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Weather-Based Quasi Dynamic Thermal Ratings for Power Transformers

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Abstract—This paper presents a preliminary study on climate change’s impact on power transformers’ ratings. This limit depends on the difference between air temperature and the maximum continuous allowable hot-spot oil temperature. On the other hand, atmospheric temperatures are expected to rise in the following years in Europe in a range between 0.52% and 8.18% Celsius degrees, according to the scenario. This will result in a rating reduction for existing and newly installed transformers.

This study proposes a methodology to quantify this phenomenon and estimate its effect on several use cases. This is achieved by combining the transformers thermal model described in the IEC 60076-7 loading guide, historical meteorological reanalyses for 1970-2021, and climatic projections for 2022-2072 based on different greenhouse gas emissions hypotheses. Simulations are carried out using a quasi Dynamic Thermal Rating approach for HV transformers in the southeastern regions of France.

Results show how the methodology proposed allows for a 6% rating increase in the cooler hours of the day and that projected future ratings are expected to be 5.031% - 0.194% lower than the historical ones.

Index Terms—Power Transformers - Transformer Thermal - Dynamic Rating - Probabilistic forecasting

I. INTRODUCTION

The climate change repercussions on the electric network have been analysed in [1], [2], showing transmission rating reductions from 5% to 15% over the long term and mainly influenced by ambient temperature. The effects of this rating reduction and new energy demand projections in [3], involve significant and costly network reinforcement or expansion to maintain the system’s reliability.

In the transmission and distribution network, power transformers (PT) are critical assets connecting power plants and customers. Their failure could lead to outages, environmental risks, up to loss of life.

Therefore, with projections that anticipated a rise in the peak temperature range between 0.52% and 8.18% for the coming five decades in Europe [4] [5] observed in Fig. 1, the thermal stress increases the risk of premature failure and reduces the PT’s rating.

According to the International Electrotechnical Commission (IEC) [6] and the Institute of Electrical Electronics Engineers (IEEE) loading guides [7], the rating of a PT is usually governed by the thermal limit or hot spot temperature (HST).

Its accurate identification will provide essential information for life estimation, asset management strategies, and flexible scheduling. It can also be used to mitigate the risk of failure and to develop monitoring strategies. For this reason, transformers operating temperature has been investigated in the last three decades under the following strategies: The conventional Static Thermal Rating (STR), which international standards have extensively analysed [6] [7] using the thermal models investigated in [8] [9], and that is based on estimation of typical and conservative assumptions, together with safety and ageing criteria. However, despite its prolonged use, it only approximates the actual thermal values because it does not consider the instantaneous atmospheric conditions and the load profile [2]. The second is the Dynamic Thermal Rating (DTR) strategy, which determines the rating limits based on time-variable environmental conditions, such as air temperature. The third option, always within the concept of DTR, relies on direct temperature measurement, usually with a fibre optic sensor, [6], but this is often possible only for new transformers [10].

In this field, the application of the DTR approach is a proven concept and is presented as an alternative to improve the flexibility of the network in many scenarios. The main objectives are 1) increased transmission system efficiency and improvement reliability [2], and 2) Decreased or deferral of investments to reinforce or expand the existing network, where PT is often among the most expensive assets [10]. As this paper focuses on combining probabilistic thermal modelling and big data to determine the DTR of oil-immersed transformers, this section only reviews relevant works from the last decade.

Relevant literature addresses the evaluation of HST effect as the main parameter for determining the insulation ageing and its rating. In [11], the authors proposed a risk-based approach using a quantile Regression (QR) model to forecast the HST from the dynamic thermal model of the transformer. The results were developed in seasonal and hourly yield, and a fixed acceptable risk level validated the proposal from an energy and economic point of view. Another approach was developed in [12], [13] that employs thermal models from the IEC and IEEE guidelines to investigate the effect of DTR on a transformer’s loss of life by calculating HST.

