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Stochastic Dynamic Thermal Rating of Transmission Lines in Heatwave Events

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***Abstract*—Heatwaves pose a significant challenge to reliable operations of electric power grids. Understanding the operational limits of the power system during stressful weather conditions can help system operators make strategic decisions to improve the system's resilience. In this paper, we propose a stochastic dynamic thermal rating model to assess the capacity of power transmission lines under heatwaves and temperature shocks. To account for the changing dynamics of diurnal temperature during a heatwave, a meteorological estimation method is incorporated into the thermal rating model. In addition, the uncertainty in the wind speed and wind direction is incorporated by stochastic variables in the model. A Monte Carlo simulation is used to develop a diurnal ampacity profile of the transmission line that can be used by system operators for tactical and strategic operations planning in the face of heatwave events. The effectiveness of the proposed model in assessing the capacity of transmission lines during heatwaves is illustrated through numerical analysis.**

Keywords—Climate resilience, dynamic thermal rating, heatwave, power systems, transmission capacity.

I. Introduction

Climate change poses an increasing risk to our planet and requires a significant amount of investment in mitigation and adaptation, including the required upgrades in electric power infrastructure. The Fifth Assessment Report [1] by Intergovernmental Panel on Climate Change (IPCC) concludes that "It is virtually certain that there will be more frequent hot and fewer cold temperature extremes over most land areas on daily and seasonal time scales, as global mean surface temperature increases. It is very likely that heatwaves will occur with a higher frequency and longer duration." As a result, power systems are expected to be highly stressed by heatwaves due to ever-increasing power demand, reduced operational capacity of the power system, and increased probability of system failures that can result in significant power outages [2].

Heatwaves can be defined as extreme meteorological events in which for at least two consecutive days/nights the maximum/minimum temperatures cross above a certain high-percentile threshold, e.g., 90th and 99th percentiles of the temperature distribution [3]. Several research work in the literature studied the adverse impacts of heatwaves. Reference [3] analyzed the link between heatwaves and mortality rates. Authors in [4] investigated the indoor temperature dynamics in low-income housing units during a heatwave. Reference [5] studied the impacts of heatwaves and subsequent thermal capacity reductions on electricity market dynamics, including spot prices, production costs, consumer and producer surplus, and emissions. In that study, an electricity market during a heatwave was simulated, and a sensitivity analysis considering future climatological and technological conditions was performed. Reference [6] presented a model for optimal generation dispatch in a power grid consisting of renewable and non-renewable distributed generation, battery storage, with demand-responsive loads under heatwave conditions. The proposed model considers the dependency between the operational limitations of grid components and ambient temperature. The proposed model was numerically evaluated on the IEEE 33-bus test system using real-world data from a heatwave event. Authors in [7] studied the adverse impacts of heatwaves on power grid operations, including on capacity and efficiency of gas turbines and combined-cycle power plants. The unit commitment problem was modified to account for the reduced capacity and efficiency of the turbines as a function of ambient temperature. The results indicate that the heatwaves can have a severe impact on system reserve and generation cost. Reference [8] investigated the effects of extreme temperatures, including both coldwaves and heatwaves, on power outages. A set of numerical analysis and case study based on temperature data from 1911, major power outages from 1971, and hourly electricity consumption from 2006 until 2013 was conducted to fit a binomial logistic regression model to predict the power supply interruptions. The obtained results indicate that the power system is significantly more vulnerable to heatwaves than coldwaves. Reference [9] presented a methodology for developing operational policies on minimal thermal variances for thermal power plants that dispose of heated effluent into rivers to ensure the reliability of the power supply. Optimal policies were determined using linear optimization with stochastic costs. The proposed method was illustrated with data from eight power plants. It was shown that the model could facilitate cooperative decision-making by power plants, power grid operators, and environmental agencies. Authors in [10] investigated the performance of high-rise residential buildings under heatwaves and power outages to study the energy efficiency and resiliency in various climate zones. Results

