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Navigating Uncertainties in Dynamic Line Rating Estimation: An Analysis of Challenges and the Benefits of Diverse Approaches

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SUMMARY

In this paper, we explore the complexities and uncertainties intrinsic to Dynamic Line Rating (DLR) estimation, underscoring the merits of employing complementary approaches to overcome these challenges. Precise DLR values are crucial to avert transmission line overloading and to prevent exceeding sag limits and Maximum Operating Temperature (MOT), while also ensuring that the true carrying capacity is not underutilized. However, variabilities in input variables and fluctuating environmental conditions often present difficulties in determining accurate conductor convection rates from wind cooling effects. This introduces DLR uncertainty and associated risk, which must be comprehended and mitigated appropriately. Our work scrutinizes the inherent risks linked with single-strategy approaches to determining a DLR and underscores the importance of deploying a multi-strategy ensemble approach for precise DLR determination. In particular, we elucidate on the limitations of the CIGRE TB-498 prescription for determining the effective wind speed as a means to a DLR calculation, especially under the frequent scenario of the conductor temperature being close to the ambient temperature.

We offer a comprehensive review of the challenges and uncertainties tied to DLR calculation, underlining the significance of accurate conductor temperature, ambient air temperature, solar loading, and loading current measurements. We discuss the implications of the CIGRE TB-498 prescription for effective wind speed determination and the ensuing DLR using the computational tools of IEEE-738. In circumstances where the conductor temperature is nearly equivalent to the ambient temperature or when the combined solar and resistive heating is low, using the overhead line as a hot-wire anemometer leads to escalated uncertainty in determining the effective wind speed. This ambiguity can engender overly conservative or overly aggressive estimations of effective wind speed, yielding outcomes of underutilized grid capacity or increased risk of MOT exceedance, respectively.

In this study, we introduce and utilize metrics to measure relative uncertainty, benefit, and risk in DLR estimations. These metrics provide an essential perspective on DLR calculations, especially when the temperature rise—a key component in the process—becomes a variable. Through the lens of these metrics, we analyze the effects of uncertainties on the capacity and potential hazards of DLR estimations, stressing the importance of meticulous evaluation and risk management. To illustrate these concerns, we use Monte Carlo methods to propagate uncertainties from measurements to DLR estimations. We apply these techniques to specific real-world scenarios that result in significantly large uncertainties in DLR estimation. Our examples offer physical intuition and a deeper comprehension of the factors contributing to higher uncertainties.

Employing real weather and line loading data for a broad range of real Overhead Lines (OHL), we model the frequency at which direct measurement of conductor temperature can lead to high DLR uncertainty. Through the consolidation of this dataset, we demonstrate the high prevalence of scenarios where using conductor temperature to derive wind speed is problematic. This comprehensive assessment underscores the necessity of refining DLR calculation methods to better address the uncertainties that commonly occur in practical applications. Moreover, it showcases the necessity for complementary, parallel approaches to DLR calculation through the empirical examples provided. By utilizing a variety of techniques, shortcomings can be compensated for in cases where specific aspects of the environment may not be captured by a single model or method alone.

KEYWORDS

Ambient Air Temperature, Conductor Temperature, Direct Line Monitoring, Dynamic Line Ratings, Error Propagation, Maximum Operating Temperature, Monte Carlo Methods, Overhead Transmission Lines, Real-World Data Analysis, Risk Mitigation, Temperature Rise, Uncertainty Quantification, Wind Speed Estimation

Dynamic Line Ratings

Dynamic Line Ratings (DLR) have emerged as an attractive alternative to Static Line Ratings (SLR) for power transmission via overhead lines (OHL) [1, 2, 3]. DLR exploit real-time environmental data to optimise the capacity of OHL, ensuring more efficient grid utilisation and improved system reliability. On the other hand, SLR provide a more conservative estimate of the power line capacity, accounting for near-worst-case scenarios. Both DLR and SLR aim to maintain line sag within safe limits and prevent overheating, by ensuring that the conductor temperature doesn't exceed the Maximum Operating Temperature (MOT). The key benefit of DLR over SLR lies in its adaptability, adjusting to environmental conditions and thus unlocking additional transmission capacity when conditions permit.