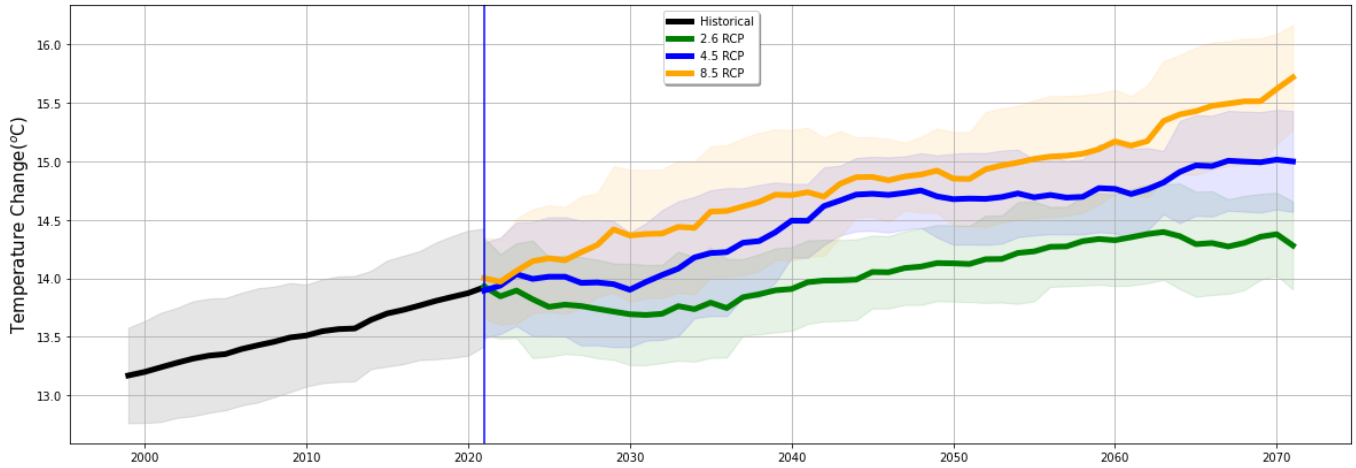


Fig. 1: Le Broc-Carros PT temperature change projection, evaluated rolling mean for 2.6, 4.5, 8.5 representative concentration pathways. Coloured shading represents one standard deviation

The results reflect that the economic application of DTR could be financially beneficial while providing equal operating performance.

Data-driven thermal loading methodology for estimating annual continuous dynamic rating are presented in [14]. The analysis of the last five years of temperature ambient and load composition data is established, resulting in the continuous dynamic rating profiles under temperature scenarios for the planning region, introducing the concept of dynamic rating into the long-term planning process. The analysis of the existing literature above suggests that the topic of transformers rating is mostly faced with relatively short (i.e., five years) historical temperature records or short-term forecasts (i.e., a day ahead).

On the contrary, this research explores the behaviour of PT ratings considering both long-term historical reanalysis and climatic projections, with a perspective of 50 years in the past and the future. Thanks to the application to PT of the quasi Dynamic Thermal Rating (qDTR) approach presented in [15], it aims at identifying initial findings on the effect of climate change on the power systems.

In particular, this paper aims to provide the following contributions:

- The application of qDTR to power transformers.
- The estimation of the influence of climate change on transformers rating.

The paper is organised as follows: Section II illustrates the thermal model and methodology. Results are described in Section III, and conclusions are drawn in Section IV.

II. METHODOLOGY

The procedure developed to quantify the long-term effect of weather conditions on transformer power rating can be described as follows: 1) Air temperature time series for the past and future years are collected for the PT location. 2) For each hourly time step, The PT rating is calculated using

the HST model described in [6]. 3) Results are grouped by month/hour. 4) A probability distribution is fit for the lower tail of each month/hour combination. 5) A rating is calculated from the probability distribution according to a chosen quantile corresponding to a tolerated risk level.

A. Thermal Model

Several models have been proposed for estimating the thermal state of loaded power oil-immersed transformers. Among the ones mentioned in Section I, the IEC 60076-7 loading guide [6] will be used due to its wide acceptance and simplicity. Other works propose more detailed models, including wind speed and solar radiations [16], [17]. Nevertheless, in this work, it was preferred to use the more recognised standard to give more general validity to the results.

PT rating is limited by the HST θ_h ($^{\circ}\text{C}$), depending on ambient temperature θ_a ($^{\circ}\text{C}$) and the hot-spot gradient rise of temperature within the transformer $\Delta\theta_h$ and it is calculated in (1). The Top-oil temperature θ_o ($^{\circ}\text{C}$) with a cold start state assumptions can be calculated in (2).

$$\theta_o = \left[\frac{1 + K^2 R}{1 + R} \right]^x (\Delta\theta_{or}) + \theta_a \quad (1)$$

$$\theta_h = \theta_o + \Delta\theta_h \quad (2)$$

Where the $\Delta\theta_{or}$ ($^{\circ}\text{C}$) describes temperature rise in steady state at rated losses; x is the exponent related to oil temperature rise due to total losses; R is the ratio of load losses at rated current to no-load losses at rated voltage. The HST is used as the critical limiting parameter for the rating and to calculate load factor K (p. u) per iteration, defined as the ratio between load current and rated current.

