K in this context. \( R \) is derived from load losses and no-load losses given in the nameplate and is equal to 8.67. Initial values for the curve-fitting are generated within ranges defined for each parameter as shown in Table 4-5.

Table 4-5: Regions defined to generate random initial values of curve-fitting

<table>
<thead>
<tr>
<th></th>
<th>( k_{21} )</th>
<th>( k_{22} )</th>
<th>( \tau_o )</th>
<th>( \tau_w )</th>
<th>( H \times g_r )</th>
<th>( y )</th>
<th>( k_{11} )</th>
<th>( x )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upper limit</td>
<td>0.5</td>
<td>0.5</td>
<td>100</td>
<td>10</td>
<td>1</td>
<td>0.1</td>
<td>0.5</td>
<td>0.1</td>
</tr>
<tr>
<td>Lower limit</td>
<td>5.0</td>
<td>5.0</td>
<td>500</td>
<td>30</td>
<td>30</td>
<td>3.5</td>
<td>5.0</td>
<td>3.5</td>
</tr>
</tbody>
</table>
Dependency on initial values is observed on some individual parameters, which shadows a degree of uncertainty on the determination of thermal model parameters through curve-fitting. However, it is also observed that initial-value-dependent parameters can be combined so that resultant combinations are immune to the variation of initial values. To demonstrate the observation, 10 out of 10,000 sets of resultant parameters from simulations are listed and analysed in Table 4-6 as an example.

Table 4-6: Example results from curve-fitting for refining thermal parameters

<table>
<thead>
<tr>
<th>Resultant parameters</th>
<th>Combinations</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_{21}$</td>
<td>$k_{22}$</td>
</tr>
<tr>
<td>2.83</td>
<td>1.76</td>
</tr>
<tr>
<td>2.83</td>
<td>1.41</td>
</tr>
<tr>
<td>2.83</td>
<td>1.80</td>
</tr>
<tr>
<td>2.83</td>
<td>1.68</td>
</tr>
<tr>
<td>2.83</td>
<td>2.08</td>
</tr>
<tr>
<td>2.83</td>
<td>1.78</td>
</tr>
<tr>
<td>2.83</td>
<td>1.60</td>
</tr>
<tr>
<td>2.83</td>
<td>1.62</td>
</tr>
<tr>
<td>2.83</td>
<td>1.85</td>
</tr>
<tr>
<td>2.83</td>
<td>1.96</td>
</tr>
</tbody>
</table>

According to Table 4-6, parameters $k_{11}$, $k_{22}$, $\tau_o$ and $\tau_w$ are varying from each set to another. However, as shown in “Combinations” columns, determinate values are obtained for $\tau_o / k_{22}$, $\tau_w \times k_{22}$ and $\tau_o \times k_{11}$. Thus the conclusion can be drawn that definite values cannot be determined for $k_{11}$, $k_{22}$, $\tau_o$ and $\tau_w$ through curve-fitting unless any of them is known so that others can be calculated based on the estimated results of $\tau_o / k_{22}$, $\tau_w \times k_{22}$ and $\tau_o \times k_{11}$. Besides this conclusion, there are some other observations made from the estimation as follows:

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

In order to obtain definite values for all thermal parameters, $\tau_o$ is set as 180 min, therefore the full set of thermal parameters for the prototype distribution transformer is determined as shown in Table 4-7.
Table 4.7: Thermal parameters refined by curve-fitting of investigated prototype distribution transformer

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$k_1$</th>
<th>$k_2$</th>
<th>$T_o$</th>
<th>$T_w$</th>
<th>$H \times g_f$</th>
<th>$y$</th>
<th>$k_{11}$</th>
<th>$x$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refined values</td>
<td>2.83</td>
<td>0.91</td>
<td>180</td>
<td>21.7</td>
<td>8.44</td>
<td>1.08</td>
<td>1.18</td>
<td>0.72</td>
</tr>
</tbody>
</table>

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 4.8. Values of parameters used for the calculation are shown in Table 4.8.

Table 4.8: Refined (by curve-fitting) and IEC recommended thermal parameters of investigated prototype distribution transformer

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$\Delta T_{or}$</th>
<th>$R$</th>
<th>$H \times g_f$</th>
<th>$x$</th>
<th>$y$</th>
<th>$T_o$</th>
<th>$T_w$</th>
<th>$k_{11}$</th>
<th>$k_1$</th>
<th>$k_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refined by curve-fitting</td>
<td>56.2</td>
<td>8.67</td>
<td>8.44</td>
<td>0.72</td>
<td>1.08</td>
<td>180</td>
<td>21.7</td>
<td>1.18</td>
<td>2.83</td>
<td>0.91</td>
</tr>
<tr>
<td>IEC Recommendation</td>
<td>60</td>
<td>9</td>
<td>18</td>
<td>0.80</td>
<td>1.60</td>
<td>180</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 4.8: Comparison between calculated (with parameters refined by curve-fitting method) and measured hot-spot temperatures under heat run test loads

By analysing errors as shown in Table 4.9, refined thermal parameters apparently offer much enhanced accuracy than IEC recommended parameters by reducing the maximum error from 25.87 to 3.61 K, and by almost eliminating the mean error.

Table 4.9: Error analysis of comparison between calculated (with parameters refined by curve-fitting method) and measured hot-spot temperature under heat run test loads

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refined parameters</td>
<td>3.53</td>
<td>-0.17</td>
</tr>
<tr>
<td>IEC recommended parameters</td>
<td>25.87</td>
<td>12.14</td>
</tr>
</tbody>
</table>

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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. IEC recommended parameters are also included in the comparison and same parameters as shown in Table 4-8 are used. The load and ambient profiles of 29 consecutive days in September 2013 are used for the calculation, which are shown in Figure 4-9 and Figure 4-10. In Figure 4-9, it can be clearly seen that the difference of loads between weekdays and weekends. Peak loads in weekends are lower than those in weekdays. For example, comparing loads in day 5 (weekday) and day 6 (weekend), the peak load in day 5 is 0.65 p.u., while the peak load in day 6 is only 0.57 p.u.

![Load profile of 29 days in September 2013](image1)

![Ambient temperature profile of 29 days in September 2013](image2)
Comparison between calculated and measured hot-spot temperatures are shown in Figure 4-11. It can be seen that IEC recommended parameters tend to overestimate the hot-spot temperature. Statistical analysis of errors in Table 4-10 shows the predicted hot-spot temperature is much less deviated from measured values when using refined thermal parameters. For example, with refined thermal parameters, only 2.4% of all predicted hot-spot temperatures are deviated from measured values for more than 3 K. As a comparison, this percentage is as large as 56.4% for IEC recommended parameters. In addition, error analysis in

Table 4-11 shows that the maximum error is reduced from 9.76 K to 6.07 K by using refined thermal parameters, which is reduced by 37.8%. In the meantime, the mean error is almost eliminated by using refined thermal parameters.

Table 4-10: Statistic of error distribution of comparison between calculated (with parameters refined by curve-fitting method) and measured hot-spot temperatures under cyclic loads

<table>
<thead>
<tr>
<th>Deviation to measured results</th>
<th>&gt;= 2 K</th>
<th>&gt;= 3 K</th>
<th>&gt;= 4 K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refined parameters</td>
<td>18.2 %</td>
<td>2.4 %</td>
<td>&lt; 0.02%</td>
</tr>
<tr>
<td>IEC recommended parameters</td>
<td>67.9 %</td>
<td>56.4 %</td>
<td>43.9 %</td>
</tr>
</tbody>
</table>
Table 4-11: Error analysis of comparison between calculated (with parameters refined by curve-fitting method) and measured hot-spot temperatures under cyclic loads

<table>
<thead>
<tr>
<th></th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Refined parameters</td>
<td>6.07</td>
<td>0.04</td>
</tr>
<tr>
<td>IEC recommended parameters</td>
<td>9.76</td>
<td>3.58</td>
</tr>
</tbody>
</table>

By verifications under heat run test loads and cyclic loads, it can be concluded that refined thermal parameters by curve-fitting much improve the accuracy of the prediction of hot-spot temperatures under either step loads (during heat run test) or dynamic loads significantly, and they should be applied under future EV scenarios for the hot-spot temperature prediction. However, recalling that the refined parameters verified above are obtained by curve-fitting the measured temperature data of the entire extended heat run test process including three individual tests and even cooling periods between each two tests, questions may be raised as

1. Is it sufficient to conduct the curve-fitting only with temperature data of one single test instead of three tests?

2. Is it sufficient to conduct the curve-fitting without the temperature data of cooling periods, which are not required by the standard procedure of conducting a heat run test?

Further investigations have been performed to seek answers to the above two questions.

c. Refinement of thermal parameters under three individual tests

The extended heat run test performed on the prototype transformer is composed of three individual tests of 0.7 p.u., 1.0 p.u. and 1.25 p.u. load respectively. Refinement of thermal parameters is conducted on temperatures measured during each individual test, and resultant thermal parameters are compared with those refined under the entire extended heat run test in terms of accuracy using measurement results as reference, as shown in Table 4-12 and Figure 4-12.
Recalling that $k_{11}$, $k_{22}$, $\tau_o$ and $\tau_w$ are interdependent, therefore $\tau_o$ is set as 180 min in all cases. In addition, it is observed that definite values of $H \times g_r$ and $y$ cannot be obtained by curve-fitting temperature data of single test, and they can only be determined with temperature data under the entire extended heat run test.

Parameters refined under one single test can fit best to the temperature data of that test, but for other tests, the fitting is not as good as parameters refined under all three tests. Error analysis given in Table 4-13 also proves this point. Therefore, refined thermal parameters under all tests are preferred when predicting hot-spot temperatures.

<table>
<thead>
<tr>
<th>Refinement of thermal parameters</th>
<th>$\Delta \theta_{or}$</th>
<th>$R$</th>
<th>$H \times g_r$</th>
<th>$x$</th>
<th>$y$</th>
<th>$\tau_o$</th>
<th>$\tau_w$</th>
<th>$k_{11}$</th>
<th>$k_{21}$</th>
<th>$k_{22}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>With 0.7 p.u. test</td>
<td>56.2</td>
<td>8.67</td>
<td>6.18</td>
<td>0.68</td>
<td>0.60</td>
<td>180</td>
<td>32.34</td>
<td>1.42</td>
<td>3.58</td>
<td>0.80</td>
</tr>
<tr>
<td>With 1.0 p.u. test</td>
<td>56.2</td>
<td>8.67</td>
<td>9.00</td>
<td>0.80</td>
<td>1.60</td>
<td>180</td>
<td>24.44</td>
<td>1.21</td>
<td>2.57</td>
<td>0.76</td>
</tr>
<tr>
<td>With 1.25 p.u. test</td>
<td>56.2</td>
<td>8.67</td>
<td>7.66</td>
<td>0.70</td>
<td>1.56</td>
<td>180</td>
<td>13.21</td>
<td>1.04</td>
<td>2.53</td>
<td>1.23</td>
</tr>
<tr>
<td>With All three tests</td>
<td>56.2</td>
<td>8.67</td>
<td>8.44</td>
<td>0.72</td>
<td>1.08</td>
<td>180</td>
<td>21.7</td>
<td>1.18</td>
<td>2.83</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Table 4-13: Error analysis of thermal parameters refined under various heat run tests

<table>
<thead>
<tr>
<th>Refinement of thermal parameters</th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With 0.7 p.u. test</td>
<td>-10.48</td>
<td>-2.99</td>
</tr>
<tr>
<td>With 1.0 p.u. test</td>
<td>7.08</td>
<td>0.66</td>
</tr>
<tr>
<td>With 1.25 p.u. test</td>
<td>-5.02</td>
<td>-0.55</td>
</tr>
<tr>
<td>With All three tests</td>
<td>3.53</td>
<td>-0.17</td>
</tr>
</tbody>
</table>
The comparison is also conducted under cyclic loads as shown in Figure 4-13, where hot-spot temperatures calculated with refined thermal parameters under various heat run test are compared to the measurements. The error analysis is presented in Table 4-14.

![Graph showing hot-spot temperatures under cyclic loads](image)

**Figure 4-13:** Hot-spot temperatures under cyclic loads calculated with thermal parameters refined under various heat run tests

**Table 4-14:** Error analysis under cyclic loads of thermal parameters refined under various tests

<table>
<thead>
<tr>
<th>Refinement of thermal parameters</th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With 0.7 p.u. test</td>
<td>8.35</td>
<td>1.28</td>
</tr>
<tr>
<td>With 1.0 p.u. test</td>
<td>6.72</td>
<td>-3.01</td>
</tr>
<tr>
<td>With 1.25 p.u. test</td>
<td>-6.50</td>
<td>-0.73</td>
</tr>
<tr>
<td>With All three tests</td>
<td>6.07</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Under cyclic loads, the lowest value of either maximum or mean error is given by thermal parameters refined under all three tests, as it is observed in the comparison under heat run test loads. Therefore, refine thermal parameters under all tests are preferred for the prediction of hot-spot temperatures.

d. **Impacts of cooling periods on refining thermal parameters**

During the extended heat run test, the transformer is shut down for cooling between two tests, and the temperature measurement during this period is not compulsory. Therefore, the
temperature data during cooling periods are probably not available nor required by current standard or best practice in heat run test.

In order to investigate the impacts of cooling periods on the refinement of thermal parameters, thermal parameters refined under the extended heat run test but without the cooling periods are compared with those refined under the entire extended heat run test including the cooling periods in terms of accuracy of hot-spot temperature prediction. Results are shown in Table 4-15 and Figure 4-14.

Table 4-15: Thermal parameters refined with or without cooling periods during extended heat run test

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \theta_{or}$</th>
<th>$R$</th>
<th>$H \times g$</th>
<th>$x$</th>
<th>$y$</th>
<th>$\tau_{or}$</th>
<th>$\tau_{ow}$</th>
<th>$k_{11}$</th>
<th>$k_{21}$</th>
<th>$k_{22}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>With cooling periods</td>
<td>56.2</td>
<td>8.67</td>
<td>8.44</td>
<td>0.72</td>
<td>1.08</td>
<td>180</td>
<td>21.7</td>
<td>1.18</td>
<td>2.83</td>
<td>0.91</td>
</tr>
<tr>
<td>Without cooling periods</td>
<td>56.2</td>
<td>8.67</td>
<td>8.88</td>
<td>0.84</td>
<td>1.27</td>
<td>180</td>
<td>15.1</td>
<td>1.20</td>
<td>1.54</td>
<td>1.08</td>
</tr>
</tbody>
</table>

![Figure 4-14: Hot-spot temperatures calculated with thermal parameters refined with or without cooling periods under heat run test loads](image)

Error analysis in Table 4-16 shows that thermal parameters refined without cooling periods lead to maximum errors doubled compared with parameters refined with cooling periods. Therefore, when refining IEC thermal parameters, temperature measurement data during the cooling periods should also be included.