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revealed that in most cases, the indoor conditions in buildings compliant with new energy codes exceed the safe thresholds. Reference [11] presented a case study on modeling extreme peak power demand during a heatwave period. Extreme value theory was adopted to assess the frequency of extreme peak loads to assist system operators in maintenance scheduling and of power dispatching processes. Reference [12] studied the public concern over energy security during a recent heatwave event. The regional variation was used to evaluate the impacts of extreme temperatures on perceptions of resource security and pro-environmental behaviors in public. The results indicate that exposure to the heatwave had a statistically significant effect on perceptions of energy security but not on the stated pro-environmental behavior. Reference [13] proposed a three-step procedure to characterize the impacts of heatwaves on failures of joints and terminals installed in an underground urban distribution system. The weather and network fault data in a 10-year period were used in the study. The maximum temperature and the minimum humidity were selected as model features, and a Gaussian Mixture model was used to classify the weather data into "critical" and "non-critical" conditions. The proposed model aimed to integrate the weather data into distribution system planning and operations. Authors in [14] presented a risk assessment framework for urban electricity systems under heatwave conditions. A case study was presented and energy flow between transmission, distribution and loads were visualized. The results highlight the higher risk of heatwaves for high-voltage transmission systems. A systematic literature review on heatwaves can be found in [15-16].

Given the increasing frequency and intensity of extreme weather events, a forward-looking framework is required to proactively manage the risk of heatwaves in the transmission networks in order to meet the required service level in the face of these shocks. However, the existing models, despite their merits, lack the features to enable diurnal thermal rating estimation for transmission lines considering the required granularity for planning as well as the need for modeling accuracy that incorporate the uncertainty associated with the heatwaves. That requires a model that can dynamically estimate the ampacity of each line during different hours of a day considering the stochasticity of the weather condition during a heatwave event. In this paper, we propose a diurnal model that provides such estimates in the course of a potential heatwave event. We aim to provide a critical input to strategic decision-making framework by operators, utilities, and policymakers for operational planning, risk management, and capital allocation for resilience enhancement.

The remainder of this paper is organized as follows. Section II describes the proposed model and presents the problem formulation. Numerical analysis is provided in Section III. Concluding remarks and direction for future work are presented in Section IV.

II. Model Description

Consider a transmission line as part of a network located in a geographical area with exposure to heatwave events. The rise in ambient temperature during a heatwave event will lead to a spike in power demand primarily due to air conditioning needs. On the other hand, the increased ambient temperature will lead to reduced power supply capacity as the ampacity of transmission lines has an inverse relationship with ambient temperature. Thus, the system is expected to be simultaneously exposed to stress from both demand and supply sides during a heatwave. Therefore, a reliable model is required to measure the reduction in the capacity of transmission network in the face of such extreme weather events.

The arrival, duration, and intensity of heatwaves are stochastic in nature and can be modeled as stochastic processes. Hence, the stresses on both supply and demand due to a heatwave event are stochastic as well. The stochasticity of the power supply capacity is due to the uncertainty in combined impacts of wind speed, wind direction, and ambient temperature on the ampacity of the transmission lines. Therefore, a stochastic approach for stress testing the capacity of the transmission network is needed to accurately quantify the system's vulnerability in meeting the demand during such events. That insight on system performance during stressed conditions is critical for the utilities and system operators in making strategic decisions on resilience investments to maintain the desired service level.

To ensure a safe and reliable transmission line operation, their surface temperature must remain below a certain threshold specified by the manufacturer. The surface temperature is a function of a transmission line's material properties, diameter, surface condition, ambient weather conditions, and electrical current flown through the conductor [17]. Therefore, the maximum capacity of a transmission line can proportionally be limited by the surface temperature threshold specified by its manufacturer. Dynamic thermal rating (DTR) incorporates weather-related factors such as ambient temperature, wind speed, and wind direction to estimate the ampacity of transmission lines. IEEE Standard 738-2006 defines the steady-state heat balance for calculating the current-temperature of bare overhead conductors, as follows [17]:

$$A_l(T_t) = \sqrt{\frac{Q_c(T_l^c, T_t, V_s, \phi_s) + Q_r(T_l^c, T_t) - Q_s}{R(T_l^c)}}\,, \tag{1}$$

where Q_c is convected heat loss rate per unit length, Q_r is radiated heat loss rate per unit length, Q_s is heat gain rate from the sun, $R(T_l^c)$ is conductor resistance at critical temperature T_l^c, and V_s and ϕ_s are the wind speed and direction in weather scenario s. In order to account for stochasticity of wind speed and direction for any given ambient temperature T_t, we replace wind speed V_s and wind direction ϕ_s variables with two independent random variables $\boldsymbol{V_s}$ *and* $\boldsymbol{\phi_s}$, respectively. Without loss of generality, the stochasticity of the wind speed can be modeled with a lognormally distributed random variable $\boldsymbol{V_s} \sim Lognormal(\mu_V, \sigma_V)$, as shown in our previous study [18]. The stochastic wind direction which takes a value in the range of [0, 2π] can be modeled with a wide range of circular distributions. Without loss of generality, we use a von Mises distribution as it was used in [19] to model the stochastic wind direction, as follows:

