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► **To cite this version:**

Andrea Michiorri, Sergio Daniel Montana Salas. Assessing Regional Capacity Expansion: The Role of Quasi-Dynamic Thermal Ratings in a Changing Climate. 2024 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Oct 2024, Dubrovnik, Croatia. hal-04868259

HAL Id: hal-04868259

<https://hal.science/hal-04868259v1>

Submitted on 6 Jan 2025

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Assessing Regional Capacity Expansion: The Role of Quasi-Dynamic Thermal Ratings in a Changing Climate

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Abstract—Proposing practical solutions to mitigate the effects of climate change on the electricity system requires thorough understanding and quantification. This paper introduces a new method of quantifying dynamic network capacity at the transmission level, using established thermal models and a set of regional expansion plan tools. The results suggest this approach can increase component capacity by up to 21% during winter and up to 16% during nighttime hours for overhead lines. This approach offers a viable option for electricity operators to address the challenge of balancing the need to reduce failure rates and capacity loss with the crucial demand for new investment in transmission assets, reducing more than 1% of system cost expansion by 2050.

Index Terms—Climate Change, Dynamic Thermal Rating, Power transmission meteorological factors, Thermal Factors.

I. INTRODUCTION

This paper presents the findings of research on regional network expansion planning, taking into account the impact of climate change on transmission network equipment. As emphasized by [1], a transmission network expansion up to 80 million kilometers in Europe is possible, whilst transmission capacity reduction from 1.9% to 5.8% is expected in the United States [2]. These challenges underscore the importance of analyzing future investments and developing new flexibility strategies using established methods.

Regarding the transmission network, various solutions have been proposed to alleviate network congestion problems. One of them is the implementation of Dynamic Thermal Rating (DTR) on critical transmission lines. This technology aims to identify network components' real-time current carrying capacity, typically higher than their static nominal value. By doing so, DTR enables the reduction of network congestion, associated curtailments, and delays or the avoidance of network reinforcements while simultaneously enhancing reliability. It can be integrated into power system expansion plans [3], [4], but its dependency on meteorological factors, such as ambient temperature, makes it particularly sensitive to climate change.

Climate scenario models and trajectories have been published for specific road maps. Among these, quantitative projections, such as Representative Concentration Pathways (RCPs) and Shared Socio-Economic Pathways (SSPs), provide valuable tools for assessing regional climate changes and their specific impacts on the energy sector. Indeed, electricity demand is expected to increase up to 21% [5], a key factor in determining capacity expansion planning.

In academic literature, the Long-Term Demand Forecasting Methods (LDFM) are often described as incorporating trend analysis, econometric modeling, or combined analysis, as discussed in [6], [7]. These methods explore linear and non-linear relationships among economic indicators, demographic factors, and weather variables such as Gross Domestic Product (GDP), ambient temperature, and population. Furthermore, statistical and machine-learning algorithms have been explored for this task.

As a main contribution, this research aims to quantify the impact of climate change on power system transmission capacity as a part of strategic planning methodology for a regional utility with the following approach:

- Deriving a quasi-Dynamic Thermal Ratings (qDTRs) algorithm as the first solution to recover the lost transmission capacity.
- Quantify the impact of climate change on power system transmission capacity considering future climatic projections datasets.

The paper is organized as follows: Section II illustrates the load demand forecast, thermal model, and methodology. The results are described in Section III, and conclusions are drawn in Section IV.

II. METHODOLOGY

A. Overview

We introduce a model to assess the long-term effects of climate conditions on regional capacity, employing qDTR as a critical metric in **II-B**. This model is delineated in Fig. 1. Initially, a regression machine learning model is trained using