Table 4-16: Error analysis of thermal parameters refined with or without cooling periods under heat run test loads

<table>
<thead>
<tr>
<th></th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With cooling periods</td>
<td>3.53</td>
<td>-0.17</td>
</tr>
<tr>
<td>Without cooling periods</td>
<td>7.43</td>
<td>-0.10</td>
</tr>
</tbody>
</table>
The same comparison is conducted under cyclic loads, and the results are shown in Figure 4-15. The error analysis in Table 4-17 shows that the accuracy of hot-spot temperature prediction is impaired by using the thermal parameters refined without cooling periods, where the maximum error is increased by 1.41 K (23%) and the mean error is increased to 3.31 K from 0.04 K.

![Figure 4-15: Hot-spot temperatures under cyclic loads calculated with thermal parameters refined with or without cooling periods](image)

<table>
<thead>
<tr>
<th></th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With cooling periods</td>
<td>6.07</td>
<td>0.04</td>
</tr>
<tr>
<td>Without cooling periods</td>
<td>-7.48</td>
<td>-3.31</td>
</tr>
</tbody>
</table>

As a summary, the IEC thermal model parameters should be refined in order to achieve better accuracy when predicting the hot-spot temperature under either step or dynamic loads. When refining the thermal parameters by curve-fitting, the measured hot-spot and top-oil temperatures during the extended heat run test are required. In addition, to achieve the most accurate values, temperatures measured during the entire extended heat run test should be used which include three individual tests and cooling periods between each two consecutive tests. With refined thermal parameters, the hot-spot temperature can thus be predicted accurately under EV scenarios, which is essential for the assessment of loss-of-life, lifetime and failure probability of distribution transformers.
4.3 Assessment of thermal performance under EV scenarios

With refined thermal parameters, thermal performance of transformers can be assessed more accurately under EV scenarios. In this section, EV scenarios are defined based on projections of EV penetration in future and EV charging load is modelled in a probabilistic manner based on data collected from EV trials in the UK. At last, the hot-spot temperature, loss-of-life and expected lifetime of the prototype transformer are estimated under defined EV scenarios.

4.3.1 EV scenarios

Department for Transport (DfT) introduced several scenarios to project the EV uptake up to 2030 in [3], 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 EV (including BEV and PHEV) would be as shown in Table 4-18.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Number of EV (million) in 2030</th>
<th>Penetration level (%) in 2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business as usual (BAU)</td>
<td>3.0</td>
<td>8.6</td>
</tr>
<tr>
<td>Mid-range</td>
<td>4.1</td>
<td>11.7</td>
</tr>
<tr>
<td>High-range</td>
<td>11.2</td>
<td>32.0</td>
</tr>
<tr>
<td>Extreme-range</td>
<td>20.6</td>
<td>58.9</td>
</tr>
</tbody>
</table>

The penetration level is the ratio of the number of EV to the total number of vehicles in the UK. Four scenarios are introduced in [3] to project the strength of demand of EV in the UK. BAU scenario assumes that the current incentives are left in place and no more actions are to be taken to promote EV. Mid-range scenario assumes the incentives keep growing at the current rate. High-range scenario assumes significant interventions to promote EV sale. Extreme-range scenario assumes an extremely high demand of EV, and the sales are only restricted by the availability of EV.

According to the statistics from DfT, the increase of registered EV in the recent five years can be seen in Figure 4-16, where the trend is extrapolated to 2020 and the projected number of EV in 2020 is compared with the number of EV predicted under four EV scenarios given in the DfT report [3]. The number of EV is expressed in logarithmic scale.
The comparison indicates that if the current trend maintains its momentum, the Extreme-range scenario would be the most likely scenario in future. Therefore, the Extreme-range scenario is of the most importance to be investigated in terms of its impacts on distribution transformers. In addition, two other scenarios are investigated as comparisons, which are High-range scenario and Business as usual (BAU) scenario. To simplify the BAU scenario, the EV penetration level is assumed as 0%.

To conclude, three EV scenarios are going to be investigated to show how distribution transformers will be affected in 2030, and they are BAU scenario, High-range scenario and Extreme-range scenario, which correspond to 0%, 32% and 58.9% EV penetration levels respectively. When modelling the EV charging load, the number of EV are determined by multiply the EV penetration level with the number of customers (domestic or non-domestic) connected to the transformer based on the undoubtedly simple assumption that one customer owns one vehicle.

### 4.3.2 EV Charging load

In order to simulate EV charging load as realistic as possible, a stochastic approach is utilised, which probabilistically models EV types, charging power, charging start time and SOC transferred to the EV battery.

**a. EV types**
According to the statistics of registered vehicles from DfT by 2015 [134], around 50% of EV on road are BEV (17826) and the other 50% are PHEV (17415), and the most popular models of EV on road are shown in Table 4-19.

Table 4-19: Most popular EV models in the UK by 2015 [134]

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

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

Li-ion batteries have a generic charging pattern as shown in Figure 4-17, which is composed of three stages, i.e. pre-charging, current regulation and voltage regulation stages [135]. 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 EV battery is simplified as a constant value as shown in Figure 4-17.

Figure 4-17: Generic charging profile of Li-ion batteries and its simplified version [135]

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 [136], 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 [137]. 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, [138] 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 [106, 109, 136] often model the charging start time based on the traffic data or home arrival time by assuming EV 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 EV trials in the UK.

The Technology Strategy Board (TSB) launched the Ultra-Low Carbon Vehicle Demonstrator (ULCVD) programme in 2008, through which 349 EV were deployed, and data were collected from over 276000 individual trips and 51000 charging events [132, 139, 140]. 8 consortia were made up of manufacturers, energy suppliers, university partners and local authorities in regions across the UK, operating 349 EV from 18 manufacturers. Charging start times were monitored and summarised as shown in Figure 4-18.
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 EV battery

ULCVD monitored how much SOC was transferred in a single charging event, and Figure 4-19 shows the statistics of the measured 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 EV were charged full with the majority of charging events (>70% of all monitored charging events) ending at over 95% SOC [139]. Therefore, in this study, it is assumed that all EV are charged once a day and they are always charged full.
4.3.3 Case study: determination of hot-spot temperature, loss-of-life and expected lifetime of prototype distribution transformer under EV scenarios

After defining EV scenarios and introducing EV charging load modelling, the hot-spot temperature of the prototype distribution transformer is calculated with refined thermal parameters under various EV scenarios, and the corresponding lifetimes are estimated.

Due to the uncertainty brought by EV charging, Monte-Carlo algorithms are applied for the simulation, and the flow chart of the simulation is presented in Figure 4-22. Basically, charging load profiles of individual EV are generated first with stochastically defined uncertainties including EV type, charging power, start charging time and SOC transferred. Then the final load profile is created by adding up all individual EV charging load profiles and the base load profile. The base load profile in this section is from the day in September 2013 with highest peak load of the substation in which the prototype transformer is installed. The ambient temperature profile is the ambient temperature recorded in the same day. The load profile and ambient temperature profile are shown in Figure 4-20 and Figure 4-21 respectively.

With the day of highest peak load investigated, the worst-case scenario is therefore considered. As a result, the resultant peak load, peak hot-spot temperature and failure probability obtained under the selected day will be exactly the same as those that should be obtained when the investigation is conducted on the whole month instead of one single day. On the other hand, in terms of the loss-of-life and expected lifetime, the results obtained with the load profile of the selected day are more conservative, i.e. overestimating the loss-of-life
and underestimating the expected lifetime, comparing to results obtained with the whole month. Studies have shown that the loss-of-life is overestimated for less than 15%, and correspondingly the expected lifetime is underestimated for less than 15%. Therefore, as a case study, the proposed strategy is here demonstrated under a selected day in September which has the highest peak load of the month.

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.
As aforementioned, three EV scenarios are investigated, i.e. BAU scenario (0% EV penetration), High-range scenario (32% EV penetration) and Extreme-range scenario (58.9% EV penetration). Resultant load profiles, hot-spot temperature profiles of one among 5000
sets of results are displayed in Figure 4-23 and Figure 4-24 as an example to demonstrate the effects of three EV scenarios.

![Load Profiles](image)

**Figure 4-23:** One example set of load profiles under three EV scenarios

![Hot-Spot Temperature Profiles](image)

**Figure 4-24:** One example set of hot-spot temperature profiles under three EV scenarios

Comparing the load and hot-spot temperature profiles under three EV scenarios, it can be seen that the hot-spot temperature profile is lagging behind the load profile for around one hour under each EV scenario. For example, the load peaks at around hour 19 under Extreme-range scenario, while the corresponding hot-spot temperature peaks at around hour 20. This lag is caused by the combined effects of transformer winding and oil time constants. For this distribution transformer, the winding time constant is 21.7 minutes while the oil time constant is 180 minutes, therefore, the combined effects lead to a lag of around 1 hour. In addition, effects of EV charging last longer on hot-spot temperature than load. The majority of EV charging occurs between hour 15 and 22 in a day. Its effects on load only last until hour 24, therefore the difference on loads under three EV scenarios is smaller than 0.05 p.u. at the beginning of the next day (hour 0). However, EV charging effects last much longer on hot-
spot temperature. Consequently, the difference of hot-spot temperature under three EV scenarios can be as large as 16.45 K at the beginning of the next day.

The peak load and peak hot-spot temperature are of key concerns 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 4-20.

<table>
<thead>
<tr>
<th>EV penetration level (%)</th>
<th>Number of EV</th>
<th>Peak load range (p.u.)</th>
<th>Peak hot-spot temperature range (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAU scenario</td>
<td>0</td>
<td>0</td>
<td>0.73</td>
</tr>
<tr>
<td>High-range scenario</td>
<td>32</td>
<td>132</td>
<td>[1.02, 1.28]</td>
</tr>
<tr>
<td>Extreme-range scenario</td>
<td>58.9</td>
<td>244</td>
<td>[1.41, 1.79]</td>
</tr>
</tbody>
</table>

Table 4-20 presents the peak load and peak hot-spot temperature ranges under three EV scenarios. It is observed that EV charging load significantly increases the peak load and peak hot-spot temperature. 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.

Uncertainties on the resultant peak load or peak hot-spot temperature are originally generated by randomness of EV charging. It is found that the distribution of peak load and peak hot-spot temperature can be expressed by normal distributions. Therefore, the mean and standard variance can be obtained for each peak load and peak hot-spot temperature distribution under High-range and Extreme-range scenarios. For example, by fitting the hot-spot temperatures under Extreme-range scenario with a normal distribution, the mean and standard variance are obtained as 107.9 °C and 1.9 °C respectively.
Figure 4-25: Histogram of peak hot-spot temperatures under Extreme-range scenario and fitted normal distribution

Figure 4-26 and Figure 4-27 display the CDF plot of peak load and peak hot-spot temperature respectively under High-range and Extreme-range scenarios.
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 temperature that can be reached under High-range scenario is 90.1°C, which is 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 temperature can go up to 115.7 °C. It means that during the EV 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. Recall that the rated hot-spot temperature rise is only 65.1 K for this 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 by the IEC ageing model. Daily loss-of-life is first derived with daily hot-spot temperature profile, and the expected lifetime is calculated with daily loss-of-life by assuming the same hot-spot temperature profile repeats for the whole year with the transformer end-of-life criterion of 17.12 years (when DP drops to 200). Results are given in Table 4-21.
CHAPTER 4 ASSESSMENT OF A PROTOTYPE DISTRIBUTION TRANSFORMER’S THERMAL PERFORMANCE UNDER EVS SCENARIOS

Table 4-21: Ranges of daily loss-of-life and expected lifetimes under EV scenarios of investigated prototype distribution transformer under selected September day

<table>
<thead>
<tr>
<th>EV penetration level (%)</th>
<th>Number of EV</th>
<th>Daily loss-of-life range (p.u.)*</th>
<th>Expected lifetime range (p.u.)*</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAU scenario</td>
<td>0</td>
<td>0</td>
<td>0.009</td>
</tr>
<tr>
<td>High-range scenario</td>
<td>32</td>
<td>132</td>
<td>[0.025, 0.045]</td>
</tr>
<tr>
<td>Extreme-range scenario</td>
<td>58.9</td>
<td>244</td>
<td>[0.151, 0.476]</td>
</tr>
</tbody>
</table>

*: 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.

Results show that the daily loss-of-life is increased by a factor of 5 (0.045 compared to 0.009) and 53 (0.476 compared to 0.009) under High-range and Extreme-range scenarios respectively. The expected lifetime is reduced by up to 80% (22.5 compared to 111) and 98% (2.1 compared to 111) with EV charging under High-range and Extreme-range scenarios respectively. Therefore, from a long-term failure perspective, EV charging will significantly reduce the thermal life of distribution transformers, and adaptive asset management strategies must be changed to face the upcoming EV scenarios.

4.4 Assessment of thermal failure probability due to bubbling under EV scenarios

Apart from reducing transformer lifetimes by accelerating the ageing in the long term perspective; EV charging may also cause immediate failure 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 this section, in order to investigate EV 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.
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4.4.1 Modelling of bubbling inception temperature

Past researches [54-56] have shown that bubbling inception temperature is highly dependent on the moisture level of the insulation paper of the transformer, and is also affected by the gas content and oil pressure. Oommen [55] proposed and verified a model for the calculation of bubbling inception temperature in transformers as shown in Equation (4-5),

\[
T = \frac{6996.7}{(22.454 + 1.4495 \times \ln W - \ln P)} - e^{0.473/W} \times (G / 30)^{1.585}
\]  

(4-5)

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. For example, the bubbling inception temperature is lifted by around 3 K when the oil depth is increased from 1 meter to 3 meters. Gas content plays a more important role when the moisture level is high. Figure 4-28 shows the calculated bubbling inception temperatures with Equation (4-5) under different moisture levels in paper and gas levels, where “low gas” represents the gas content of 0.5% (5000 ppm in volume) and “high gas” represents 9% (90000 ppm in volume) [55]. Free-breathing transformers or sealed transformers with nitrogen blanket can be reflected by the high gas curve.