B. Quasi Dynamic Thermal Rating

As proposed in [15], the DTR is determined by a three-step procedure: First, calculated ratings are grouped by month and hour to consider the yearly and daily weather periodicity.

Secondly, a probability distribution is fit to each one of these subgroups; after an initial benchmark, the power law was chosen for this task. The model is shown in (3), where the constant parameter α is known as the exponent or scaling parameter and x represents the quantity in whose distribution is interested, for our case, the rating (I).

$$p(x) = Ax^\alpha \quad (3)$$

At this point, the rating is chosen from a predetermined distribution quantile. In this paper, the 0.1 % quantile is chosen. This corresponds to a temperature exceedance of roughly 8 hours per year.

C. Data

This study requires data from 1) the Transformer and 2) the Weather.

1) *Transformer Data*: At this stage, the transformer is evaluated based on the values of the typical guideline parameters [6], listed in Table I.

According to the given conditions, a population of five different transformers in the Provence region was analysed, listed in Table II. For these transformers, the rating is calculated from the available data.

TABLE I: Thermal Characteristic listed in IEC 60076-7 used in PT model equations

Parameter, Units	Symbol or Reference	Value
Oil exponent	x	0.8
Winding Exponent	y	1.3
Loss Ratio	R	6
Hot-Spot Temperature ($^{\circ}C$)	θ_h	98
Hot-Spot to top-oil ($^{\circ}C$)	$\Delta\theta_{hr}$	26
Tap-Oil Temperature Raise ($^{\circ}C$)	$\Delta\theta_{or}$	52
Constant	K_{21}	2

TABLE II: Power transformer list with parameters for qDTR analysis

Unit	Name	Calculated Power (MVA)	Resistance R(Ω)	Reactance X(Ω)
T_1	Le Broc-Carros	1194	0.1	42.3
T_2	Biaçon	1168	0.24	43.1
T_3	Realtor	1210	0.12	41.7
T_4	Tamareau	1119	0.25	45
T_5	Tavel	1184	0.14	42.6

The static grid model in [18] provides the description, electrical parameters as voltage level, and seasonal ratings for the PT, and is complemented with the Enedis open data portal that contains the geographical reference for each transformer [19], illustrated in Fig. 2.

2) *Weather*: The ambient temperature data is retrieved from:

- ECMWF ERA5 dataset provides the historical weather reanalysis, with resolution of $0.25^{\circ} \times 0.25^{\circ}$ (~ 24.5 km)

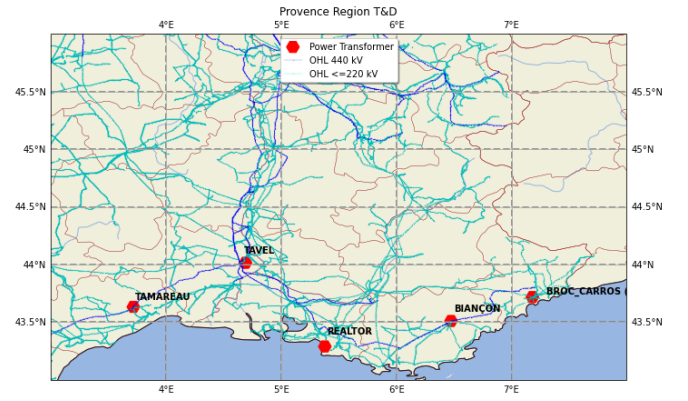


Fig. 2: Map of Provence transmission network with a location of PT highlighted in red dots

and hourly time step. It is used in a 50-years period from January 01, 1970, to December 31, 2021 [4].

- Copernicus climate change service (C3S) - Climate and Energy indicators offers the Europe climate projections with a Representative Concentration Pathway (RCP) of 2.6, 4.5, and 8.5. The dataset has a resolution of $0.25^{\circ} \times 0.25^{\circ}$ (~ 24.5 km) and 3 hourly resolution [5]. The temperature ambient time series of the 50-year period from January 01, 2022, to December 31, 2072 were used.
- Climatic projections are linearly interpolated with a time resolution of 1 hour to match the frequency of the historical reanalysis.