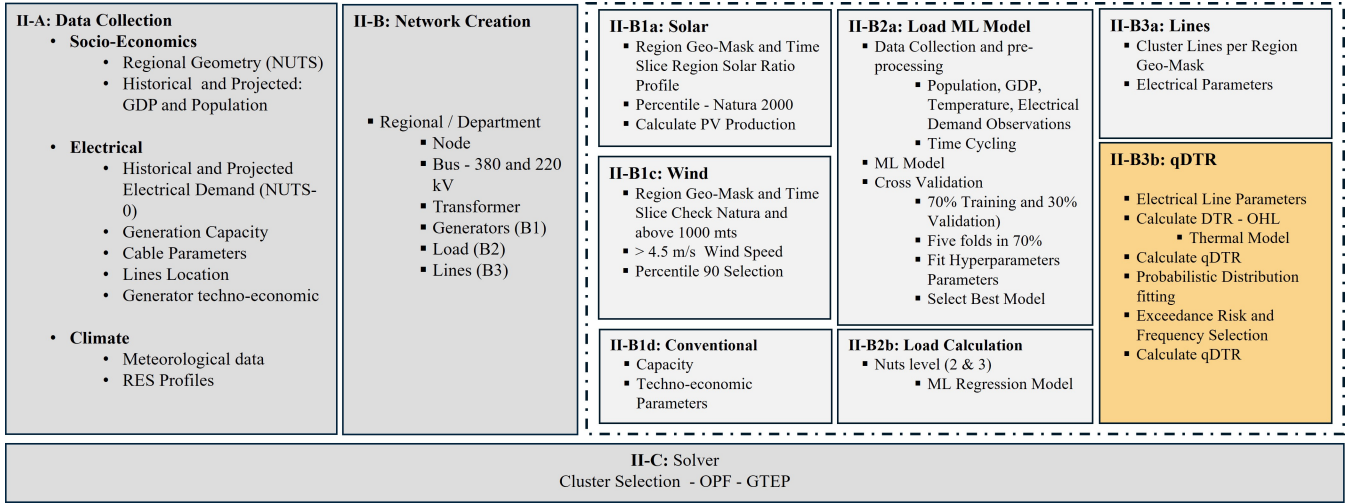


Fig. 1. Proposed block diagram: It is divided into three sections representing the estimation of network capacity using qDTR, the preparation of the network, and its economic analysis via GTEP.

historical techno-economic regional and meteorological data to project demand by regions **II-C**. Subsequently, data describing the electrical grid configuration are gathered to cluster and construct the network **II-D**. The transmission information, including location details and meteorological time series, is then utilized in components' thermal models to estimate the capacity **II-B**. These ratings are subsequently incorporated into a G&TEP, enabling the calculation of optimal investments and operating costs.

B. Quasi Dynamic Thermal Ratings

qDTR, as proposed in [8], [9], are employed to quantify ratings for a long-term horizon. After gathering the time series and parameters outlined in Section II-G, the DTR is estimated using a component thermal model. This model is based on the thermal balance between the heat generated by the Joule effect (I^2R) and the heat dissipated in the environment through convection or conductivity (Q_c), radiation (Q_r), and solar heat gain (Q_s), as described in (1) and applying the model outlined in [10]. These time series data are fitted with a probability distribution, as detailed in [11], focusing on the lower tail of the simulations for each month/day combination. A predetermined tolerance level to the risk of thermal overload (0.1% in this case) is then selected.

$$I^2R + Q_s = Q_r + Q_c \quad (1)$$

C. Load Model

Long-term regional energy demand forecasting comprehensively assesses factors that drive future energy consumption patterns, such as economic parameters, seasonal variations, and spatial behaviors. With an hourly resolution, this module targets each sub-grid's load demand profile in MWh. The pre-selection of features was conducted using a combination of time series meteorological data, demographic factors, and

demand observations, guided primarily by bibliographic analyses in [6]. This selection process adheres to the nonlinear relationship described in (2), where i represents the year, and a , b , and c are parameters derived from historical data. To ensure the spatiality of the system throughout the European region, we rely on the open sources described in section II-G. The profile and shape of the hourly demand result depend mainly on economic influences and the temperature condition of the region. Demand curves are calculated for the sub-grid by gathering the profile demand of the above region (Country or region) from [12], GDP, population, and hourly temperatures.

$$D_i = a(\text{per capita income})^b_i(\text{population})^c_i \quad (2)$$

Due to the problem's complexity, we implemented the following preprocessing and numerical transforms: a) Minimum and maximum scaling, b) Encoding of cyclical Day of the Year, and c) Hourly interpolation. During the initial phase, we assessed a range of regression machine-learning techniques to determine the most fitting approach for our method. This evaluation centered on key error metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The dataset is divided by geographical regions to train and test the models. The training set is initially randomly partitioned into 70%, with an additional 10% reserved for tuning the model hyperparameters, employing techniques outlined in [13]. The remaining 30% is designated as the validation set for model testing. N-fold cross-validation is employed to mitigate overfitting, dividing the test dataset into five folds. This ensures that all region sizes are represented in each fold, thus maintaining homogeneity of selection.