Understanding how the OHL temperature changes over time is crucial in estimating its load-carrying capacity. This is dictated by the heat equation which represents the balance of heat gained and lost by the conductor, given its mass and specific heat capacity, *Equation 1*. Once in steady-state, *Equation 2*, where there is no further change in temperature, the line rating is defined as the line loading which maintains this equilibrium, ensuring the conductor temperature doesn't exceed the MOT. A popular technique for estimating convective cooling is treating the conductor as a giant hot-wire anemometer [4], exchanging thermal energy with its surroundings.

$$mc\frac{dT_c}{dt} = q_R + q_s + q_r + q_c \tag{1}$$

$$I_{LR} = \sqrt{-\frac{q_s + q_r + q_c}{R}} \tag{2}$$

However, accurately estimating DLR is a complex task. It hinges on the precise measurement of many variables, including but not limited to air and conductor temperatures, line current, solar irradiance, wind speed and direction, and specific material properties [5]. Errors in any of these measurements propagate into the final DLR estimate, which is highly sensitive to these variables. This paper aims to dissect this complex process, focusing on how measurement uncertainties propagate through the hot-wire DLR (HWDLR) estimation method. Using Monte Carlo methods, we will explore the intricate interplay between uncertainty, benefit, and risk inherent in the DLR estimation process.

Monte Carlo in DLR Estimation

Known for its robustness in dealing with uncertainties and inter-dependencies, the Monte Carlo method employs random sampling techniques that can be used to evaluate the effect of measurement uncertainty on DLR values. To do this, we maintain the DLR machinery, a direct "measurement in, DLR out" process, while also introducing a preliminary step of generating a random sample of potential measurements in proportion to their likelihood, based on our actual condition and the estimated confidence in our measurement. Each of these potential sets of measurements is then processed, producing a spectrum of DLR outcomes, each associated with its specific likelihood. This method modifies the conventional approach, essentially transforming it to "many possible measurements in, many possible DLR out". In particular, this approach yields a probability distribution of potential DLR outcomes, where each outcome corresponds to the probability of attaining a particular DLR given the current conditions and our assumptions about measurement uncertainty.

This is directly applicable to understanding how uncertainties navigate through the DLR mechanism. In this work, we begin with a predetermined set of true conditions. We use these conditions to simulate the actual conductor temperature according to *Equation 1*, and to determine the true DLR following *Equation 2*. From this point, we generate a random sample of N potential measurements around these true values, encompassing all input variables that would be involved in an actual scenario. We then take each set of potential measurements and feed them, one at a time, through the same DLR computation process. Though any single iteration of the simulation deals with one set of inputs, derived heat densities in the middle, and one DLR value at the output, viewed from above we see a distribution for each quantity at every stage of the way. This process is depicted in *Figure 1*.

In applying the Monte Carlo method, we assess potential OHL temperatures under a specified load at a chosen rating from our DLR distribution. This creates a probability distribution of potential conductor temperature evolutions, providing tangible data related to the safety of the OHL. By analyzing these potential temperature evolutions and their corresponding steady-state temperatures relative to the MOT, we reveal crucial insights for line safety management. Consistent

Parameter	Value	Uncertainty (σ)
Air Speed	1.5 m/s (0.61 m/s)	—
Air Temperature	25.0 °C (40.0 °C)	1.0 °C
Cond. Name / Type	Drake / ACSR	—
Cond. Absorptivity / Emissivity	0.8 / 0.8	0.02 / 0.02
Cond. Loading	200 A	5.0 A
Cond. Temperature	—	1.0 °C
Solar Irradiance (Noon)	1027 W/m^2 (1025 W/m^2)	50 W / m^2

Table 1: All of the results involved in this work, unless otherwise stated, were derived from the assumed conditions and measurement uncertainties tabulated here. The parenthetical values are the conditions used to generate the static line rating.

with the guidelines in [6], our attention is focused on the 1^{st} percentile of DLR. Selecting the 1^{st} percentile DLR aligns the 99^{th} percentile of the evolved conductor temperature distribution precisely with the MOT, reflecting an intentional alignment rather than a coincidence. By choosing a P-1 DLR value, we implicitly accept a 1% risk of exceeding the MOT. Opting for a higher p-value from our DLR distribution not only invites a greater probability of surpassing the MOT but also allows the P-99 temperatures to exceed the MOT by increasingly larger margins. We will quantify of these discrepancies further in the following section.