![Figure 4-28: Bubbling inception temperatures varying with moisture in paper and gas content](image_url)
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.

### 4.4.2 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 [141]. Different equilibrium curves have been developed by several authors [142-145], and Fessler [146] proposed equations of the equilibrium curves which are shown as Equation (4-6) to (4-9).

\[
W = 2.173 \times 10^{-7} \times p_v^{0.6685} \times e^{4725.6/T_E}
\]  
(4-6)

\[
p_v = \frac{PPM}{PPM_{sat}} \times p_{v, sat}
\]  
(4-7)

\[
PPM_{sat} = 10^{(A-B/T_E)}
\]  
(4-8)

\[
p_{v, sat} = \frac{p_c}{760} \times 10^{\frac{(T_E-T_c)\times (a+bx(T_E-Tc)+c(T-E)^3)}{1+d(T-E)^3}}
\]  
(4-9)

where \( W \) is the moisture in paper in \%; \( T_E \) 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 4-22.

<table>
<thead>
<tr>
<th>( A )</th>
<th>( B )</th>
<th>( a )</th>
<th>( b )</th>
<th>( c )</th>
<th>( d )</th>
<th>( p_c )</th>
<th>( T_c )</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.44</td>
<td>1686</td>
<td>3.24</td>
<td>5.86\times10^{-3}</td>
<td>1.17\times10^{-8}</td>
<td>2.19\times10^{-3}</td>
<td>1.66\times10^{-5}</td>
<td>647.26</td>
</tr>
</tbody>
</table>

Table 4-22: Constant values in Fessler’s equations
CHAPTER 4 ASSESSMENT OF A PROTOTYPE DISTRIBUTION TRANSFORMER’S THERMAL PERFORMANCE UNDER EVS SCENARIOS

To briefly explain the equations of equilibrium curves, Equation (4-6) is proposed by Fessler [146] 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 (4-7), 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 (4-8), where $A$ and $B$ are constant parameters. $p_{v, sat}$ can be calculated by Equation (4-9) which is proposed by Foss in [147].

Resultant equilibrium curves are shown in Figure 4-29.

![Figure 4-29: Equilibrium curves obtained by Fessler's equations](image)

**4.4.3 Determination of failure probability under EV scenarios**

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 4-30 demonstrates how the failure probability of transformers is modelled 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.

EV charging affects mainly the peak hours of a day, and it is assumed that the moisture in paper does not change significantly by EV 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 EV 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.

To demonstrate the method, failure probability is determined for the prototype transformer under three EV scenarios, i.e. BAU, High-range and Extreme-range EV scenarios. The base load and ambient profiles are taken in the September day as used in section 4.3.3 and shown in Figure 4-20 and Figure 4-21. The measured hot-spot temperature profile on that day is shown in Figure 4-31. The hot-spot temperature 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 (4-5), 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 (4-6) to Equation (4-9). 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 [148] 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 4-23, which also includes the various moisture in oil conditions and resultant moisture in paper values.
EV charging load is modelled based on the method introduced in section 4.3. Refined thermal parameters of the prototype transformer in Table 4-8 are applied for the calculation of hot-spot temperatures under EV scenarios. Resultant hot-spot temperatures are shown in Figure 4-27 and Table 4-20, where the peak hot-spot temperature is 65.1°C under BAU EV scenario; varies from 80.5 °C to 90.1 °C under High-range EV scenario; varies from 101.2 °C to 115.7 °C under Extreme-range EV scenario.

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 4-32, 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 4-32, 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 (4-5) to (4-9).
Determined results of moisture in paper, bubbling inception temperature and failure probability under three EV scenarios are shown in Table 4-23.

Table 4-23: Results of failure probability under Extreme-range scenario of investigated prototype transformer under selected September day

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

Results show that the prototype distribution transformer only faces failure risks under Extreme-range 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. 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.

Another point worth mentioning is that, considering the transition of moisture between oil and paper, higher average loads or higher operational temperature inside the transformer would be in favour of moisture moving from paper to oil. Therefore, the moisture in paper level will be reduced and lead to a higher bubbling inception temperature and a lower failure probability assuming the same hot-spot temperature. So, considering the EV scenarios, it would be possible to lower the failure probability by increasing the average load level prior to EV penetration in order to promote the movement of moisture from paper to oil.

4.5 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. In long term, accelerated thermal ageing and reduced lifetime are concerned. In short term, immediate failure is concerned which occurs as assumed when the hot-spot temperature exceeds the bubbling inception temperature. The developed methodology first calculates the hot-spot temperature under EV scenarios using IEC thermal model with refined thermal parameters which reflect the realistic thermal characteristics of the transformer, based on which loss-of-life and expected lifetime are assessed. Then by comparing the hot-spot temperature with bubbling inception temperature, failure probability can be determined.

Three models are introduced in the assessment strategy in this chapter. The first model is to refine thermal parameters based on optical fibre measured temperatures during the extended heat run test. Verifications under step loads and dynamic loads show that the accuracy of hot-spot temperature prediction is much improved by refined parameters as compared to IEC recommended values. Also, further studies show that in order to obtain the most optimised thermal parameters, the refinement should be conducted with temperature data measured during the whole process of the extended heat run test which includes not only three test periods under three load conditions, but also the cooling periods between each two consecutive tests.
The second model introduced is for EV charging modelling, which models EV charging in a probabilistic way with as realistic as possible data obtained either from government statistics or EV trials in the UK.

The third model is for assessment of failure probability due to the bubbling failure mechanism. Two sub models are used here which are bubbling inception model and moisture in paper model.

With the strategy introduced and demonstrated in this chapter on a single prototype transformer, a population of distribution transformer can be assessed using the same strategy. However, individual transformers in a population are likely lack of optical fibre measured temperature data during heat run test and load data as well. To solve this problem, an alternative method of refining thermal parameters is introduced in next chapter. In addition, an approach of load modelling is also introduced.
In Chapter 4, assessment strategy for the future adaptability of distribution transformers under EV scenarios is introduced, where the transformer is assessed with refined thermal parameters so that prediction of hot-spot temperatures as accurate as possible under EV scenarios can be achieved. An optimisation method of refining IEC thermal parameters by curve-fitting optic fibre measured top-oil and hot-spot temperatures is proposed.

However, unlike the prototype transformer, most of existing transformers in the population do not have optic fibre sensors installed; therefore, the measurement data of hot-spot temperature in the heat run test is not available. In addition, unlike the prototype transformer, the load and ambient profiles are generally not recorded for the majority of distribution transformers in the population.

In this chapter, in order to apply the assessment strategy on individual transformers of the population, an alternative method of refining IEC thermal parameters is introduced. Also a load modelling tool and an ambient temperature modelling tool are introduced so that the load and ambient profiles of individual transformers can be generated when there are no recorded data.

5.1 An alternative method of deriving IEC thermal parameters for transformers without hot-spot temperature measurements

The method introduced here is to calculate each IEC thermal model parameter with thermocouple measured temperatures during the heat run test and nameplate information of the transformer.

The nameplate of a transformer usually looks like the example shown in Figure 5-1, which is the nameplate of the transformer demonstrated in Chapter 4.
The nameplate offers ratings and specifications of the transformer. Solely with the information provided in the nameplate, no thermal model parameters can be determined. However, the information of oil mass, untanking mass and total mass is essential for the derivation of the oil time constant. In addition, with the power rating and the cooling type, it can be determined which set of recommended parameters given in the IEC loading guide is suitable for this transformer when no heat run test results are available.

In practice, heat run tests can be generally summarised as two regimes, which are conventional and extended heat run test. As explained in Chapter 3, 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 5-1, 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.
5.1.1 Derivation of IEC thermal parameters with heat run test results

a. Conventional heat run test

Measured data include ambient, top-oil, bottom-oil temperatures and the winding resistance under the rated load. With the measured data, the following thermal model parameters can be derived.

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

$$\Delta \theta_{o, \text{rated}} = \theta_{o, \text{rated}} - \theta_a$$  \hspace{1cm} (5-1)

where $\theta_{o, \text{rated}}$ is the stabilised rated top-oil temperature, and $\theta_a$ is the ambient temperature when $\theta_{o, \text{rated}}$ is measured.

- The rated average winding to oil gradient $g_r$

$$g_r = \Delta \theta_{w, \text{rated}} - \Delta \theta_{\text{ave, rated}}$$  \hspace{1cm} (5-2)

where $\Delta \theta_{\text{ave, rated}}$ is the rated average-oil rise, and $\Delta \theta_{w, \text{rated}}$ is the rated average winding rise.
\( \Delta \theta_{\text{ave, rated}} \) is the average of rated top-oil rise and bottom-oil rise. \( \Delta \theta_{w, \text{rated}} \) is derived from the measured winding resistance curve. 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 [19].

- The winding time constant \( \tau_w \)

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

\[
\theta_{w, \text{rated}}(t) = \theta_{\text{ave, rated}} - k \times t + g_r \times e^{-\frac{L}{\tau_w}}
\]  

(5-3)

where \( \theta_{w, \text{rated}}(t) \) is the rated average winding temperature, \( \theta_{\text{ave, rated}} \) is the rated average-oil temperature at the instant of transformer shutdown. \( k \) is the decline rate of the average-oil temperature. \( g_r \) is the rated average winding to oil gradient.

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 [19]. 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, \( \tau_w \) 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 \( \tau_w \).

In addition, a numerical method for the calculation of the average winding temperature and the winding time constant is introduced in IEC 60076-2 [19].

- The top-oil time constant \( \tau_{o, \text{top}} \)

\( \tau_{o, \text{top}} \) 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 (5-4). This requires the top-oil temperature regularly measured, and also the test load should remain the same for the entire test.
\[ \Delta \theta_{o, \text{rated}}(t) = \Delta \theta_{o, \text{ini}} + (1 - e^{-t/\tau_{o,\text{top}}}) \times (\Delta \theta_{o, \text{rated}} - \Delta \theta_{o, \text{ini}}) \]  
\hspace{1cm} (5-4)

Where \( \Delta \theta_{o, \text{rated}}(t) \) is the transient top-oil temperature rise under the rated load, and \( \Delta \theta_{o, \text{ini}} \) is the initial top-oil temperature rise.

Another method is through an equation given in IEEE loading guide [15],

\[ \tau_{o, \text{top}} = \frac{C \times \Delta \theta_{o, \text{rated}} \times 60}{p} \]  
\hspace{1cm} (5-5)

\[ C = 0.132 \times M_A + 0.0882 \times M_T + 0.4 \times M_O \quad \text{(for ONAN cooling)} \]  
\hspace{1cm} (5-6)

where \( \Delta \theta_{o, \text{rated}} \) is the rated top-oil temperature rise; \( p \) is the rated total power losses; \( C \) is a constant calculated by Equation (5-6); \( M_A, M_T \) and \( M_O \) are mass of core & coils, tank & fittings and oil in kg respectively.

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

- The average oil time constant \( \tau_o \) and thermal constant \( k_{11} \)

\[ \tau_o \] and \( \tau_{o, \text{top}} \) are linked by \( k_{11} \), as,

\[ k_{11} = \tau_{o, \text{top}} / \tau_o \]  
\hspace{1cm} (5-7)

\( \tau_o \) can be also calculated as,

\[ \tau_o = \frac{C \times \Delta \theta_{\text{ave}, \text{rated}} \times 60}{p} \]  
\hspace{1cm} (5-8)

where \( \Delta \theta_{\text{ave}, \text{rated}} \) is the rated average-oil rise, \( p \) is the rated total power losses as in Equation (5-5); and \( C \) is the constant calculated by Equation (5-6).
b. Extended heat run test

The extended heat run test measures the time-varying top-oil and bottom-oil temperatures and the winding resistance under each step load. Additional thermal parameters that can be derived from the extended heat run test results are oil and winding exponents.

- The oil exponent $x$

$x$ can be derived based on Equation (5-9).

$$\Delta \theta_o = \left[ \frac{1 + R \times K^2}{1 + R} \right]^x \times \Delta \theta_{o, \text{rated}}$$

(5-9)

where $R$ is load loss to no-load loss ratio; $K$ is the load factor, and $\Delta \theta_o$ is the top-oil rise under load $K$.

To derive $x$, $\Delta \theta_o / \Delta \theta_{o, \text{rated}}$ 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 (5-10).

$$g = g_r \times K^y$$

(5-10)

where $g$ is average winding to oil gradient under load $K$.

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. Further discussion with support of examples will be given later in this chapter.
c. Undeterminable thermal model parameters from heat run test results

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.

5.1.2 Demonstration of alternative method of derivation of IEC thermal parameters for transformers without hot-spot temperature measurements

The method of refining thermal parameters is demonstrated on the same prototype transformer used in Chapter 4. Differently, it is now assumed that no optic fibre sensors are installed in this transformer.

Oil temperatures are measured by thermocouples, which is a common practice when conducting heat run tests. Bottom-oil is measured on the radiator outlet surface, due to the difficulty in inserting thermocouples inside the bottom of transformer. Top-oil is measured at two locations. One is, corresponding to the bottom-oil, on the inlet surface of the same radiator. The other is in the oil pocket, which is inserted in the top bulk oil. Thermocouple measured top-oil and bottom-oil temperatures are shown in Table 5-2. Hot-spot temperature rise measured by optic fibre sensors are also displayed since they are used for verification later in this section.

| Table 5-2: Stabilised oil and hot-spot temperature measurements during extended heat run test |
|-----------------------------------|----------------|----------------|----------------|
| Top-oil rise (oil pocket) (K)     | 29.8           | 50.4           | 67.7           |
| Top-oil rise (radiator inlet surface) (K) | 23.1           | 45.0           | 60.8           |
| Bottom-oil rise (radiator outlet surface) (K) | 15.6           | 22.3           | 31.6           |
| Hot-spot rise (K)                 | 40.4           | 65.1           | 91.1           |
| Ambient (°C)                      | 25.7           | 25.0           | 27.0           |

a. Derivation based on conventional heat run test

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

$\Delta \theta_{o,\text{rated}}$ in this section is taken from the oil pocket measurement inside the transformer tank, 50.4 K.
• The rated average winding to oil gradient $g_r$

$g_r$ is the difference between rated average winding rise to the average-oil rise, which is 13.2 K in this example.