III. RESULTS

This section presents the results of the qDTR calculation, evaluated according to the methodology presented in Section II. The distribution fitting can be seen in Fig. 3 where green dots represent the calculated PT ratings using the thermal model represented in (1) and (2), and the dashed line represents the estimated probability distribution for the month of June at 2:00 pm. For each month/hour combination, the power law distribution fits the lowest 2% of the calculated ratings. For all the month/hour combinations, r^2 is greater than 0.94.

A set of hourly and monthly qDRTs for the analysed PT is shown in Fig. 4. Those are calculated considering an exceedance probability of 0.1% and compared with seasonal ratings calculated with the same exceedance probability, whose values were verified with the summer/winter ratings provided by the TSO in [16] for the same transformers. This resulted in an average error of 4.2%, considered acceptable.

From the analysis of this chart, it is possible to imply that: i) as expected, qDTRs allow us to better exploit the colder hours of the night, both in summer and winter. This has particular relevance to the integration of night winter load peaks. ii) This gap is also more significant in summer than in winter based on minimum and maximum values. This is a consequence of higher temperature differences in summer. iii) It must be noted

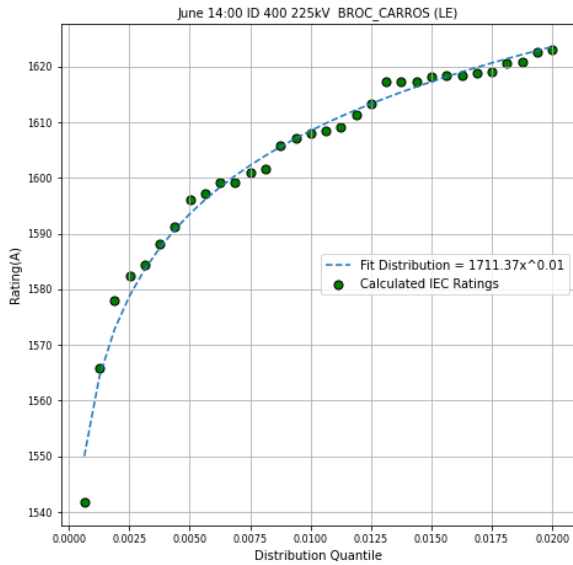


Fig. 3: Example of power law distribution fitting and calculating dots of the lower quantile

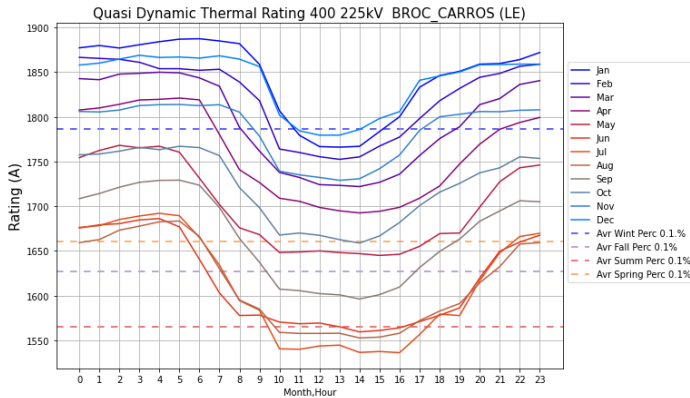


Fig. 4: qDTR for Broc-Carros PT with an exceedance probability of 0.1%

that in the hottest daily hours, qDLRs tend to be lower than the seasonal rating.

The same procedure is applied to the three projected RCP scenarios. The effect of increased ambient temperature in the three RCP scenarios for the Broc-Carros PT, is shown in Fig. 5. The variations – albeit small – correspond, for example, to a maximal rating reduction of 4.1% in July for RCP 8.5 and 1.1% for RCP 4.5. This could be translated in terms of variation in the level of risk or the useful lifetime of the equipment for the network operator. On the other hand, it is possible to observe the opposite effect in specific months and hours, such as February or December and the late mornings.

Finally, Table III reports the average, minimum, and maximum values for the qDTRs calculated for the five transformers studied. This is done in absolute values for the historical reanalysis and percentage variations for the three climatic projections. It is possible to observe an average reduction in