D. Dimensional Reduction

The objective is to analyze the electricity network of European regions, focusing on long-term generation and demand patterns. The process starts with the regions categorized at

level zero of the Nomenclature of Territorial Units for Statistics (NUTS) (countries) and extends to the departments (level three of NUTS). This analysis is based on geographic information about electricity transmission and generation networks as well as technical-economic data.

A regional strategic approach to the power system follows the same methodology, utilizing geographical boundaries from [14]. To account for the fluctuating nature of renewables, each region is analyzed using wind production density [15]. A coordinate is selected based on the criterion of reflecting an average speed of more than 4.5 m/s during the period analyzed, ensuring that it is not located above 1000 m above sea level and within a protected natural area [16], the production is extrapolated to form a defined curve. Similarly, a profile for the PV (photovoltaic) system is generated, with the distinction that coordinate selection is based on a statistical analysis of the 50th percentile.

The transmission lines' geographical locations and electrical parameters are imported, analyzed, and established. A geographic mask is generated for each line based on its departure and arrival locations using its NUTS two and three regional codes. The lines are sorted by voltage and linearly aggregated in their bundles to maintain transmission capacity. In addition, a single transformer is configured between the high- and low-voltage buses at each regional location.

E. Representative days Selection

In order to keep the problem computationally manageable, a representative set of days is chosen, applying a clustering algorithm per region described in (3). This set incorporates diverse input time series and is evaluated over the scenario horizon. A scaling method is selected to normalize all data points, and one representative day and one extreme day are chosen per month, region, and country. This ensures critical points from each sub-region are included and maintains the representation of typical days for the entire system.

$$\arg \min_{\{\mu_1, \dots, \mu_k\}} \sum_{j=1}^k \sum_{\mathbf{x}_i \in C_j} \|\mathbf{x}_i - \mu_j\|^2 \quad (3)$$

Where μ_k are the centroids of the k clusters, each representing a typical day for a specific region and month.

F. Generation, Transmission and Expansion Planning

Economic implications arising from reduced capacity due to climate change are evaluated through Generation, Transmission, and Expansion Planning (G&TEP) analyses [17]. G&TEP studies are carried out using $qDTR_{RCP}$ based on three climatic projections. This comparison illuminates the errors incurred when the impact of climate change on transmission capacity is overlooked.

In generation, conventional power plans (CCGT, OCGT, Oil, and Hydro) include some technical constraints such as capacity constraints, $p_{nom,max}$, CO₂ emissions, and technology efficiency.

In addition, G&TEP utilizes STR alongside the year calculated from each RCP data. This comparison highlights the advantages of qDTRs, which vary over time to recover lost transmission capacity.

G. Datasets

The impact on quasi-Dynamic Thermal Rating (qDTR) capacity is quantified by organizing data into three primary categories:

- **Socio-Economics data:** This includes national/regional accounts data such as GDP ^(a) [18] and population ^(b) [19]. Geographical boundaries are defined based on the Eurostat regional classification of territorial units for statistics (NUTS3 & NUTS2) ^(c) [14]
- **Electrical Data:** Electrical Data: Hourly historical time series of electricity demand profiles for each country and region ^(d) [12], [20], combined with annual geolocated generation plants with physical characteristics^(e) [21], such as fuel type and capacity, and techno-economic assumptions such as fuel prices, VOM ^(f) [22]–[24]. OHLs electrical parameters and locations are also considered^(g) [17].
- **Climatologists Datasets:** Historical reanalysis and Representative Concentration Pathway (RCP)-based climate projections from ECMWF ERA5 and Copernicus C3S, with a high resolution of 0.25°, covering the period from January 01, 1970, to December 31, 2072^(h) [20], [25].