In our analysis of DLR estimates, we first investigate a scenario where an OHL, originally under high load and intense solar irradiance with moderate wind speed, undergoes a methodical decrease in both load and irradiance, while other factors remain constant. This scenario, along with its resulting impacts on DLR estimates, is illustrated in *Figure 2*. As the load and irradiance decrease, the conductor temperature follows suit, leading to modifications in the DLR distribution. The initial stages of this reduction process reveal moderate changes in the DLR distribution, with an extension of the high DLR tail and a shift of the P-99 DLR beyond our immediate view. As we continue the reduction, the distributions of air and conductor temperatures start to converge[1], while the conductor temperature remains persistently equal to or higher than the air temperature.

The HWDLR approach, which uses the temperature difference between the conductor and the ambient air to estimate the effective wind speed, faces a significant challenge as these temperatures increasingly overlap. This overlap notably

[1] Even though the air and conductor temperature distributions may overlap, the conductor temperature is always generated to be greater than or equal to the air temperature in any given iteration of the Monte Carlo Simulation.

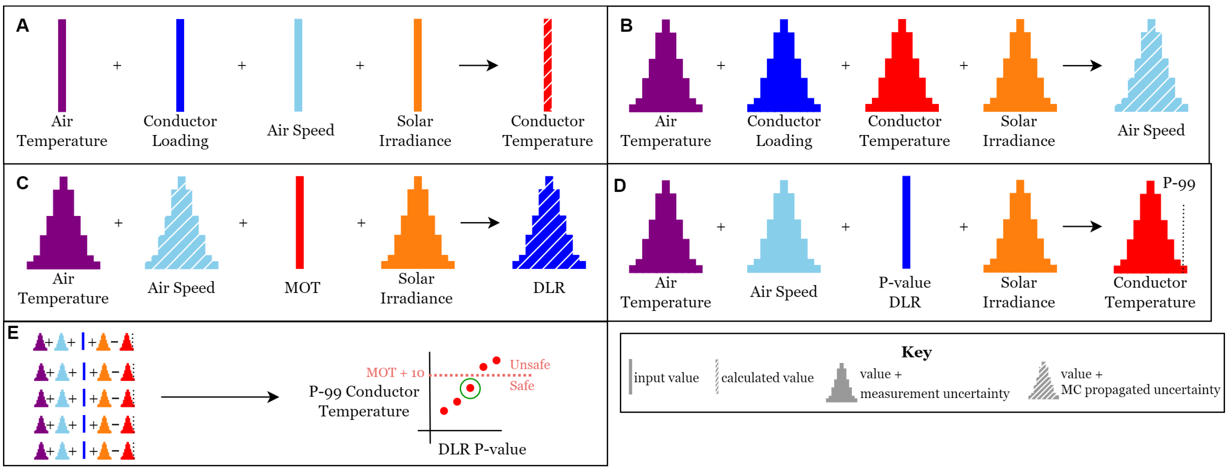


Figure 1: Diagram illustrating the Monte Carlo technique used here. (A) True conditions used to generate the true conductor temperature. (B) Effective air speed is derived from convective cooling. (C) Derived air speed and input distributions in (B) are used in the MOT context to calculate the DLR distribution. (D) Each DLR p-value is combined with, the input to calculate a distribution of possible conductor temperatures tand the 99th percentile conductor temperature is extracted. (E) Step (D) is repeated for all DLR values. The highest DLR value with a P-99 conductor temperature of less than MOT + 10$°C$ is considered to be the maximum safe DLR for the given scenario.