$$f(\phi_s \mid \mu_\phi, \kappa) = \frac{e^{\kappa \cos(\phi_s - \mu_\phi)}}{2\pi I_0(\kappa)}\,, \tag{2}$$

where $I_0(\kappa)$ is a modified Bessel function of order 0, μ_ϕ is a measure of location and κ is a measure of concentration. With this replacement, the ampacity of transmission line l under ambient temperature T_t at time t in weather scenario s, is transformed into a stochastic process. The convected heat loss rate, which is a function of ambient temperature, wind speed, and direction is obtained, as follows [17]:

$$Q_c = \max(Q_{cn}, Q_{c1}, Q_{c2}), \tag{3}$$

$$Q_{cn} = 0.0205\rho_f^{0.5} d^{0.75} (T_l^c - T_t)^{1.25}, \tag{4}$$

$$Q_{c1} = \left(1.01 + 0.0372\left(\frac{d\rho_f V_s}{\gamma_f}\right)^{0.52}\right) k_f K_s (T_{cl} - T_t), \tag{5}$$

$$Q_{c2} = 0.0119\left(\frac{d\rho_f V_s}{\mu_f}\right)^{0.6} k_f K_s (T_l^c - T_t), \tag{6}$$

$$K_s = 1.194 - \cos(\phi_s) + 0.194\cos(2\phi_s) + 0.368\sin(2\phi_s) \tag{7}$$

where Q_{cn} is the convected heat loss when there is no wind, Q_{c1} is the convected heat loss at low wind, Q_{c2} is the convected heat loss at high wind, ρ_f is the air density, d is the conductor diameter, γ_f is the dynamic viscosity of the air, k_f is the thermal conductivity of the air, and K_s is the wind direction factor. The radiated heat loss—that is also a function of the ambient temperature—is obtained, as follows:

$$Q_r = 0.0178 d\varepsilon\left(\left(\frac{T_l^c + 273}{100}\right)^4 - \left(\frac{T_t + 273}{100}\right)^4\right), \tag{8}$$

where ε is the coefficient of emissivity. Finally, the rate of solar heat gain is calculated as follows:

$$Q_s = \alpha Q_{se} \sin\left(\arccos\left(\cos(H_c)\cos(Z_c - Z_l)\right)\right) A, \tag{9}$$

where α is the solar absorptivity, Q_{se} is the total heat flux rate elevation correction factor, H_c is the altitude of the sun, Z_c is the azimuth of the sun, Z_l is the azimuth of line l, and A is the projected area of conductor per unit length.

Predicting the diurnal pattern of temperature is a challenging task that involves a modeling uncertainty. To address this issue, we use the expected maximum and minimum daily temperatures during a heatwave scenario to develop a daily temperature profile using the methods presented in [20]. The ambient temperature during the daytime, i.e., the hours between the *apparent* sunrise and sunset, is obtained using the sinusoidal relationship between time of the day and daily temperature extrema, as follows [20]:

$$T_t = T^{min} - \frac{T^k}{2} + \frac{1}{2}\sqrt{(T^k)^2 + 4\left(T^{max} - T^{min}\right)\left(1 + \frac{T^{max} - T^{min}}{T^k}\right) T^k S_t}, \tag{10}$$

$$S_t = \sin\left(\pi \frac{t - LSH + (DL/2)}{DL + 2Y}\right), \forall t = t_r, t_r + 1, \ldots, t_s, \tag{11}$$

where T^k is a parameter that specifies the temperature increment that sensible heat flux is doubled compared to a situation without buoyancy, LSH is the time of maximum solar height, DL is the day length, and Y is the delay between T^{max} and LSH. The ambient temperature during the night, i.e., from apparent sunset to apparent sunrise in the next day, is modeled using the exponentially declining relationship between time and temperature during those hours, as follows [20]:

$$T_t = \left(T_{ND}^{min} - T_{t_s}\exp\left(-\tfrac{NL}{h}\right) + \left(T_{t_s} - T_{ND}^{min}\right)\exp\left(-\tfrac{t - t_s}{h}\right)\right) \Big/ \left(1 - \exp\left(-\tfrac{NL}{h}\right)\right)$$
$$\forall t = t_s, t_s + 1, \ldots, t_r - 1, t_r, \tag{12}$$

where T_{ND}^{min} is the minimum temperature on next day, NL is the night length (i.e., 24−DL), t_s is the time of sunset, and h is a time coefficient.