In principle, $\Delta \theta_{\text{ave, rated}}$ is the average of top-oil and bottom-oil temperatures measured inside the transformer, however the bottom-oil temperature inside the transformer is not available, so a practical approach is commonly used.

$$\Delta \theta_{\text{ave, rated}} = \Delta \theta_{o, \text{inside}} - \frac{\Delta \theta_{o, \text{surface}} - \Delta \theta_{b, \text{surface}}}{2}$$  \hspace{1cm} (5-11)

where $\Delta \theta_{o, \text{inside}}$ is the inside top-oil rise under rated load (taken from the oil pocket measurement). $\Delta \theta_{o, \text{surface}}$ and $\Delta \theta_{b, \text{surface}}$ are surface-measured top-oil and bottom-oil rises under rated load respectively.

The idea is to calculate the top to bottom oil temperature difference with surface-measured temperatures, so that the systematic error from ‘measuring on the surface’ can be cancelled out. Then $\Delta \theta_{\text{ave, rated}}$ is obtained by subtracting half of the difference from the inside top-oil temperature. $\Delta \theta_{o, \text{inside}} = 50.4$ K, $\Delta \theta_{o, \text{surface}} = 45.0$ K and $\Delta \theta_{b, \text{surface}} = 22.3$ K, thus $\Delta \theta_{\text{ave, rated}} = 39.1$ K according to Equation (5-11).

The derivation of $\Delta \theta_{w, \text{rated}}$ can be seen from Figure 5-2, which is 75.1°C (average winding temperature) - 25°C (ambient temperature) + 2.2°C (average-oil temperature drop) = 52.3 K.

• The winding time constant $\tau_w$

Derivation of $\tau_w$ is shown in Figure 5-2. The tangent line of the fitting curve at time zero crosses the average-oil temperature line at $t = 11.3$ min, thus $\tau_w = 11.3$ min.
Figure 5-2: Derivation of $\Delta \theta_{\text{w, rated}}$ and $\tau_w$ [71]. (a) Measured winding resistance (b). Average winding temperature and winding time constant

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

When the top-oil temperature is regularly measured during the entire test, $\tau_{o,top}$ can be derived by curve-fitting as shown in Figure 5-3 with Equation (5-4). As a result, $\tau_{o,top} = 201.6$ min.
When the conventional heat run test without continuous regular temperature measurements is conducted, the complete top-oil temperature curve cannot be constructed, thus Equation (5-5) is used to calculated $\tau_{o, top}$, and the calculation is shown as Equation (5-12). The result in this case is $\tau_{o, top} = 205.7$ min.

$$
\tau_{o, top} = \frac{C \times \Delta \theta_{o, rated} \times 60}{p} = \frac{677.9 \times 50.4 \times 60}{9965} = 205.7
$$

(5-12)

Values of $\tau_{o, top}$ obtained by two methods are of negligible difference, which justifies that measuring the steady-state value of the top-oil temperature and combining with nameplate information is sufficient and reliable to derive the time constant by using Equation (5-5).

- The thermal model constant $k_{II}$

Using Equation (5-8), $\tau_o$ is obtained as 159.6 min. $k_{II}$ is the ratio of $\tau_{o, top}$ to $\tau_o$, thus $k_{II} = \tau_{o, top}/\tau_o = 201.6/159.6 = 1.26$

b. Derivation based on extended heat run test

- The oil exponent $x$

$x = 0.77$ is derived based on three load tests as presented in Figure 5-4 (a). The required oil temperatures are taken from the oil pocket measurements. The load loss to no-load loss ratio is 8.67.
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Meanwhile, different values of $x$ can be obtained if only one non-rated load test is used as shown in Figure 5-4 (b) and Table 5-4.

- The winding exponent $y$

$y=2.39$ is derived based on three load tests as shown in Figure 5-4 (a). Required winding to oil gradients under different loads are given in Table 5-3.

<table>
<thead>
<tr>
<th>Average winding to oil gradient (K)</th>
<th>0.7 p.u.</th>
<th>1.0 p.u.</th>
<th>1.25 p.u.</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.9</td>
<td>13.2</td>
<td>23.5</td>
<td></td>
</tr>
</tbody>
</table>

Table 5-3: Average winding to oil gradient under different loads obtained during extended heat run test

Similar to $x$, different values of $y$ can be obtained if only one non-rated load test is used as shown in Figure 5-4 (b) and Table 5-4.

Figure 5-4: Derivation of $x$ and $y$ (a). Derivation of $x$ and $y$ based on three load tests (b). Derivation of $x$ and $y$ based on under-load and overload tests separately.
Table 5-4: Oil component $x$ and winding component $y$ values derived under various heat run tests

<table>
<thead>
<tr>
<th></th>
<th>With under-load and rated load tests</th>
<th>With overload and rated load tests</th>
<th>With under-load, rated load and overload tests</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x$</td>
<td>0.86</td>
<td>0.72</td>
<td>0.77</td>
</tr>
<tr>
<td>$y$</td>
<td>1.44</td>
<td>2.58</td>
<td>2.39</td>
</tr>
</tbody>
</table>

Oil and winding exponents are parameters reflecting the non-linear change of top-oil rise and winding to oil gradient based on load. Generally, more representative values to arbitrary loads can be obtained by fitting more data from different non-rated load tests. In addition, possible measurement errors would affect the derivation of oil and winding exponents, especially when only one non-rated load test is applied. For example, assuming the measurement error is $\pm 1^\circ$C, the derivation of winding exponent would be affected as shown in Table 5-5. It can be seen that winding exponent derived by under-load and rated load tests is the most vulnerable to measurement errors. This might also explain why the winding exponent derived with under-load and rated load tests in Table 5-4 is so much deviated from that derived with overload and rated load tests.

Table 5-5: $\pm 1^\circ$C measurement error’s effects on derivation of winding exponent

<table>
<thead>
<tr>
<th></th>
<th>0.7 p.u.</th>
<th>1.0 p.u.</th>
<th>1.25 p.u.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average winding to oil gradient (K)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$g / g_r$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum value</td>
<td>0.73</td>
<td>1</td>
<td>2.01</td>
</tr>
<tr>
<td>Actual value</td>
<td>0.60</td>
<td>1</td>
<td>1.79</td>
</tr>
<tr>
<td>Minimum value</td>
<td>0.49</td>
<td>1</td>
<td>1.57</td>
</tr>
<tr>
<td>$y$ (with under-load and rated load tests)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum value</td>
<td>2 (39%)</td>
<td>N/A</td>
<td>3.13 (21%)</td>
</tr>
<tr>
<td>Actual value</td>
<td>1.44</td>
<td></td>
<td>2.58</td>
</tr>
<tr>
<td>Minimum value</td>
<td>0.88 (39%)</td>
<td>N/A</td>
<td>2.02 (22%)</td>
</tr>
<tr>
<td>$y$ (with overload and rated load tests)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum value</td>
<td>N/A</td>
<td>3.13 (21%)</td>
<td></td>
</tr>
<tr>
<td>Actual value</td>
<td></td>
<td>2.58</td>
<td></td>
</tr>
<tr>
<td>Minimum value</td>
<td></td>
<td>2.02 (22%)</td>
<td></td>
</tr>
<tr>
<td>$y$ (with under-load, rated load and overload tests)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum value</td>
<td>2.98 (25%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual value</td>
<td>2.39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum value</td>
<td>1.97 (18%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Ideally, it is preferred to use oil and winding exponents derived with all three load tests for the calculation of hot-spot temperature under arbitrary loads. If oil and winding exponents derived with one non-rated load test are used, errors on the calculation of hot-spot temperature would occur. Figure 5-5 compares hot-spot temperature rise calculated with different sets of $x$ and $y$ as shown in Table 5-4. Measured hot-spot temperature rises under 0.7 p.u., 1.0 p.u. and 1.25 p.u. load tests are also plotted for comparison.
Results show that hot-spot temperature rise calculated with \( x \) and \( y \) obtained with under-load test is underestimated especially under overload conditions. The difference is negligible at around 1.0 p.u., but increases when the load either increases or decreases. For example, under 2.0 p.u. load, the underestimation can be as large as 21.5 K.

c. Comparisons between hot-spot temperatures calculated with IEC recommended parameters and parameters derived by heat run test data

In Table 5-6, IEC recommended thermal parameters for distribution transformers are compared with those derived by aforementioned heat run test data.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>( \Delta \theta_{so} )</th>
<th>( R )</th>
<th>( g_r )</th>
<th>( H )</th>
<th>( x )</th>
<th>( y )</th>
<th>( \tau_o )</th>
<th>( \tau_w )</th>
<th>( k_{11} )</th>
<th>( k_{21} )</th>
<th>( k_{22} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Derived by heat run test data</td>
<td>50.4</td>
<td>8.67</td>
<td>13.2</td>
<td>1.1</td>
<td>0.77</td>
<td>2.39</td>
<td>159.6</td>
<td>11.3</td>
<td>1.26</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>IEC Recommended</td>
<td>60</td>
<td>9</td>
<td>16.36</td>
<td>1.1</td>
<td>0.8</td>
<td>1.60</td>
<td>180</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Calculated hot-spot temperatures are compared with measured values during the extended heat run test as shown in Figure 5-6. Error analysis in Table 5-7 shows that the accuracy of the hot-spot temperature is improved by using thermal parameters derived by heat run test data, where the maximum error is more than halved. Therefore, when the heat run test data are available for a transformer, it is suggested to derive IEC thermal parameters with heat run test data for better accuracy of the prediction of hot-spot temperatures. On the another hand, considering the sensitivity of the derivation of thermal parameters to the accuracy of
measurements obtained during the heat run test (refer to Table 5-5), it would be beneficial to derive thermal parameters based on results of more than one heat run test, which can be conducted either on the same transformer or at least the similar transformers. So that the accuracy and representativeness of derived thermal parameters can be improved.

![Figure 5-6: Comparison between calculated (with heat run test derived thermal parameters) and measured hot-spot temperature](image)

<table>
<thead>
<tr>
<th>Parameters derived by heat run test data</th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEC recommended parameters</td>
<td>25.87</td>
<td>12.14</td>
</tr>
<tr>
<td>Parameters derived by heat run test data</td>
<td>10.25</td>
<td>0.91</td>
</tr>
</tbody>
</table>

5.1.3 Comparison to refinement of thermal parameters by curve-fitting

The method of refining IEC model thermal parameters is to calculate each parameter separately with thermocouple measured temperature data which are required by the standard procedure of the heat run test. It is an alternative method to the method introduced in Chapter 4 that refines thermal parameters by curve-fitting the hot-spot and top-oil temperature data measured by optic fibre sensors during the heat run test. Both methods are aimed to refine IEC thermal parameters for individual distribution transformers so that more accurate prediction of hot-spot temperatures under arbitrary loads can be obtained than using generic values recommended in the loading guide.

To compare two methods, a general comparison is first performed as shown in Table 5-8. The method introduced in Chapter 4 is referred as “curve-fitting” method, and the method introduced in this chapter is referred as “calculating” method.
Table 5-8: A general comparison between two methods for refinement of thermal parameters

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

 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.

a. **Comparison under heat run test loads**

To prove that the curve-fitting method provides better accuracy, a comparison is made on the hot-spot temperatures calculated with thermal parameters refined by two methods under heat run test loads and cyclic loads. Thermal parameters refined by two methods are shown in Table 5-9.

Table 5-9: Thermal parameters refined by two methods

<table>
<thead>
<tr>
<th>Refinement method</th>
<th>$\Delta \theta_c$</th>
<th>$R$</th>
<th>$H \times g_f$</th>
<th>$x$</th>
<th>$y$</th>
<th>$\tau_o$</th>
<th>$\tau_w$</th>
<th>$k_{11}$</th>
<th>$k_{21}$</th>
<th>$k_{22}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curve-fitting method</td>
<td>56.2</td>
<td>8.67</td>
<td>8.44</td>
<td>0.72</td>
<td>1.08</td>
<td>180</td>
<td>21.7</td>
<td>1.18</td>
<td>2.83</td>
<td>0.91</td>
</tr>
<tr>
<td>Calculating method</td>
<td>50.4</td>
<td>8.67</td>
<td>14.5</td>
<td>0.77</td>
<td>2.39</td>
<td>159.6</td>
<td>11.3</td>
<td>1.26</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Calculated hot-spot temperatures under the heat run test load are shown in Figure 5-7, with the error analysis shown in Table 5-10.
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Figure 5-7: Calculated hot-spot temperatures with thermal parameters refined by two methods under heat run test loads

Table 5-10: Error analysis of hot-spot temperatures calculated with thermal parameters refined by two methods under heat run test loads

<table>
<thead>
<tr>
<th>Refinement method</th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curve-fitting method</td>
<td>3.53</td>
<td>-0.17</td>
</tr>
<tr>
<td>Calculating method</td>
<td>10.25</td>
<td>0.91</td>
</tr>
</tbody>
</table>

b. Comparison under cyclic loads

Calculated hot-spot temperatures under the heat run test load are shown in Figure 5-8, with the error analysis shown in Table 5-11.

Figure 5-8: Calculated hot-spot temperatures with thermal parameters refined by two methods under cyclic loads
Table 5-11: Error analysis of hot-spot temperatures calculated with thermal parameters refined by two methods

<table>
<thead>
<tr>
<th>Refinement method</th>
<th>Maximum error (K)</th>
<th>Mean error (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curve-fitting method</td>
<td>6.07</td>
<td>0.04</td>
</tr>
<tr>
<td>Calculating method</td>
<td>-7.21</td>
<td>-2.35</td>
</tr>
</tbody>
</table>

Comparison of hot-spot temperatures calculated with thermal parameters refined by two methods under heat run test loads and cyclic loads show that the curve-fitting method leads to better accuracy under either load. Under heat run test loads, similar mean errors are resulted by two methods, but the curve-fitting method improves the maximum error to 3.53 K from 10.25 K. Under cyclic loads, curve-fitting method has lower mean and maximum errors than the calculating method. Therefore, the curve-fitting method is preferred to refine the thermal parameters when the required hot-spot temperature measurements are available. Otherwise, the calculating method should be used and it still provides better accuracy when predicting hot-spot temperatures than the generic values recommended in the loading guide.

c. Comparison on assessment of long term thermal ageing and short term failure probability under EV scenarios

Thermal parameters refined by calculating method are applied for the assessment of long term ageing and short term failure probability under three EV scenarios, i.e. BAU, High-range and Extreme-range scenarios. The same methodology as the one used in Chapter 4 is applied here. The same base load and ambient temperature profiles are used here. In order to consider the randomness of EV charging load, 5000 repetitions, the same as in Chapter 4, are conducted on each simulation. Results are compared with those obtained by using the thermal parameters refined by curve-fitting method.