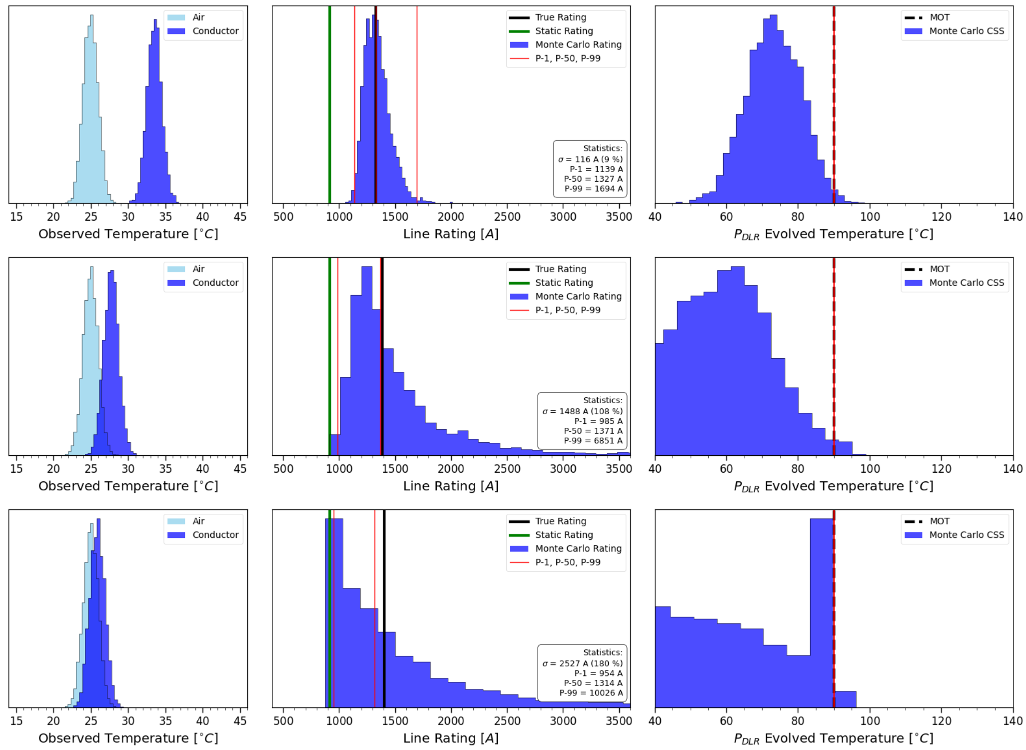


Figure 2: This series of figures showcases the Monte Carlo DLR and CSS temperature distributions under a scenario of decreasing OHL heating. As the distinguishability of the temperature rise wanes with the falling heating, the consequential impact on the DLR and CSS distributions becomes apparent.

reshapes the DLR distribution. The DLR distributions start to move away from their typical Gaussian-like forms, leaning towards the SLR and extending the high DLR tail. This shift heightens the likelihood of obtaining a DLR estimate that falls below the true rating and increases the chances of a DLR estimate surpassing the P-99 of the initial conditions. This scenario accentuates the intricate dance between the ambient and conductor temperatures with the precision of the DLR measurement.

Uncertainty, Benefit, and Risk

Our next objective is to translate the uncertainty in the DLR estimation into terms more relevant to the additional capacity we are after and the risks inherent in striving to utilize that capacity. We define here the relative uncertainty $\mathbb{U}$, the relative benefit $\mathbb{B}$, and the relative risk $\mathbb{R}$. These metrics are defined in terms of two p- value choices that we make from our Monte Carlo distributions. The first is the choice of p-value from our DLR distribution, P_{DLR}, which we then use to generate the conductor steady-state temperature (CSS) distribution. We next choose a p-value from this distribution, P_{CSS}, which corresponds to the conductor temperature probability. Concerned with even low probability events leading to a conductor temperature evolution exceeding the MOT, we conservatively work with $P_{CSS} = 99$. The interpretation and application of these metrics can be best understood by referring to *Figure 3*, where we plot these values against the temperature rise, which we showed in the last section to play a crucial role in exploding the HWDLR error.

$$\mathbb{U} = \frac{\sigma_{DLR}}{DLR} \tag{3}$$

$$\mathbb{B} = \frac{P_{DLR} - SLR}{DLR - SLR} \tag{4}$$

$$\mathbb{R} = P_{CSS} - MOT \tag{5}$$

The relative uncertainty is the uncertainty as a proportion of the true DLR value; a value of 1 corresponding to a an error of the same magnitude as the true rating. As we move towards lower relative temperature values, relative uncertainty increases exponentially. This observation is in line with our discussions in the previous section. The top axis in *Figure 3* shows that even moderate temperature rise leads to significant uncertainty, sometimes exceeding well beyond 100% of the true DLR. This is a quantification of the accuracy and precision of the DLR estimation, but it is not the whole story.