TABLE I
DATASETS AND PARAMETERS

Variable	Units	Process	Source
Socio-Economics			
GDP	MEuros	II-C	a
Population	M	II-C	b
Territorial Classification	°	II-C,II-B,II-D	c
Electrical			
Load Profile	MW	II-C	d
Power Plant Capacity	MW	II-F	e
Power Plant Techno-Economic	-	II-F	f
OHL Electrical and Location	-	II-B , II-F	g
Climate			
Temp. Air at 2 m	K	II-C,II-B	h
Net surface solar radiation	Jm ⁻²	II-B, II-F	h
u - v - wind at 10 m and 100m	ms ⁻¹	II-B, II-F	h

III. RESULTS

The hourly simulations were performed based on a selection of representative days over the projected horizon, delineating the electricity benefits attributable to the adoption of qDTR. The spatial distribution, comprising sixty-nine pre-selected regions, is shown in Fig. 3. The data for each region were processed and assimilated as set out in the II-G.

The model is designed to optimize the expansion and operation of the existing grid capacity, projected from 2021, to

meet the anticipated growing demand by 2050. The simulation parameters, delineated in Table II, dictate the framework within which these optimizations are performed. As mentioned in II-C a LDFM leveraging regression-based methodologies at an hourly step was trained, validated, and selected. Although the results are not shown in this paper, the outcomes underscore the efficacy of linear regression and XG-Boost methodologies, manifesting an average deviation of 12% from observed values.

TABLE II
MODEL SPECIFICATIONS PARAMETERS

Variable	Units	Value
Socio-Economics		
Technology Financial	$\frac{MEUR}{MW_e}$	[22]–[24]
CO ₂ Emission	$\frac{tCO_2}{MW_h}$	[22]
Spatial Resolution	Km^2	25
Electrical		
Thermal Risk	%	0.1
PV Density	$\frac{MW}{Km^2}$	2.60
Wind Density	$\frac{MW}{Km^2}$	6.64
Hydro p_{max}	%	9
OHL Conductor	-	490-AL1/64-ST1A
Bus Voltage	kV	220 / 380
Scenarios Description		
Projection	RCP	2.6, 4.5, 8.5
Timeframe	Year	2021 - 2050
Resolution	Hour	24
Days Selection	Days	(2) Representative + (1) Extreme
Expansion Limit	-	1.5 to 4.5 times (220kV - 380kV)
Modeling tools		[17]

A. Benefits of qDTR vs STR

As described in II-B and detailed for a specific line in Fig. 2, qDTR is used to determine the maximum capacity of OHLs, considering future meteorological projections from 2021 to 2050 across different RCP scenarios (qDTR_{RCP x} , where x represents the RCP scenario evaluated). Table III illustrates the percentage mean variation of the average rating compared with the STR. In all three scenarios, qDTR_{RCP} consistently exceeds STR_{RCP} with increases of 16% and 20% specifically for the 2.6 scenario. In contrast, as a trade-off, using a risk probability of 0.1 %, we ensure that during the high-temperature season, the rating operates within the safety zone, with an average decrease of -7% during the day and summer. This trend persists across all seasons and projections. Consequently, enhancing the capacity increases loadability, thereby reducing the necessity for transmission expansion by 3% in the high-emission scenario.