Firstly, the comparison is made on the peak load and peak hot-spot temperature ranges as presented in Table 5-12. Since the same base load profile is applied, and sufficient simulations are conducted, the peak load ranges are almost the same for two calculation cases with thermal parameters refined by curve-fitting and calculating 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 5-12: Comparison of peak load and hot-spot temperature ranges under EV scenarios with thermal parameters refined by two methods

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

Figure 5-9: Comparison of CDF of hot-spot temperature under EV scenarios with thermal parameters refined by two methods

In terms of long term thermal ageing, the comparison of assessment results is presented in Table 5-13. 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.
CHAPTER 5 ASSESSMENT OF EXISTING INDIVIDUAL DISTRIBUTION TRANSFORMERS UNDER EVS SCENARIOS

Table 5-13: Comparison of assessment of long term thermal ageing under EV scenarios with thermal parameters refined by two methods

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

*: 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.

In terms of short term failure probability, the comparison of assessment results is presented in Table 5-14. Same as the curve-fitting method, no failure risks are faced by the transformer under BAU and High-range scenarios with the calculating method. 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.

Table 5-14: Comparison of assessment of short term failure probability under EV scenarios with thermal parameters refined by two methods

<table>
<thead>
<tr>
<th>Moisture in oil @ 20 °C (ppm)</th>
<th>Failure probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>15</td>
<td>0</td>
</tr>
<tr>
<td>17.5</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>25</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Percentage to the saturation (%)</th>
<th>Failure probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.5</td>
<td></td>
</tr>
<tr>
<td>9.1</td>
<td>0</td>
</tr>
<tr>
<td>18.2</td>
<td>0</td>
</tr>
<tr>
<td>27.3</td>
<td>0</td>
</tr>
<tr>
<td>31.8</td>
<td>0</td>
</tr>
<tr>
<td>36.4</td>
<td>0</td>
</tr>
<tr>
<td>45.5</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Conditions according to IEC 60422</th>
<th>Failure probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry</td>
<td></td>
</tr>
<tr>
<td>Moderate wet</td>
<td>0</td>
</tr>
<tr>
<td>Wet</td>
<td>0</td>
</tr>
<tr>
<td>Extreme wet</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Moisture in paper (%)</th>
<th>Failure probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.54</td>
<td></td>
</tr>
<tr>
<td>2.44</td>
<td>0</td>
</tr>
<tr>
<td>3.88</td>
<td>0</td>
</tr>
<tr>
<td>5.09</td>
<td>0</td>
</tr>
<tr>
<td>5.65</td>
<td>0</td>
</tr>
<tr>
<td>6.17</td>
<td>0</td>
</tr>
<tr>
<td>7.17</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Bubbling inception temperature (°C)</th>
<th>Failure probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>154.99</td>
<td></td>
</tr>
<tr>
<td>137.90</td>
<td>0</td>
</tr>
<tr>
<td>121.80</td>
<td>0</td>
</tr>
<tr>
<td>112.47</td>
<td>0</td>
</tr>
<tr>
<td>108.80</td>
<td>0</td>
</tr>
<tr>
<td>105.48</td>
<td>0</td>
</tr>
<tr>
<td>99.39</td>
<td>0</td>
</tr>
</tbody>
</table>

As a summary, the curve-fitting method is proved better in terms of accurately predicting hot-spot temperature under either heat run test loads or cyclic loads. However, the calculating method has to be used when measured hot-spot temperatures during heat run test are not
available. A comparison between two refinement methods on the assessment of long term thermal ageing and short term failure probability under EV scenarios shows that the calculating method tends to lead to overestimated loss-of-life and failure probability under high penetration of EV, such as Extreme-range scenario, when transformers are heavily overloaded.

5.2 Load modelling method for operating individual distribution transformers

A load profile is required for the calculation of the hot-spot temperature. However, most distribution transformers of the population do not have load data monitored and recorded. Therefore, 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.

In the UK, load profiles of electricity customers in the distribution level are defined as eight Profile Classes (PC) [149]. Definition of each profile class is presented in Table 5-15.

| PC 1   | Domestic unrestricted customers                      |
| PC 2   | Domestic economy 7 customers                         |
| PC 3   | Non-domestic unrestricted customers                  |
| PC 4   | Non-domestic economy 7 customers                     |
| PC 5   | Non-domestic maximum demand customers with a peak load factor* of less than 20% |
| PC 6   | Non-domestic maximum demand customers with a peak load factor* between 20% and 30% |
| PC 7   | Non-domestic maximum demand customers with a peak load factor* of between 30% and 40% |
| PC 8   | Non-domestic maximum demand customers with a peak load factor* over 20% |

*: Peak load factor is the ratio of the number of kWh supplied during a given period to the number of kWh that would have been supplied if the maximum demand has been maintained throughout that period.

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, who administers the Balancing and Settlement Code in the UK. 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. For each sub class, different profiles are created for weekdays, Saturdays and Sundays. Therefore, for each
profile class, Elexon produces 15 individual half-hour daily load profiles depending on the date of the day, among which winter weekdays have the highest load values. The winter weekday load profile of each profile class is shown in Figure 5-10.

![Graphs showing load profiles of profile classes](image)

Figure 5-10: Winter weekdays load profiles of each profile class [149] (a). Profile class 1 to 4. (b). Profile class 5 to 8.

5.2.1 Accuracy of modelling load profiles with Elexon profiles

With Elexon profiles, yearly half-hour 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 for its distribution transformer population, yearly half-hour load profiles of any transformers can be modelled by 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.

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First of all, for illustration purpose, load profiles of Tx 232659 of the two weeks in October 2013 are modelled and compared with measured values as shown in Figure 5-11. Customer numbers used for the modelling are displayed in Table 5-16.

Table 5-16: Example of customer composition of Tx 232659

<table>
<thead>
<tr>
<th>Profile Class</th>
<th>PC 1</th>
<th>PC 2</th>
<th>PC 3</th>
<th>PC 4</th>
<th>PC 5</th>
<th>PC 6</th>
<th>PC 7</th>
<th>PC 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer numbers</td>
<td>248</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 5-11: Comparison between loads modelled by Elexon profiles and measured values of Tx 232659

According to the comparison in Figure 5-11, loads modelled by Elexon profiles can well match the load pattern of the transformer. In terms of accuracy, the mean error is -16%, and the maximum error occurs on day 12th, which is -62.5%. It is unknown that what happened on the load of that day, however, this kind of unmatching is observed on around 10% of the total data. This also indicates a limitation of Elexon profiles that it could not model the abnormal behaviours of the cyclic loads, as what is observed in day 12.

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 5-17.

Table 5-17: Error analysis of loads modelled by Elexon profiles of 84 investigated distribution transformers

<table>
<thead>
<tr>
<th></th>
<th>Underestimation</th>
<th>Overestimation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error</td>
<td>&lt; -60%</td>
<td>&gt; 60%</td>
</tr>
<tr>
<td>Percentage of data</td>
<td>11.3%</td>
<td>23.3%</td>
</tr>
<tr>
<td></td>
<td>&lt; -40%</td>
<td>&gt; 40%</td>
</tr>
<tr>
<td></td>
<td>31.9%</td>
<td>6.9%</td>
</tr>
<tr>
<td></td>
<td>&lt; -20%</td>
<td>&gt; 1%</td>
</tr>
<tr>
<td></td>
<td>53.9%</td>
<td>&lt; 0.1%</td>
</tr>
<tr>
<td></td>
<td>&lt; 0%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>76.7%</td>
<td></td>
</tr>
</tbody>
</table>
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 thesis when using Elexon profiles to model loads of distribution transformers that do not have recorded load data. A more sophisticated way of modelling the calibration factor, for example modelling it probabilistically, might be investigated as a potential future work if more measured load data could be obtained for further comparison.

5.3 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 (5-13) based on the assumption that the real ambient temperature varies sinusoidally during the load cycle [11]. Where $\theta_E$ is the equivalent ambient temperature; $\theta_{ya}$ is the yearly average temperature and $\theta_{ma, max}$ is the monthly average temperature of the hottest month.

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

(5-13)

5.3.1 Determination of yearly weighted ambient temperature

The value is determined by Equation (5-13) with historical monthly ambient temperature data since 1910 in northwest England obtained from Met Office [150].
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 Equation (4-3) as 13.4 °C.

Since the ambient temperature by 2030 is concerned, historical increases of the annually averaged ambient temperatures are investigated in order to discover the annual increment of the ambient temperature in the northwest England. Linear regression in Figure 5-12 reveals that the annual increase of the ambient temperature is 0.007 °C, and it is therefore omitted in this work.

5.3.2 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 5-18. The extra temperature rise of the rated top-oil temperature rise is half of the increase in the yearly weighted ambient temperature.
Table 5-18: Correction for increase in ambient temperature due to enclosure [11]

<table>
<thead>
<tr>
<th>Type of enclosure</th>
<th>Number of transformers installed</th>
<th>Correction to be added to weighted ambient temperature (K)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Transformer size (kVA)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>250</td>
</tr>
<tr>
<td>Underground vaults with natural ventilation</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>14</td>
</tr>
<tr>
<td>Basements and buildings with poor natural ventilation</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>10</td>
</tr>
<tr>
<td>Buildings with good natural ventilation and underground vaults and basement with forced ventilation</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>6</td>
</tr>
</tbody>
</table>

In this work, when assessing individual transformers of the population, the type of enclosure is not known for indoor installed transformers. Therefore, it is all assumed that all indoor installed transformers are in basements or buildings with poor natural ventilation.

5.4 Summary

Ideally, load data modelled by Elexon profiles for the distribution transformer investigated in this chapter should be compared with the measured values. However, due to the information unavailability on the number and composition of customers connected to the transformer, the comparison is not performed. A comparison should be conducted, if the customer information of the investigated distribution transformer is obtained in the future.

Unlike prototype transformers, existing transformers of the population probably do not have optic fibre sensors installed for monitoring the hot-spot temperature, and it is likely that the load current and ambient temperatures are not monitored neither. In this case, the three elements for determination of hot-spot temperature should be estimated alternatively to achieve a reasonable accuracy of transformer thermal parameters, load model and ambient temperature model.

A method of refining IEC thermal parameters with heat run test results is introduced and verified assuming the hot-spot temperature measurements by optical fibres are not available.
The method calculates each parameter separately with temperature measurements required by a standard heat run test.

Elexon profiles are introduced as an approach for load modelling. With Elexon profiles, daily half-hour loads can be modelled by using customer numbers of each profile class, which are provided by the operator. A comparison between the modelled and measured load data shows that Elexon profiles are more likely to underestimate, and the mean error is -30.6%.

At last, the ambient temperature for the calculation of hot-spot temperature can be modelled as an equivalent constant based on historical data of the region. The advantage of this model is that impacts of the enclosure of transformers on their thermal performance can be evaluated.

With the above methods and models, the strategy for assessing individual transformers under EV scenarios can be applied on individuals of the distribution transformer population, which is presented in the next chapter.
CHAPTER 6 ASSESSMENT OF DISTRIBUTION TRANSFORMER POPULATION UNDER EV SCENARIOS

ENW has a population of more than 35,000 distribution transformers. They are composed by transformers of two voltage levels, i.e. 6.6 kV and 11 kV, where 6.6 kV transformers count for 32.5%. Various power ratings ranging from 25 kVA to 1500 kVA are covered. Five most common power ratings are 300 kVA, 315 kVA, 500 kVA, 750 kVA and 1000 kVA, which stand for around 86% of the population. Transformers of the population are manufactured by more than 240 manufacturers; however the top 10 manufacturers make up 65% of the population. Manufacture years of these transformers can be dated back up to 85 years ago, but 60% transformers are less than 40 years old. In terms of installation, 30% of transformers are installed indoor.

The strategy of assessing individual transformers under EV scenarios proposed in Chapter 4 and 5 is applied on a group of selected transformers from the distribution transformer population of ENW Ltd. for the demonstration purpose.