The relative benefit quantifies the added value that our DLR estimation provides over the conventional SLR. This value depends the P_{DLR}; the greater the P_{DLR}, the greater the benefit. The relationship between the relative benefit and temperature rise is shown in the second axis in *Figure 3*. The benefit is defined such that 0 corresponds to the SLR and 1 to the true DLR. As the temperature rise decreases and the uncertainty increases, the benefit decreases, our P_{DLR} choice tending toward the SLR. At first glance, it might seem counter-intuitive that our DLR calculation becomes more conservative as uncertainty increases, but this aligns with our previous discussions about the asymmetry of the DLR distribution favoring the SLR as the distribution spread increases. With high separation between the conductor and air temperature, we are able to confidently estimate the DLR and maximize the benefit.

The final metric, relative risk, is the temperature difference between the steady-state conductor temperature (the P-99 CSS) and the MOT when the line is operated at the chosen P_{DLR} value. Here, we pay specific attention to the risk of surpassing MOT + 10$°C$, in accordance with limits suggested by CIGRE TB-299. The behavior of this metric in relation to the temperature rise is a bit more complex than the previous two. As we move from high to low temperature rise, it becomes evident that, like uncertainty, the possible P-99 CSS temperature increases with decreasing temperature rise. As we continue towards very low values, this temperature starts to decrease. This might seem unexpected, considering that we know the high end of the DLR distribution tends to increase as the DLR distribution widens. But keep in mind, we're observing the conductor temperature after choosing one P_{DLR} value, and using one value of conductor temperature, the P-99 CSS, from the next set of Monte Carlo simulations. This value can be seen as the outcome of the trends observed in the axes above.

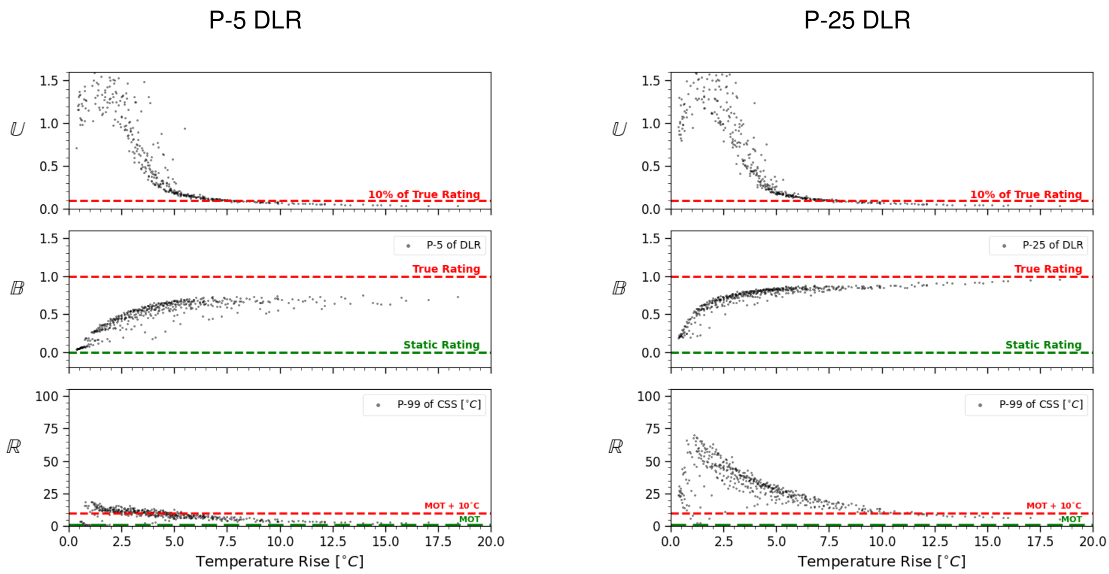
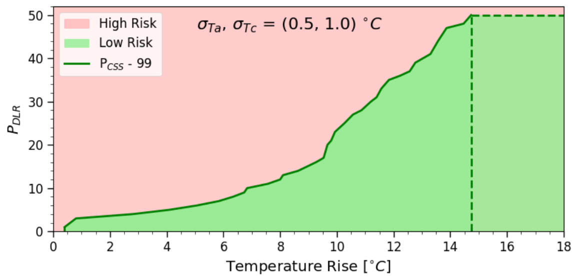
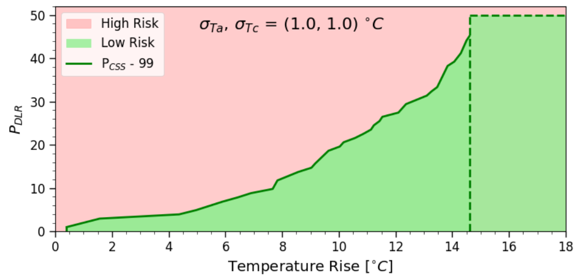


Figure 3: This figure presents Uncertainty, Benefit, and Risk (UBR) analyses for P-5 and P-25 Dynamic Line Ratings (DLR). These analyses allow for a comparative assessment of the benefits and risks associated with these DLR percentiles under varying temperature conditions.