By plugging in (3)-(12) in (1) and replacing wind speed and wind direction variables with corresponding random variables described earlier, we can compute the ampacity of a transmission line on hourly basis during a heatwave scenario for a given return period, that is defined as the inverse of the probability of occurrence of that event in a given year.

III. Numerical Analysis

For the sake of illustration, we assumed an Aluminum Conductor Steel Reinforced cable (ACSR) for a transmission line with physical characteristics provided in [17]. We obtained the weather data from the weather station in Chicago Midway International Airport (MDW) from January 1990 through December 2020 via two different open data sources. The hourly wind data, including wind speed and wind direction in MDW during this timeframe were obtained through Iowa Environmental Mesonet (IEM) [21], while the hourly temperature data were obtained through NOAA's National Centers for Environmental Information (NCEI) [22]. The solar position data, including the sunrise and sunset on various days of the year in Chicago were obtained from NOAA's Earth System Research Laboratories [23]. We use the weather data during the warm and hot seasons, starting from April 1st through September 30th of each year from 1990 to 2020. Finally, we assumed an azimuth of 135° for the line, and used Chicago's latitude and elevation above the sea level (obtained from Google Earth), i.e., 41°N and 190 m, respectively. We obtained the maximum and minimum daily temperature in a once in a 100 years heatwave in Chicago (or a heatwave event with 100-year return period). Using Python and through maximum likelihood estimation (MLE) method, we estimated the parameters for corresponding distributions for wind speed and directions (i.e., a lognormal distribution for wind speed, and a von Mises distribution for wind direction). Table I summarizes the derived weather-related parameters for corresponding distributions along with daily temperature extremes for once in a 100 years event in Chicago.

To illustrate the model, we analyze three scenarios, as follows:

1) Expected Value: The expected value of stochastic variables in this model, where wind direction and wind speed are used to carry out the calculations.

2) Monte Carlo Simulation: To account for stochasticity of the model, a Monte Carlo simulation approach is used to estimate the average durinal ampacity of the line. An *ad hoc* value of 10,000 iterations for each hour of the day is adopted.

3) No Wind: With zero wind speed, natural convection occurs as described in (4). We use this scenario to illustrate the significance of wind data in diurnal thermal rating.

TABLE I. SUMMARY OF WEATHER-RELATED PARAMETERS

Variable	Parameter	Value
Temperature	T^{max} T^{min}	41.5 °C 29.3 °C
Wind Speed	μ_V σ_V	1.773 1.182
Wind Direction	μ_ϕ κ	-0.007 0.048

Using the observed maximum and minimum daily temperatures for each of these scenarios and through (10)-(12), we develop a diurnal temperature profile. Next, we use (3)-(9) to calculate the value of the parameters needed as input to calculate the ampacity. For the first scenario, the expected values for wind speed and direction from fitted distributions are 1.8 mps and 2.7 rad, respectively. Fig. 1 illustrates the diurnal thermal rating of the transmission line in each of these three scenarios. As shown, by using the expected value of the wind direction and wind speed, the ampacity of the line is significantly overestimated. On the other hand, without consideration of wind dynamics in the model, the ampacity of the transmission line is dramatically underestimated. Therefore, it is critical to accurately account for stochasticity of the wind behavior in capacity planning of the transmission lines and networks. Intuitively, this finding justifies the value of information (VOI) required for stochastic thermal rating.

To further illustrate the dynamics of the wind speed in the diurnal thermal rating model, we conduct a set of sensitivity analysis by changing the value of wind speed, *ceteris paribus*. For the sake of illustration, the expected value of wind direction was used (i.e., 2.7 rad). Fig. 2 illustrates the changes in the diurnal thermal rating in various wind speeds. As shown, the diurnal thermal rating is more sensitive to the changes in the wind speed in the lower range of this variable where its value exponentially increases by linear increments in the value of wind speed. However, from certain point in the range of wind speed variable, while the ampacity increases by these linear increments in the value of the wind speed, they are not as significant as it is the case of lower ranges.