6.1 Introduction to distribution transformer population

6.1.1 General information

Analysis in Figure 6-1 shows that transformers with higher power ratings are more likely to be installed indoor. The possible reason is that transformers with higher power ratings tend to be installed in urban areas due to higher demand than in the rural areas, and they are more likely to be installed indoor based on safety and environment concerns. However, transformer closure leads to extra temperature rises in ambient and top-oil as introduced in Chapter 5, and the higher the power rating is, the larger the extra temperature rise would be. Therefore, distribution transformers in the population with higher power ratings would be more concerned in terms of their thermal performances due to enclosures.
Transformer power ratings are selected according to the expected load a transformer is going to undertake. For distribution transformers, power ratings are associated with the number and type of customers they are connected to. Eight types of customers in the distribution network can be defined according to the load types they represent, among which type 1 and 2 are domestic customers, and the others are non-domestic customers. ENW has numbers of each type of customers for majority distribution transformers in the population. To help analyse the results, a distribution transformer is categorised as domestic if over 90% of its customers are either type 1 or 2; otherwise, it is categorised as non-domestic. Analysis in Figure 6-2 shows the percentage of domestic and non-domestic transformers in each power rating class. It is firstly observed that domestic customers are dominating the distribution network, where over 94% of total customers are either type 1 or 2, i.e. domestic. Secondly, except for 1000 kVA transformers, a consistent ratio of domestic to non-domestic transformers is observed for other power rating classes. Considering that distribution transformers connected to more domestic customers are more impacted under EV scenarios due to the clustering of EV charging in the residential areas, 1000 kVA transformers are less concerned under EV scenarios since they are connected to more non-domestic customers than transformers with other power ratings.
For distribution transformers, their power ratings are determined by how many customers they are connected to. Take domestic distribution transformers as an example, Figure 6-3 shows how power ratings are increasing with the number of customers. Basically, the box plot in Figure 6-3 shows the distribution of customer numbers of transformers in each power rating class. Each column in the box plot represents transformers in the same power rating class. The blue box in each column represents transformers from first to the third quartiles of the power rating class, and the red line inside indicates the second quartile. Observing the upwards movement (indicating more customers are connected) of the blue box from the left side (lower power rating) to the right side (higher power rating), it can be concluded that distribution transformers in the population tend to have more customers with higher power ratings.
Recalling that with numbers of each type of customers connected to distribution transformers, the yearly load profiles can be calculated with Elexon profiles as introduced in Chapter 5. The yearly RMS and peak loads in per unit values can be calculated for distribution transformers to reflect their load levels. Results in Figure 6-4 show that ENW distribution transformers have been operated under low load values, where over 90% transformers are under 0.5 p.u. of the yearly RMS load. In terms of yearly peak loads, more than 99% transformers have a yearly peak load lower than 1.0 p.u., and the highest value obtained is 1.14 p.u. In addition, around 90% transformers are under 0.5 p.u. of the yearly peak load. Considering that yearly loads calculated with Elexon profiles tend to give underestimated values with a mean error of -30.6%, (according to the comparison to the measured load values presented in the Chapter 5), the real loads that ENW transformers are undertaking should be higher than what are presented here. However, even take the error correction into consideration by applying a calibration factor of 1.3, more than 90% of all transformers are under a yearly RMS load of 0.65 p.u.; and in terms of peak loads, around 1.4% transformers have peak loads over 1.0 p.u. in a year.

![Diagram](Figure 6-4: Load distributions of distribution transformer population calculated with Elexon profiles. (a). Yearly RMS load. (b). Yearly peak load)
Apart from the general information available for the population such as power ratings, installation conditions and customer compositions, the oil test data are also available for a limited number of transformers, which are analysed in the following part.

### 6.1.2 Moisture content in oil

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. Before analysing, data filtering work is conducted. After data filtering work, some 1000 transformers have remained, on which the analysis is conducted. In the data filtering, the oil test data are first screened by picking out erroneous data such as abnormally high values of moisture or acidity (e.g. 325 ppm of moisture; 12 transformers have moisture values over 100 ppm), or the oil test year is earlier than the transformer manufacture year. Then the remaining transformers are cross-matched with their general information such as power ratings, installation conditions and customer numbers.

The oil test data contain diverse information such as moisture, acidity, furan compounds, breakdown voltage, appearance and sediment. The analysis is concentrated on moisture values, since they are associated to the moisture in paper values which are eventually applied for the estimation of bubbling inception temperatures when assessing the failure probability of distribution transformers under EV scenarios. 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 an oil test, the moisture in oil is measured under a sampling temperature that is depending on the operational condition of the investigated transformer. Since the solubility of moisture in oil is significantly affected by the temperature, larger amount of moisture tend to be absorbed by the oil under higher temperature. In order to compare the wetness of the oil, which indicates the ageing status of a transformer, the effects of the sampling temperature must be removed. Therefore, it is important to convert the moisture in oil under a standard sampling temperature, which is 20°C and recommended in IEC 60422 [151] with Equation
where \( PPM_{20} \) is the moisture in oil at 20°C; \( PPM_t \) is the moisture in oil under temperature \( t \) in °C.

\[
PPM_{20} = PPM_t \times 2.24 \times e^{-0.04t}
\]

(6-1)

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 5 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 4-21.

<table>
<thead>
<tr>
<th>( R )</th>
<th>( \Delta \theta_{or} )</th>
<th>( g_r )</th>
<th>( H )</th>
<th>( \tau_o )</th>
<th>( \tau_w )</th>
<th>( x )</th>
<th>( y )</th>
<th>( k_{11} )</th>
<th>( k_{21} )</th>
<th>( k_{22} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>8.7</td>
<td>50.6</td>
<td>16.8</td>
<td>1.1</td>
<td>180</td>
<td>11.4</td>
<td>0.8</td>
<td>1.6</td>
<td>1.1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Resultant mean yearly top-oil temperatures are presented in Figure 6-5, which shows that all moisture data recorded in the database are sampled over 20°C, so when converted to 20°C with Equation (6-1), all moisture values will be reduced after correction.
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 6-6. 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.

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 in Figure 6-7. 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.

![Figure 6-7: Corrected moisture in oil data of distribution transformers from three most popular manufacturers](image)

\[ \text{Figure 6-7: Corrected moisture in oil data of distribution transformers from three most popular manufacturers} \]


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 6-8. 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. This could be due to the rainfall or other precipitation weathers from which are protected by transformer enclosures.

![Figure 6-8: Corrected moisture data of indoor and outdoor installed distribution transformers](image)

### 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 6-9. 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 6-9, 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 (6-2), 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.

$$PPM_{in} = 5 + 0.23\times t + N(0,3)$$ (6-2)

Similar to indoor transformers, the fitting is conducted to outdoor transformers as shown in Figure 6-10, and the resultant equation is shown as Equation (6-3). 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.

\[
PPM_{\text{out}} = 5 + 0.35t + N(0,5) \quad (6-3)
\]

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 with the method introduced in Chapter 4, and the obtained moisture in paper will be used for the calculation of bubbling inception temperature with the bubbling inception temperature model introduced in Chapter 4. Eventually, the bubbling inception temperature will be utilised for the estimation of failure probabilities of distribution transformers under EV scenarios.

However, Equation (6-2) and (6-3) are insufficient in representing the accumulation of moisture in oil. 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.
6.2 Analysis of population under current conditions

Before concerning the adaptability of distribution transformers under future EV scenarios, it is essential to understand their current conditions in terms of thermal ageing. With measured values or Elexon profiles, yearly load profiles of individual distribution transformers can be obtained for the calculation of hot-spot temperatures with IEC thermal model, which can be used to calculate transformer loss-of-life. And it is concerned most when considering the long term thermal ageing of distribution transformers.

Traditionally, minute-based load profiles are required for the calculation of the loss-of-life with IEC thermal model, which involves massive computations when the whole population is subject to assess. Therefore, a quick way of calculating the loss-of-life of a transformer is introduced here with simplified load profiles, i.e. 2 step load or constant RMS load. Analysis shows that although the resultant daily loss-of-life is not as accurate as calculated with original load profiles, the accuracy is varied with the peak value of the original load. So a correction factor can be defined to improve the accuracy.

The 2 step load profile is commonly used in the industrial practice as an equivalent to the actual daily load profile for the quick calculation of hot-spot temperatures and loss-of-life [133]. The 2 step load profile is consisted of a constant prior-peak load and a constant peak load. The value of the peak load is defined as the RMS value of the actual load values during the peak duration, while the peak duration is determined by restricting the peak load value of the 2 step load no less than 90% of the integrated half-hour maximum value of the actual load profile. The prior-peak load is the RMS value of the off-peak duration.

Apart from the 2 step load profile, an even simpler equivalent of the actual daily load profile is to use the daily RMS value. Comparison between the simplified daily load profiles and the original one is shown in Figure 6-11. Daily loss-of-life of each load profile is calculated with IEC thermal model and refined thermal parameters presented in Table 6-2. Results show that daily loss-of-life calculated with either 2 step load or daily RMS load is accurate enough to reflect the actual value with a relative accuracy over 98% for the example load profile.
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Figure 6-11: Simplification of daily load profiles – 2 step load and daily RMS load

Table 6-2: Daily loss-of-life and relative accuracy of simplified load profiles

<table>
<thead>
<tr>
<th>Load profile</th>
<th>Accumulated loss-of-life (minute per day)</th>
<th>Relative accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original load profile</td>
<td>1.37</td>
<td>100</td>
</tr>
<tr>
<td>2 step load profile</td>
<td>1.36</td>
<td>98.96</td>
</tr>
<tr>
<td>Daily RMS load profile</td>
<td>1.35</td>
<td>98.38</td>
</tr>
</tbody>
</table>

2 step load and daily RMS load can be used to replace the actual daily load profile for the calculation of loss-of-life with acceptable error in the example. In order to generalise this conclusion, the same comparison is conducted on a set of measured daily load profiles. Due to the limited data availability, these load profiles are from around 100 transformers. Fortunately, diverse load compositions (such as pure domestic load or pure non-domestic load or the mixture) and levels are covered. Results are shown in Figure 6-12, and the analysis of the relative accuracy in Table 6-3 shows that when the peak values are lower than 0.5 p.u., the relative accuracy is more than 90% for 2 step load and 85% for daily RMS load. Recalling that more than 90% of transformer in the ENW population have the yearly peak load values lower than 0.5 p.u. (as previously demonstrated in Figure 6-4), it would be acceptable to apply 2 step load and daily RMS daily for the quick calculation of loss-of-life of distribution transformers in the ENW population.
Figure 6-12: Decrease of relative accuracy of daily loss-of-life with peak load values. (a). 2 step load profile. (b). Daily RMS load profile.

Table 6-3: Analysis of relative accuracy of daily loss-of-life calculated with simplified load profiles

<table>
<thead>
<tr>
<th>Relative accuracy</th>
<th>&gt;95%</th>
<th>&gt;90%</th>
<th>&gt;85%</th>
<th>&gt;80%</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 step load</td>
<td>&lt;0.55 p.u.</td>
<td>&lt;0.70 p.u.</td>
<td>&lt;0.80 p.u.</td>
<td>N/A</td>
</tr>
<tr>
<td>Daily RMS load</td>
<td>&lt;0.30 p.u.</td>
<td>&lt;0.45 p.u.</td>
<td>&lt;0.65 p.u.</td>
<td>&lt;0.70 p.u.</td>
</tr>
</tbody>
</table>

Additionally, it can be seen from Figure 6-12 that the relative accuracy is decreasing with the peak load value of the actual load profile in an exponential way. Therefore, exponential curves are utilised to fit the results and a goodness of fitting over 0.95 is achieved for either case. Obtained equations are displayed as Equation (6-4) and (6-5), where $RA$ is the relative accuracy, and $L_p$ is the peak load value of the actual daily load profile. Furthermore, correction factors of 2 step load and daily RMS load can be obtained by taking the reciprocal of their relative accuracies respectively.
$$RA_2 - step = 100 - 0.1238 \times e^{L_p/0.1569}$$  \hspace{1cm} (6-4)

$$RA_{RMS} = 100 - 0.2027 \times e^{L_p/0.1538}$$  \hspace{1cm} (6-5)

With the method introduced here, yearly loss-of-life under BAU EV scenario (no EV penetration) is estimated for a selected demonstrative group of distribution transformers of the population in the following part.

### 6.3 Assessment of distribution transformer population under EV scenarios

Chapter 4 and 5 introduce the strategy proposed in this work for the assessment of the distribution transformer population in terms of long term and short term risks under future EV scenarios. 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 transformers, which are essential for the calculation of the yearly loss-of-life. 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 introduced 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, either the conventional or the extended. The advantage of this method over the curve-fitting one is that the data required are more accessible since many transformers have heat run test data but not hot-spot temperature measurements.

The second element is the load element, which will be the total load of the current load plus potential EV charging load under future EV scenarios. The current load refers to the day to day load cycles that distribution transformers are carrying. Measurements would be always preferred if available. Otherwise, Elexon profiles are introduced for the generation of yearly
half-hour load profiles of distribution transformers with the information of the number and type of its customers. Interpolation can be applied if a smaller time interval like a minute between two load data points is required. As to EV charging load, considering the random charging behaviours of EV owners, probabilistic modelling is implemented in order to simulate the randomness of charging power, charging duration and charging start time of individual EV.

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. Therefore, it is derived based on historical data of the northwest region collected by the Met Office, and used for distribution transformers which 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. 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 [55] 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. It has been shown in Chapter 4 that 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 and operational temperature.
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 is 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, the strategy proposed in this work for the assessment of the future adaptability of the distribution transformer population can be represented by the diagram shown in Figure 6-13 (the red words are indicating where this method / model is introduced). The required input data include transformer age and rating, installation condition (indoor / outdoor), customer information (number and type), ambient temperature, thermal parameters and EV penetration levels (defined by EV scenarios). The final outputs are yearly loss-of-life, expected lifetime and failure probability under different EV scenarios.

Figure 6-13: Detailed diagram of assessment strategy
6.3.1 Simulation Procedure

Simulations are conducted with the assessment strategy introduced above on a group of demonstrative transformers of the population. Simulation procedure is introduced step by step in this section.

1. Select the demonstrative transformers of population

This is the very first step of the simulation. 150 distribution transformers are selected randomly from the population for the simulation.

2. Assess long-term risks under EV scenarios

Simulations are first conducted to calculate the load, hot-spot temperature, loss-of-life and expected lifetime of demonstrative transformers under BAU scenario with IEC thermal model and refined thermal parameters. Then after analysing the results, the same simulation process is carried out under High-range and Extreme-range scenarios.

3. Assess short-term risks under EV scenarios

Simulations are first conducted to calculate moisture in paper and oil, bubbling inception temperature, hot-spot temperature and failure probability under three EV scenarios. Sensitivity studies are then performed to investigate which factors such as transformer age, peak load and installation condition are affecting the failure probability

Following the simulation procedure, the results of each step are presented and analysed below.

6.3.2 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 6-14 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.
The majority of transformers (over 75%) have peak loads lower than 0.7 p.u. The largest peak load observed is 1.09 p.u. of a 47 years old transformer, along with another two transformers possessing peak loads over 1.0 p.u.

### 6.3.3 Long term risks under EV scenarios

Yearly loss-of-life is calculated for each transformer under three EV scenarios, i.e. BAU scenario (no EV), High-range EV scenario (32% of penetration level) and Extreme-range EV scenario (58.9% of penetration level). Firstly, BAU scenario is assessed by the method introduced in section 6.2, where the yearly loss-of-life is calculated under the RMS load and corrected by the factor calculated by the original peak load with Equation (6-5). Yearly loss-of-life, mean and peak hot-spot temperatures are calculated and shown in Figure 6-15.
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 6-4. 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.