The HWDLR estimation, when interpreted through the lens of UBR metrics, unveils some crucial details about its strengths and potential hazards, especially concerning temperature rise. *Figure 3* shows the UBR for a range of scenarios and for two selected P_{DLR} values. As the temperature rises become smaller, the P-99 CSS value tends to rise, indicating increased risk. We find that for less conservative DLR probabilities, CSS temperatures might increase considerably beyond the MOT, exceeding it by over $50°C$ and even reaching beyond $100°C$ in extreme instances. This risk remains even with more conservative DLR probabilities, with temperatures potentially exceeding the MOT by $10 - 20°C$. *Figure 4* shows the p-values needed to ensure safe operation for different temperature rises, where safe indicates a less than 10% chance of surpassing the MOT + 10$°C$ threshold define in CIGRE TB- 299. It's also important to note that the advantages that DLR has over SLR start to diminish as the estimates become more conservative.





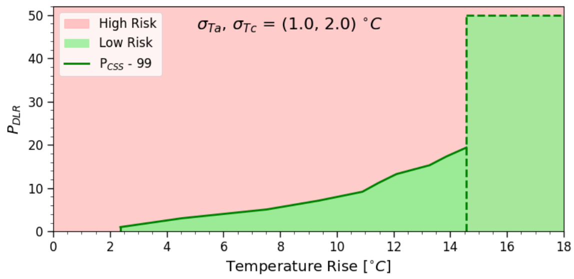


Figure 4: The P_{DLR} values (green region) for which the P-99 evolved conductor temperatures remain below the MOT + 10$°C$ for a given observed temperature rise for different assumed air and conductor temperature measurement uncertainties. The temperature rise space was explored by incrementing through many combinations of values of the effective air speed [0 m/s, 7 m/s], line loading [0 A, 300 A], and solar irradiance [100 W/m^2, 1200 W/m^2].

Frequency of High-Risk Scenarios

In previous sections, we have shown that using HWDLR in situations where the conductor temperature is near ambient temperature forces the user to make a choice between safety and benefit. In this section we evaluate the frequency with which such situations occur in real-life scenarios. To do so, we pulled data for 9 different locations across LineVision's portfolio. These locations represent 9 different lines operated by 9 different utility companies on 3 continents, with a wide range of geographical and operating conditions. More information on the range of sites studied can be seen in *Table 2*. By selecting a broad range of locations, we aim to show that situations where HWDLR is at risk of exceeding the $MOT + 10°C$ temperature threshold are not limited to certain locations or utilities, but are common across many lines.

Variable	Range Included within Study
Latitude	$34.5 - 53.5\ °$
Cond. Type	ACSS, ACSR, ACAR, various sizes
Cond. Absorptivity / Emissivity	$0.5 - 0.9$
Average / Maximum Loading	$34 - 557\ A\ \ /\ \ 366 - 1,388\ A$
Time Period Observed	$122 - 348\ days$

Table 2: Range of conditions for the 9 locations studied. Loading values are on a per sub-conductor basis.

For each location in this study, we model the evolution of conductor temperature over time using *Equation 1*. The duration between time intervals was based on the input data interval (typically 10 minutes). The rate of change is calculated using real line current data, location-specific conductor properties, and local weather data as inputs. The solar rate is calculated using the location's conductor heading and assuming a cloud-free sky. The wind speed input is calculated by applying LineVision's location-specific, measurement-trained wind speed correction factor to regional wind speed data.