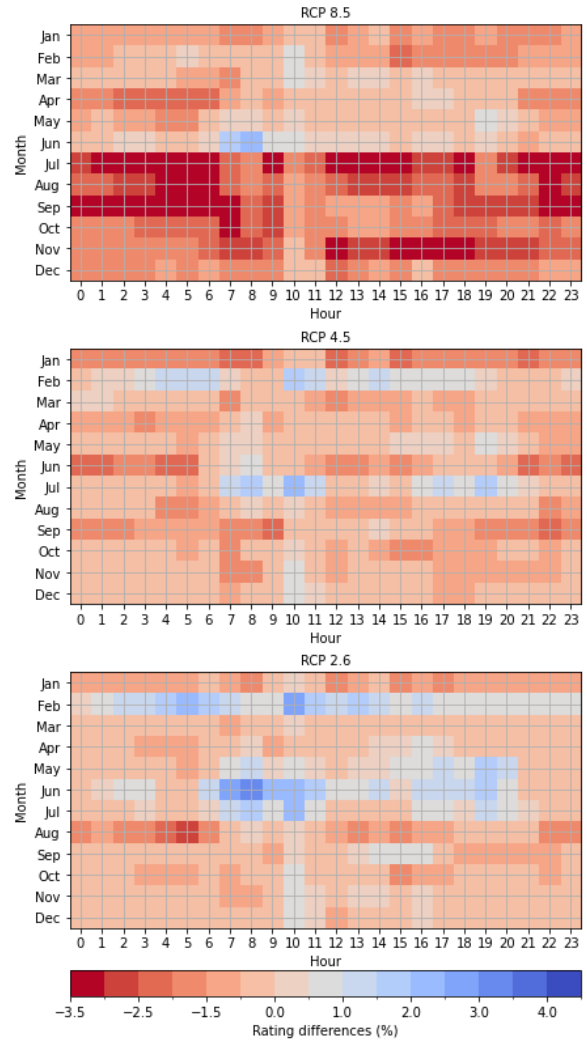


Fig. 5: Difference of the calculated qDTR month/hour between historical values and RCP projections 2.6, 4.5, 8.5

ratings in the order of 0.2%, 0.7%, and 1.5%, respectively, for the 2.6, 4.5, and 8.5 RCP.

IV. CONCLUSIONS

This paper presents a preliminary study on the influence of climate change on the rating of power transformers, using the qDTR approach. Its results can be summarised as follows:

- The qDTRs methodology introduced has the advantage of a higher average rating throughout the year in contrast to seasonal rating (an average uplift in the region of 7.7%). On the other hand, this rating is lower than that of DTRs.
- The hourly/month qDTR in PT yields rating improvements in specific periods, mainly at night. Network operators could use more straightforward approaches such as day/night in practical applications.
- The qDTRs are not intended to be an alternative to DTRs, but a more straightforward solution that does not require telecommunications or controls and can be easily applied

TABLE III: Average, minimum and maximum qDTR values compared to historical values

Description	Realtor	Biaçon	Broc-Carros	Tamareu	Tavel
Hist Avg (A)	1716	1652	1711	1575	1636
Hist Max (A)	1851	1787	1862	1706	1805
Hist Min (A)	1543	1455	1519	1363	1340
2.6 RCP Avg	-0.3%	-0.1%	-0.2%	-0.3%	-0.4%
2.6 RCP Max	0.2%	0.7%	0.0%	0.6%	0.31%
2.6 RCP Min	0.0%	-0.4%	-1.0%	-2.1%	-0.8%
4.5 RCP Avg	-0.9%	-0.6%	-0.7%	-0.5%	-0.8%
4.5 RCP Max	-0.5%	0.5%	-0.8%	0.3%	-0.08%
4.5 RCP Min	-0.7%	-0.9%	-0.5%	-1.7%	-0.7%
8.5 RCP Avg	-1.7%	-1.6%	-1.6%	-1.0%	-2.1%
8.5 RCP Max	-1.0%	-0.1%	-1.4%	-0.2%	-0.7%
8.5 RCP Min	-3.7%	-3.0%	-3.8%	-2.2%	-1.8%

to network components. Leaving the application of DTRs to more critical assets.

- qDTRs, in contrast to DTRs, are known in advance and can be easily used in network expansion planning and operational scheduling.
- qDTRs are calculated in this work considering an exceedance probability level set at 0.1%. However, the impact of ageing needs to be taken into account. Network operators could use more or less stringent values depending on the specific load expected in each transformer or plan for slower or faster ageing.
- Future qDTRs are expected to be lower than past qDTRs due to projected temperature increases. In particular, 0.2%, 0.7%, and 1.5% on average, respectively, for the 2.6, 4.5, and 8.5 RCP.
- The availability of climate projections makes it possible to calculate time-dependent variables, such as qDTRs, under expected future conditions. Their use should be further explored for other transition and distribution network assets.
- The results of this work are influenced by the small size of the use case, limited to five transformers in a single region. Nevertheless, they reveal interesting patterns that deserve further study.

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