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 EV 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. Firstly, the yearly mean and peak load values under EV scenarios are compared as shown in Figure 6-16.
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Figure 6-16: Yearly RMS and peak loads under three EV scenarios. (a). Yearly RMS loads (b). Yearly peak loads

EV charging mostly occurs within a few hours during the peak time of a day, therefore the peak load is significantly increased under High-range and Extreme-range scenarios. To interpret Figure 6-16, a statistical analysis of yearly RMS and peak loads under three EV scenarios is presented in Table 6-5, which shows the percentages of transformers in different load ranges.

Table 6-5: Statistical analysis of yearly RMS and peak loads under three EV scenarios

<table>
<thead>
<tr>
<th>RMS load (p.u.)</th>
<th>[0, 0.3)</th>
<th>[0.3, 0.6)</th>
<th>[0.6, 0.9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAU scenario</td>
<td>46%</td>
<td>51.3%</td>
<td>2.7%</td>
</tr>
<tr>
<td>High-range scenario</td>
<td>34.7%</td>
<td>59.3%</td>
<td>6%</td>
</tr>
<tr>
<td>Extreme-range scenario</td>
<td>28.7%</td>
<td>56%</td>
<td>15.3%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Peak load (p.u.)</th>
<th>[0, 1.0)</th>
<th>[1.0, 2.0)</th>
<th>[2.0, 3.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAU scenario</td>
<td>98%</td>
<td>2%</td>
<td>0</td>
</tr>
<tr>
<td>High-range scenario</td>
<td>58%</td>
<td>41.3%</td>
<td>0.7%</td>
</tr>
<tr>
<td>Extreme-range scenario</td>
<td>30%</td>
<td>57.3%</td>
<td>12.7%</td>
</tr>
</tbody>
</table>
The number of overloaded transformers is increasing with the penetration of EV. 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 EV 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%. The similar observation is made on hot-spot temperatures as shown in Figure 6-17.

Figure 6-17: Yearly mean and peak hot-spot temperatures under three EV scenarios. (a). Yearly mean hot-spot temperature (b). Yearly peak hot-spot temperature
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To interpret Figure 6-17, a statistical analysis of yearly mean and peak hot-spot temperatures under three EV scenarios is presented in Table 6-6. It can be seen the peak hot-spot temperature is significantly influenced by EV 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 6-6: Statistical analysis of yearly mean and peak hot-spot temperatures under three EV scenarios

<table>
<thead>
<tr>
<th>Mean hot-spot temperature (°C)</th>
<th>[6, 40)</th>
<th>[40, 60)</th>
<th>[60, 80)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAU scenario</td>
<td>76%</td>
<td>24%</td>
<td>0</td>
</tr>
<tr>
<td>High-range scenario</td>
<td>61.3%</td>
<td>37.3%</td>
<td>1.4%</td>
</tr>
<tr>
<td>Extreme-range scenario</td>
<td>48.7%</td>
<td>47.3%</td>
<td>4%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Peak hot-spot temperature (°C)</th>
<th>[0, 60)</th>
<th>[60, 120)</th>
<th>[120, 180)</th>
<th>[180, 240)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAU scenario</td>
<td>85.3%</td>
<td>14.7%</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High-range scenario</td>
<td>43.3%</td>
<td>52.7%</td>
<td>4%</td>
<td>0</td>
</tr>
<tr>
<td>Extreme-range scenario</td>
<td>20.7%</td>
<td>52%</td>
<td>24%</td>
<td>3.3%</td>
</tr>
</tbody>
</table>

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 EV charging only poses a limited impact on it. Consequently, the yearly loss-of-life is only limited affected by the EV penetration, as shown in Figure 6-18.
A statistical analysis on the loss-of-life under three scenarios is displayed in Table 6-7. The majority of investigated distribution transformers is not over-aged even under Extreme-range EV scenario. Under High-range EV scenario, only 2 out of 150 transformers (1.4%) have a yearly loss-of-life larger than the rated value. Under Extreme-range EV scenario, the number is 28 out of 150 transformers (18.7%). 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 6-19 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.
Therefore, it might be concluded that EV 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 EV penetration such as Extreme-range EV scenario. Occasionally, the thermal ageing can be increased to significantly exceed the rated value; however, under such occasions, the peak load and hot-spot temperature will be large enough to prioritise the concerns on short time failure over the reduction of lifetime due to thermal ageing.

6.3.4 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 6-20 shows the moisture levels respectively in oil and paper which are derived by the models introduced in Chapter 4. In accordance to the moisture in oil model, i.e. Equation (6-2) and (6-3), 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.
Simulation results in Figure 6-20 show that the moisture in oil of a young transformer (e.g. less than 10 years old) can be as large as 8 ppm, which can be considered as moderate wet. This value is calculated based on the empirical model derived with limited measured data from past oil tests which might not be sufficient to represent the general situation of the population. Although the value might be overestimated, it still can be investigated as the worst-case scenario, revealing the potential risks of transformers if they are as wet as the past oil test data reflect.

In addition, results in Figure 6-20 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 8 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 6-21. Since the hot-spot temperatures of each repetition during the Monte-Carlo simulation are different due to the randomness of EV charging load, the data plotted are mean values of all repetitions of each transformer.
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 6-22.
Figure 6-22: Failure probability under three EV scenarios

Under BAU scenario, when no EV 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 EV. 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 6-8.

Table 6-8: Number of transformers with failure probability over 50%

<table>
<thead>
<tr>
<th>EV scenarios</th>
<th>BAU scenario</th>
<th>High-range scenario</th>
<th>Extreme-range scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indoor/outdoor installation</td>
<td>Indoor</td>
<td>Outdoor</td>
<td>Indoor</td>
</tr>
<tr>
<td>Age group</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 – 20 years</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>20 – 40 years</td>
<td>0</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>40 – 60 years</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>0</td>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

Under High-range EV scenario, only 19 out of 150 transformers are in high risk, which is less than 13%. While under Extreme-range EV scenario, where the EV penetration level increases to 58.9%, 51 transformers are facing high risks, which are 34% of the demonstration group.

In terms of age, young transformers, i.e. below 20 years old, have fewest individuals in high risk. Interestingly, instead of old transformers over 40 years old, the middle age transformers between 20 and 40 years old have the largest number of individuals in high risks. Therefore, solely based on results in Table 6-8, 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 6-23, where the peak loads of high risk and low risk transformers under Extreme-range EV scenario are compared.

![Figure 6-23: Comparison of peak loads between high risk transformers and low risk transformers under Extreme-range scenario](image)

A boundary line as shown in Figure 6-23 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 EV 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. Generally speaking, according to Table 6-8, fewer indoor transformers are in high risk comparing to outdoor ones under either High-range or Extreme-range scenarios. However, the difference is insignificant, and it is difficult to claim outdoor installation is an essential factor causing higher failure probabilities.

The failure is determined by the bubbling inception temperature and the peak hot-spot temperature. The former is controlled by the transformer age and installation condition, and the latter is dependent on the load, especially the peak load under EV scenarios. Therefore, transformers in high risk under Extreme-range EV scenario are picked up for further analysis.
The peak load and failure probability are plotted against the age of these transformers in Figure 6-24 with the installation condition indicated.

According to Figure 6-24, in spite of larger number of individuals in high risk, outdoor transformers generally have higher peak loads but lower failure probabilities. The average peak load of outdoor transformers is 2.00 p.u., while it is 1.88 p.u. for indoor transformers. The average failure probability of outdoor transformers is 93.5%, while it is 95.3% for indoor transformers. Therefore, the outdoor installation is not necessarily a decisive factor leading to
higher failure probabilities, although it may cause a faster moisture accumulation in transformer oil and paper insulations, its contributions to the potential failure is cancelled off by the relatively lower hot-spot temperature rise comparing to the indoor installation.

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 13% of investigated distribution transformers will be in high risk; and this percentage will increase to 34% 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.

6.4 Summary

The main purpose of this chapter is to use a group of representative transformers to demonstrate the strategy for assessing the adaptability of distribution transformer population under EV scenarios.

Results show that EV 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 EV penetration such as Extreme-range scenario. Occasionally, the thermal ageing can be increased to significantly exceed the rated value, however, under such occasions, the peak load and hot-spot temperature will be large enough to prioritise the concerns on short time failure over the reduction of lifetime due to thermal ageing. For example, under Extreme-range scenario, only 18.7% of investigated distribution transformers are over-aged, and all of them have peak hot-spot temperatures over 130°C, which would cause bubbling and lead to direct failures.

In terms of short time risks, firstly, no transformers are facing failure risks due to bubbling under current conditions (BAU scenario). Around 13% 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 34% 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. This observation could be applied to assist the asset management under future EV scenario that the peak load of a transformer should be restricted below 1.5 p.u. to prevent potential failure due to bubbling.
7.1 Conclusions

7.1.1 Assessment strategy of future adaptability of distribution transformer population

This thesis introduces an assessment strategy for the future adaptability of distribution transformers under EV scenarios. Assessing the adaptability is to assess the load, hot-spot temperature, loss-of-life, expected lifetime and failure probability of the distribution transformer population. Concentration of EV 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, distribution transformers are facing shortened lifetime due to extra loads and potential failures due to overloads.

In the long term, extra loads brought by the EV charging accelerate the ageing of paper insulation of distribution transformers by lifting up the hot-spot temperature. The higher the hot-spot temperature is, the larger the unit loss-of-life will be, which results in shortened lifetime of distribution transformers. Therefore, deciding the hot-spot temperature is the prerequisite for the determination of the corresponding loss-of-life and expected lifetime of distribution transformers under EV scenarios.

Hot-spot temperatures can be determined by the IEC thermal model with three input elements. The first element is IEC thermal model parameters, which reflect the thermal characteristics of distribution transformers. Instead of using recommended generic values, it is preferred to refine the thermal parameters for individual distribution transformers with methods introduced in this thesis for improved accuracy when predicting the hot-spot temperature under arbitrary loads especially EV charging loads. Two methods are introduced for the refinement of thermal parameters. One is to curve-fit the optic fibre measured hot-spot and top-oil temperatures during the extended heat run test. It is verified as the most desirable method due to the resultant most accurate hot-spot temperatures. Case studies find that the
maximum error of the prediction of hot-spot temperature is reduced to 3.53 K from 25.87 K when using the curve-fitted thermal parameters instead of recommended values under heat run test loads. More importantly, under dynamic loads, the accuracy is improved by using curve-fitted values, where the maximum error is reduced to 6.07 K from 9.76 K, and the mean error is reduced to 0.04 K from 3.58 K. The improvement of 3 K is small yet significant since the ageing rate could be double for an increase of each 6 K according to the IEC ageing model [11]. The other method is to calculate each thermal parameter with standard measurements during extended or conventional heat run test. The maximum error of the prediction of hot-spot temperature is reduced to 10.06 K from 25.87 K by using the calculated parameters comparing to recommended values. To compare two refinement methods, the curve-fitting one leads to more accurate results but requires optic fibre measured hot-spot temperatures which are often not available for distribution transformers. However, the other method only requires standard heat run test results, which are more accessible for distribution transformers.

The second element determining the hot-spot temperature is load. Under EV scenarios, the load refers to the sum of the EV charging load and the cyclic load when EV are not plugged in. A modelling approach is introduced in this thesis to simulate the EV charging load in a probabilistic manner in order to emulate the stochastic nature of charging behaviours of EV customers. Realistic data of key information for the modelling such as charging start time and energy transferred per charge collected by past EV trials in the UK are utilised in the introduced modelling approach in order to model the EV charging load as accurate as possible. In terms of the cyclic load without EV, ideally, monitored data should be used. However, if not monitored, an alternative method is introduced to model the cyclic load profile with Elexon profiles using the customer information provided by the operator of distribution transformers.

The last element is environmental element, which refers to the ambient temperature and the installation condition. It is the ideal case when the ambient temperature is monitored; otherwise, IEC loading guide provides a method to model the ambient temperature based on the historical data of the region. Moreover, to consider the effects of the installation condition, extra rises of ambient temperature should be added if the transformer is installed indoor.

The hot-spot temperature is the dominant factor when deciding the long term thermal risks under EV scenarios, and also it is a key factor when considering the short term risks of direct
failures due to bubbling which causes breakdown of distribution transformers under EV scenarios.

In the short term, overloads brought by EV charging would cause a dramatic increase of the hot-spot temperature, and breakdown will be triggered if the hot-spot temperature rises beyond the bubbling inception temperature. The bubbling inception temperature can be estimated by a literature model which requires three inputs including the gas content in oil, oil depth and the moisture in paper. Sensitivity studies have shown that the moisture in paper is the dominant factor, thus it is the controlled parameter when utilising the model. Due to the difficulty in measuring the moisture in paper of operational distribution transformers, a model is introduced in this thesis to roughly estimate the moisture in paper by using the moisture in oil, which can be easily obtained via oil tests. The model is based on the equilibrium curve of moisture dynamics between oil and paper in distribution transformers. Necessary assumptions are made; such as the equilibrium state is assumed reached at a temperature equal to the average hot-spot temperature of a day under cyclic loads, and the reached equilibrium state is assumed unchanged when EV charging occurs considering the EV charging duration is too short for the moisture to transit between paper and oil.

The failure probability is defined as the probability of hot-spot temperature reaching the bubbling inception temperature under EV scenarios. Monte-Carlo simulations are conducted to determine the failure probability under anticipated EV scenarios in this thesis.

To summarise, the assessment strategy introduced in this thesis assesses the long term and short term thermal risks of distribution transformer population under EV scenarios. It requires inputs including 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 EV penetration levels. Depending on the data availability of individual distribution transformers of the population, different situations of the application of the assessment strategy are described in the thesis.

7.1.2 Application of strategy depending on data availability

The thesis is organised in a way to present the application of the introduced strategy under various conditions of data availability. For the ideal case, the strategy is applied on a prototype distribution transformer, which has all the required input data available. Optic fibre
sensors can be ordered and installed for the monitoring of the hot-spot and top-oil temperatures, with which the thermal parameters can be refined by curve-fitting method to represent the thermal characteristics of the transformer. Cyclic load profiles and ambient temperatures are recorded during the operation and the moisture in oil can be obtained by oil test when required.