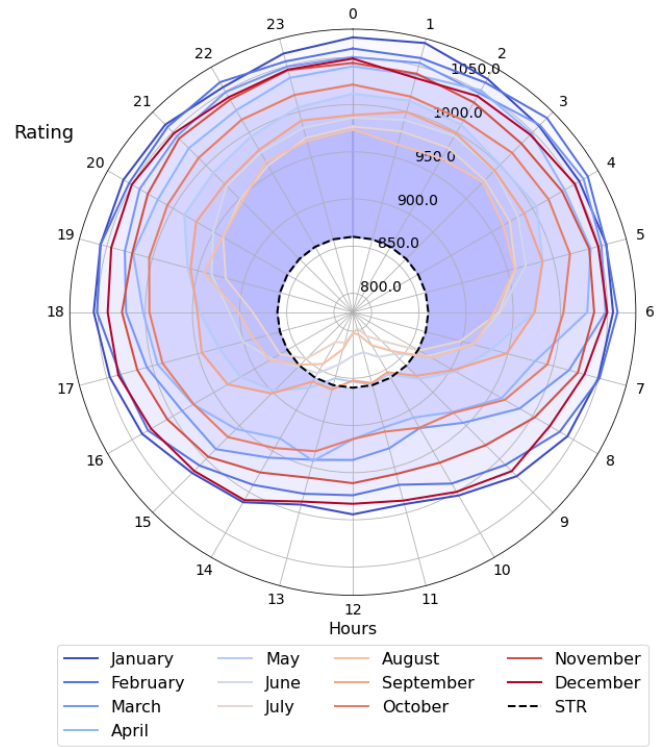


Fig. 2. qDTR for Line FRC1 - FRF2 with an exceedance probability of 0.1%

TABLE III
 $\Delta\%$ QDTR / STR MEAN CAPACITY DIFFERENCES OVER A FIFTY-YEAR WITH RCP_{2.6, 4.5, 8.5}

Description	Summer	Winter	Autumn	Spring	Day	Night
qDTR_{RCP8.5,STR}						
Min	-7	12	-2	-1	-7	3
Max	13	21	18	20	20	21
Average	4	18	12	12	8	15
qDTR_{RCP4.5,STR}						
Min	-6	12	-2	-1	-7	3
Max	13	13	20	22	20	21
Average	5	21	13	12	8	15
qDTR_{RCP2.6,STR}						
Min	-7	12	-1	-1	-7	2
Max	13	23	20	21	23	23
Average	5	20	13	12	9	16
	RCP_{8.5,STR}		RCP_{4.5,STR}		RCP_{2.6,STR}	
Loading	7		7		8	

B. Impact on network costs

This section delves into investment decisions in the G&TEP, integrating climate-variant supply and qDTR for power system components. We apply STR_{RCP} and qDTR_{RCP} based on climate projections. The ensuing G&TEP estimates changes in CAPEX, OPEX, and renewable curtailment. Results in Table IV highlight: ¹ enhancements with qDTR_{RCP} over STR_{RCP} with a maximum increase above 20 % in Winter and during nights. ² Significant reductions in curtailment over 14%, resulting in reductions of more than 1% in the total cost of the system.

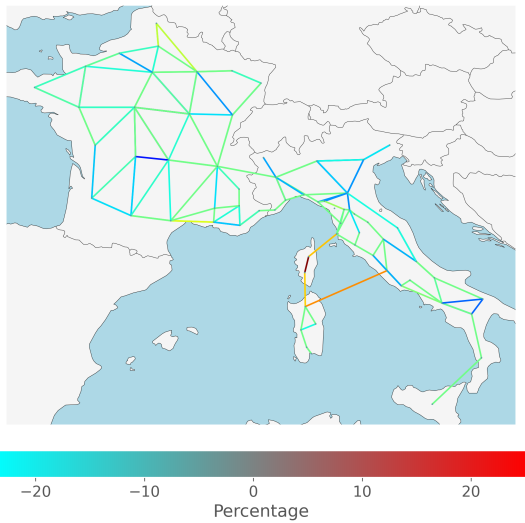


Fig. 3. Geographical representation highlights the analyzed regions, illustrating the variance in line expansion from STR to RCP 4.5.

TABLE IV

VARIATION (IN %) FOR THE THREE SCENARIOS CONCERNING YEARLY FIX RATING AND COSTS

	RCP _{8.5} .STR	RCP _{4.5} .STR	RCP _{2.6} .STR
CAPEX			
Renewable	-1	-2	-1.8
Fossil	-2	-1	-2
Nuclear	0	0	0
Total	-1	-1	-1
OPEX			
Renewable	-3	-4.3	-3.4
Fossil	0	-1	-1
Nuclear	4	5	3
Total	-0.3	-1	-1
Curtailement	-14	-16	-17
System Cost	-0.4	-1	-1

IV. CONCLUSIONS

In summary, this study verifies that:

- Climate predictions, marked by increased ambient temperatures, lead to a decline in transmission capacity within the power system. Specifically, reductions of approximately -7% in the worst-case scenario.
- The proposed qDTR approach facilitates heightened transmission capacities, countering the rating reduction stemming from climate change. This method enhances component capacity by an average of up to 12%.
- Overall network costs demonstrate strong fluctuations while a consistent decline in renewable production curtailment and Load Shedding is achieved, on average 15% and 9%.
- The qDTRs is presented as a straightforward solution that does not require telecommunications or controls and can be easily applied to network components. Leaving the application of DTRs to more critical assets.

- qDTR allows for higher transmission capacities, concluding in a 1% reduction in the system's total cost, potentially saving billions of Euros.

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