The numerical analysis suggests that the stochastic nature of wind dynamics deserves a significant level of attention in formulation of diurnal thermal rating problems for heatwave events. However, considering the complex nature of wind dynamics, a diurnal modeling of wind direction and wind speed is a challenging task. In this study we assumed an independent statistical relationship between temperature, wind direction, and wind speed during heatwave events. Given the importance of wind dynamics, it has become evident that an in-depth meteorological investigation on wind behavior during the course of a heatwave event is needed, so it can be incorporated into a stochastic dynamic thermal rating model with a higher level of granularity. That will reduce the *model risk*—i.e., the risk of potential adverse consequences from decisions made based on incorrect or misused models—by system operators in making resilience enhancement decisions.

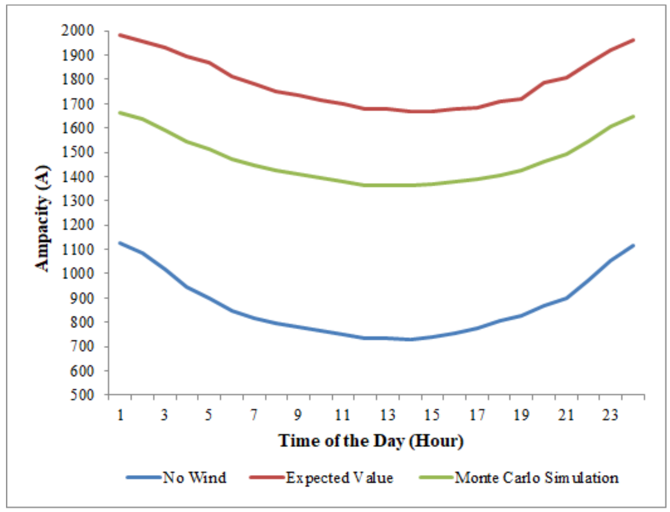

Fig. 1. Diurnal ampacity of the line in three different scenarios

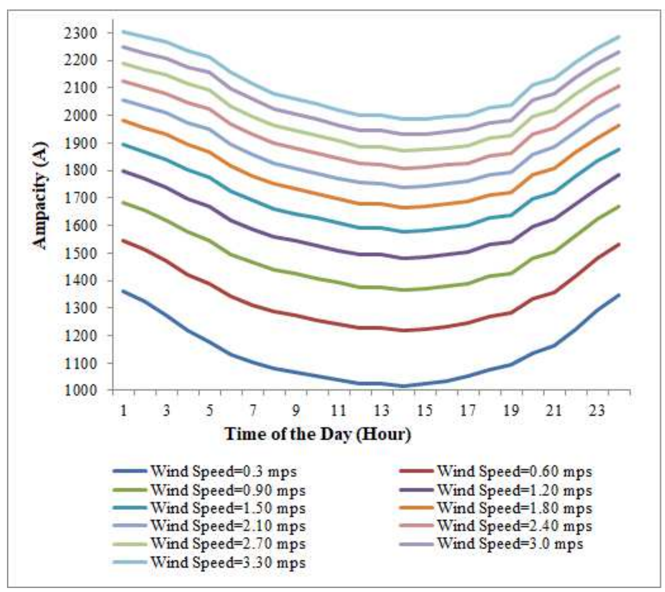

Fig. 2. Sensitivity analysis of wind speed in diurnal thermal rating

IV. Conclusion

We proposed a diurnal thermal rating model to assess the capacity of transmission lines during heatwave events. The model incorporates stochastic dynamics of wind speed and wind direction, along with changing dynamics of diurnal ambient temperature during such extreme weather events. It was shown that inadequate representation of the wind dynamics—either by making simplifying assumption of zero wind speed, or an inadequate modeling framework which does not account for the stochasticity of the wind dynamics—can lead to underestimation or overestimation of the diurnal thermal rating calculations. The sensitivity analysis conducted in this study indicates that diurnal thermal rating is more sensitive to incremental changes in wind speed in lower ranges of this variable. The proposed framework can be effectively used by utilities, system operators, urban planners, and policymakers as a strategic decision-making tool in managing the transmission capacity of the system and making expansion planning decisions in the face of heatwaves and extreme temperature conditions.

In our future work, we will extend the proposed model by incorporating the diurnal pattern of wind behavior and by investigating its statistical relationship with diurnal ambient temperature during the course of a heatwave event. That will reduce the model risk in making strategic investment and operational decisions for strengthening the resilience of the system in the face of heatwaves.

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