For a number of existing distribution transformers, optic fibre sensors are not installed, but heat run test data are likely existing, with which thermal parameters can be calculated. When cyclic load profiles and ambient temperatures are not monitored, modelling approaches introduced in this thesis have to be used. Cyclic loads can be estimated by customer information provided by the distribution network operator with Elexon profiles, and the ambient temperature is calculated by historical data with the model provided in IEC loading guide [11].

Lastly, when applying the strategy on the whole population of distribution transformers, for transformers whose heat run test data are not existing, representative values refined for other transformers in the population could be applied for the calculation of hot-spot temperatures. In addition, taking the oil sample for every transformer of the population may be unnecessary, since an empirical model can be built between the transformer age and the moisture in oil level according to the available data. Therefore, the moisture in oil of every transformer can be estimated by its age.

**7.1.3 Main contributions**

Main contributions of this thesis 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 cyclic loads of distribution transformers with customer information by using Elexon profiles
- Modelling of EV charging load in a probabilistic manner with realistic data collected by EV 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
- Introducing an empirical model to simplify the calculation of loss-of-life of distribution transformers

### 7.1.4 **Main findings**

Main findings of this thesis 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 thesis as the ideal approach to refine the IEC thermal model parameters for distribution transformers. The maximum error of prediction of hot-spot temperature can be reduced to 3.53 K by using refined thermal parameters from 25.87 K by using recommended values under heat run test loads. Under dynamic loads, the maximum error can be reduced to 6.07 K from 9.76 K, and the mean error is reduced to 0.04 K from 3.58 K. However, when refining the thermal parameters by curve-fitting, by varying the initial values, inter-dependence is observed among $k_{11}$, $k_{22}$, $\tau_o$ and $\tau_w$. It is observed that curve-fitted results of these four parameters are depending on the initial values, but the determinate values are achieved for their combinations such as $\tau_o / k_{22}$, $\tau_w \times k_{22}$ and $\tau_o \times k_{11}$. It is therefore found that $\tau_o$ is proportional to $k_{22}$; $\tau_w$ is reversely proportional to $k_{22}$; $k_{11}$ is reversely proportional to $\tau_o$. In order to obtain definite values for these parameters, a definite value should be assumed for any one of the parameters so as to determine the others, while the calculation of hot-spot temperature is not affected by the value assumed.

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. For example, the maximum error can be increased from 3.53 K to 7.43 K under heat run test loads if the cooling period is not included when conducting the curve-fitting. Considering that more accurate thermal parameters can be achieve when including the cooling period into the curve-fitting, it is suspected that a transformer could perform differently during temperature decrease from increase in thermal aspects. However, in the standard heat run test procedure [73], temperature measurements during the cooling
periods are not mentioned and discussed. Therefore, it is recommended in this thesis 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.

The other method introduced in this thesis of the refinement of IEC thermal model parameters would be more widely applicable since it only requires standard results of a heat run test, which are likely available for existing distribution transformers. This method calculates each parameter by developed equations given in the loading guide [11].

- 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 so that the age profile of the population can be covered. Three EV scenarios, i.e. BAU, High-range and Extreme-range scenarios, are investigated, which represent no EV penetration, 32% penetration and 58.9% penetration respectively. Impacts of EV penetration are investigated in terms of load, hot-spot temperature, loss-of-life, expected lifetime and failure probability.

Statistical analysis shows that the investigated distribution transformers are currently operated under a low load level, where more than 75% are loaded under 0.7 p.u., and the highest peak load observed is 1.09 p.u. When EV 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 EV 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, the hot-spot temperature under BAU Scenario is at a safe level. The largest peak hot-spot temperature observed is 87.5 °C, and the yearly average value is 59.3 °C. When EV 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.

Due to low hot-spot temperature levels under BAU Scenario, yearly loss-of-life calculated by the yearly hot-spot temperature profile with the IEC ageing model is obtained in a value lower than the rated value by a factor ranging from 0.1 to 0.0001 for 150 distribution transformers, where the rated value is defined as the yearly loss-of-life of a transformer constantly operated at 98 °C under a rated load. Therefore, the lifetime is expected to be as large as 10 to 10000 times of the expected lifetime of a constantly rated load transformer, which can be considered as 17.12 years according to IEC loading guide [11]. As a result, expected lifetimes of the investigated distribution transformers will be far 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.

Under High-range and Extreme-range scenarios, effects of the increased hot-spot temperatures on the thermal ageing are limited by the duration of the EV charging. Results show that despite of the high hot-spot temperatures during the peak time (when EV 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 2 out of 150 transformers (1.4%) have a yearly loss-of-life over the rated value. Under Extreme-range scenario, the number is 28 out of 150 transformers (18.7%). 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 EV 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 EV penetration such as Extreme-range scenario. Occasionally, the thermal ageing can be increased to significantly exceed the rated value, however, under such occasions, the peak load and hot-spot
temperature will be large enough to prioritise the concerns on short term failure over the reduction of lifetime due to thermal ageing.

Short term failure is defined as transformer breakdown due to bubbling. Considering the stochastic nature of EV charging load, failure probability is defined as the probability of the hot-spot temperature exceeding the bubbling inception temperature under EV scenarios. Bubbling inception temperature is dominantly determined by the moisture in paper, which is derived by the moisture in oil. In this thesis, a linear model is applied to estimate the moisture in oil by the oil age, which is obtained by fitting the measured data collected in the past oil tests. The model is considered conservative, since it is observed from the measured data that the oil is wetter than expected even under a young age. For example, a less than 10 years old distribution transformer could have moisture in oil of 8 ppm @ 20 °C. Therefore, it should be noted that the moisture in oil may be overestimated, and the resultant bubbling inception temperature may be lower than it should be. This can be regarded as the worst-case scenario that investigates into the potential bubbling risks if the transformers are as wet as the past oil test data reflect.

By comparing the peak hot-spot temperatures and the bubbling inception temperatures through 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 13% of transformers are in high risk under High-range scenario, while 38% 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.

In terms of the installation condition, fewer indoor transformers are found in high risk comparing to outdoor ones. However, the difference is not significant, and it is difficult to claim outdoor installation is an essential factor causing higher failure probabilities. In addition, although the indoor installation tend to result in higher hot-spot temperature due to the extra temperature rise in ambient and top-oil, it also leads to higher bubbling inception
temperature due to a lower moisture in oil level. Consequently, the failure probability is not found dominated by either effect, so the installation condition should not be considered as an essential factor potentially increases the failure probability.

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.

7.2 Potential future work

The work completed in this thesis has fulfilled the initially defined goals and produced some meaningful conclusions. In the meantime, it also raises some potential future work.

7.2.1 Ranking of distribution transformers based on furan data and load profiles

Methods to assess the thermal characteristics of distribution transformers are introduced in Chapter 4 and 5, which are deriving IEC thermal parameters with heat run test data. With derived thermal parameters, the hot-spot temperatures can be calculated and assessed under arbitrary loading conditions with IEC thermal model. These methods aim to quantitatively define thermal characteristics of a transformer and apply for the prediction of its thermal performance under arbitrary loads. However, when the purpose is simply to identify individuals who have been performing relatively better or worse than their peers based on their current operational conditions, a much simpler method than deriving IEC thermal parameters can be applied. Preliminary work has been done and presented here, yet the idea is worth further investigating; therefore it is included as a potential future work in this chapter.

The idea is to assess a group of transformers in a collective manner based on their furan data obtained by oil test and the customer information. Furan values are used to derive the equivalent yearly hot-spot temperature that a transformer had been experienced during its past lifetime. The customer information containing numbers of each type of customers of a transformer is applied to derive yearly load profile with Elexon profiles, with which the yearly RMS load can be calculated as the equivalent yearly load. With equivalent yearly hot-
spot temperature and load, the thermal performance of a transformer in its past lifetime can be therefore assessed by defining a ratio of the temperature to the load. Higher values of the ratio indicate poorer thermal performances since under the same equivalent load a higher hot-spot temperature tend to be caused.

It has been confirmed by accelerated ageing experiments that as paper degrades in transformer oil, a variety of furanic compounds are produced as intermediate ageing by-products [152]. Among five main furanic compounds, it has been identified that 2-furural (2-FAL) has the highest generation rate and greatest stability in oil. Thus, concentrations of 2-FAL are most commonly determined in furan measurements. For simplicity, 2-FAL is represented by the term “furan” in this work.

The correlation between the increase of furan and the reduction of paper’s DP has been found in ageing experiments by different researchers [153, 154], who established different models to describe this correlation. In [152], Feng compared different models, and refined the model coefficients by fitting the model with measured furan and DP values of 49 National Grid transformers. The refined model is presented as Equation (7-1), and is applied in this work.

\[ DP = \frac{1674}{Furan + 2.09} \]  

(7-1)

With derived DP values, the average yearly ageing rate can be determined by the ageing model given in the loading guide with assumed initial and final DP values of a transformer of 1000 and 200 respectively, and the expected transformer life is set as 17.12 years according to the same loading guide [11]. The yearly equivalent hot-spot temperature can be calculated by IEC ageing model with the average yearly ageing rate.

To demonstrate the method, a group of 200 distribution transformers which have the furan data available are applied. Corresponding yearly equivalent hot-spot temperature and load are plotted in Figure 7-1. Transformers with similar thermal characteristics should be found in a close area of the plot, therefore ranking can be applied. Three groups can be defined as Poor, Average and Good. The ratio of the hot-spot temperature to the load is applied as the indicator for ranking. Calculation shows that the indicator ranges from 60 to 700 for the group of transformers. After a few trials of grouping, threshold values of the indicator for three groups are preliminarily defined for the demonstration purpose. The Poor group has an
indicator value larger than 210; Average group an indicator value between 100 and 210; and Good group an indicator value less than 100.

A further application of the ranking is to quantitatively determine the rated hot-spot temperature rise for each group of transformers. A simplified relationship between the hot-spot temperature rise and the load based on IEC thermal model is applied as shown in Equation (7-2), where $\Delta \theta_w$ is the rated hot-spot temperature rise; $K$ is the load factor; $\Delta \theta_h$ is the hot-spot temperature rise under load $K$, and $\zeta$ is the exponent.

$$\Delta \theta_h = \Delta \theta_w \times K^\zeta$$  \hspace{1cm} (7-2)

$K$ can be known as the yearly equivalent load, and $\Delta \theta_h$ can be known as the yearly equivalent hot-spot temperature rise. Remaining two parameters can thus be estimated by curve-fitting the data points of each group of transformers. Estimated results are shown in Table 7-1, from which it can be seen that group Good transformers have the lowest rated hot-spot temperature rise, while group Poor transformers have the highest value.

Table 7-1: Estimated parameters for each group of distribution transformers

<table>
<thead>
<tr>
<th>Groups</th>
<th>Estimated results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\Delta \theta_w$ (K)</td>
</tr>
<tr>
<td>Group Poor</td>
<td>116.42</td>
</tr>
<tr>
<td>Group Average</td>
<td>92.64</td>
</tr>
<tr>
<td>Group Good</td>
<td>76.03</td>
</tr>
</tbody>
</table>
Although the values obtained from the simplified relationship of hot-spot temperature rise and load may not be accurate, they can be used as a quantitative indicator showing the relative goodness of the thermal performance of different groups of distribution transformers to validate the grouping. Also based on the estimated values and the simplified relationship, it can be roughly estimated that what the temperature rise level would be if the average level of load of transformers increases, which may be used as a general guidance tool for the management of the thermal capacity of the distribution transformer population.

This work could be potentially continued further by firstly defining more justified threshold values of the indicators for ranking. Secondly, the verification work should be conducted if the load and hot-spot temperature data could be obtained.

### 7.2.2 Other future work

As a systematic methodology for the assessment of future adaptability of distribution transformers, the proposed strategy still has some uncertainties that deserve sufficient attention and future work to cope with. Firstly, the proposed methods for thermal modelling and thermal failure modelling require sufficient accuracy and representativeness of parameters set-ups in order to deliver accurate results. Secondly, necessary assumptions are made in the thermal failure modelling in order to quantify the failure probability. Lastly, statistical uncertainties are introduced in the modelling of EV charging load and moisture in oil, which inevitably poses a degree of randomness on the final output of the strategy. To cope with the uncertainties, potential future works are proposed here.

- **Derive more representative thermal parameters for the distribution transformer population**

Thermal parameters are reflecting the thermal characteristics of transformers; therefore, a single set of parameters may be used for transformers with similar design when refinement of thermal parameters for each transformer is not possible due to the data restriction. To identify and define the “similarity” of transformer design in terms of thermal parameters could be investigated as a potential future work.

- **More accurately estimate moisture in paper with equilibrium curve of moisture dynamics in oil and paper**
Equilibrium state is actually never reached during the daily operation of transformers due to the oil temperature variation, let alone under EV scenarios. Therefore, for more accurate estimation of moisture in paper, the transient transition of moisture between oil and paper should be investigated and modelled.

- Improve the short term failure model defined by bubbling

When bubbles are formed in transformers, the failure is a highly likely hazard rather than inevitability. The failure is caused by breakdown when the dielectric strength of the liquid insulation is reduced by bubbles to a level that cannot stand the voltage strength. Therefore, ideally, the short term failure model should be built from a perspective of the drop of dielectric strength of transformer insulation systems. However, this would involve understanding the process of the reduction in dielectric strength of the liquid insulation during the bubbling event, which could be a potential future work.
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REFERENCES


REFERENCES


REFERENCES


REFERENCES


REFERENCES


REFERENCES


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### APPENDIX A  THERMAL PARAMETERS DERIVED BY HEAT RUN TEST DATA OF 20 DISTRIBUTION TRANSFORMERS REPRESENTING POPULATION

#### Table A-1: Thermal parameters derived by heat run test data of 20 distribution transformers

<table>
<thead>
<tr>
<th>Index</th>
<th>Power rating (kVA)</th>
<th>Voltage rating (kV)</th>
<th>$R$</th>
<th>$\Delta \theta_{\infty}$ (K)</th>
<th>$g^r$ (K)</th>
<th>$H^*$ (min)</th>
<th>$\tau_w^*$ (min)</th>
<th>$x^*$</th>
<th>$y^*$</th>
<th>$k_{11}$</th>
<th>$k_{21}^*$</th>
<th>$k_{22}^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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*: Generic values recommended in IEC loading guide are applied, since required data for the derivation are not available.
APPENDIX B  LIST OF PUBLICATIONS