In the three relatively optimistic uncertainty scenarios discussed in previous sections (*Figure 4*), the relationship between conductor temperature rise and safe DLR p-value was shown. Looking specifically at the uncertainty scenario of $\sigma_{Ta} = 1.0°C$, $\sigma_{Tc} = 1.0°C$, the conductor temperature rise needed to safely use P-50 DLR is $14.6°C$. When conductor temperature rise is below this threshold, there is a greater than 1% risk of reaching a conductor temperature of more than $MOT + 10°C$. For each of the 9 locations studied here, the median temperature rise was well below this threshold, with a range of median temperature rises of $1.1 - 8.2°C$, and only two of the sites had a temperature rise greater than the $14.6°C$ threshold more than 5% of the time. The aggregate percentage of time each p-value is considered safe for the three uncertainty scenarios can be seen in *Table 3*.

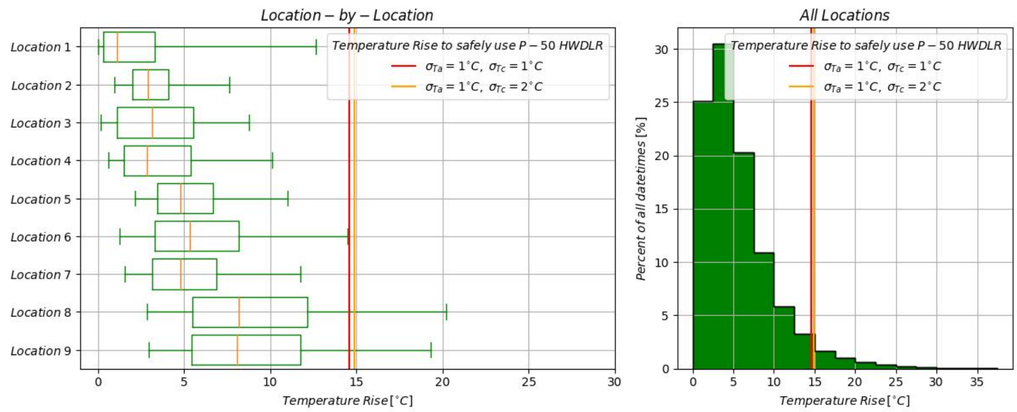


Figure 5: The distribution of modeled conductor temperature rises across the 9 study locations.

P-DLR	**Percentage of Time Safe: Aggregated Across All Sites**		
	$\sigma_{Ta},\ \sigma_{Tc}\ =\ (0.5,\ 1.0)\ {}^{\circ}C$	$\sigma_{Ta},\ \sigma_{Tc}\ =\ (1.0,\ 1.0)\ {}^{\circ}C$	$\sigma_{Ta},\ \sigma_{Tc}\ =\ (1.0,\ 2.0)\ {}^{\circ}C$
50	4.4 %	4.4 %	4.4 %
25	13.2 %	10.2 %	4.6 %
10	29.0 %	27.9 %	11.3 %
1	100 %	100 %	100 %

Table 3: Percentage of time that each DLR p-value is safe for the given uncertainty scenario, where safe indicates a 99% confidence that the conductor temperature will not exceed $MOT + 10\ {}^{\circ}C$. Shown here are three relatively low uncertainty situations. Higher uncertainty values would lead to lower percentages of time safe.

Conclusion

In this study, we have illuminated the intricacies of error propagation in the hot-wire Dynamic Line Rating (HWDLR) calculation and its acute sensitivity to temperature rise. This has been demonstrated even under optimistic assumptions of the confidence in temperature measurements. Extending the narrative beyond mere uncertainty, we introduced additional metrics for evaluating the benefits and risks across various temperature rises, painting a stark landscape where uncertainty and risk escalate exponentially as the temperature rise diminishes, even as the associated benefit plummets. Our investigation has revealed that conditions resulting in a low temperature rise are far from rare; they occur frequently, challenging our ability to select a beneficial P_{DLR} value. Even under the most generous assumptions about temperature measurement confidence, we found that the P-50 DLR is safe for operation less than 5% of the time.

Recognizing these limitations is instrumental in making informed decisions about safe and accurate DLR estimation. This work underscores the necessity of considering complementary approaches to achieve more informed wind speed assessments in the low temperature rise regime, where the accuracy of HWDLR estimation is particularly compromised. Techniques such as terrain-specific computational fluid dynamics, conductor blowout anemometry, and statistical analysis of conductor temperatures could offer invaluable insights. The implementation of additional constraints on wind speed in these critical regimes may be a key to unlocking more benefits and alleviating the associated risks.

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