Evaluating the Feasibility of Replacing Physical Sensors with Meteorological Services for Dynamic Line Rating in Power Systems

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***Abstract*—This paper presents an in-depth study on the feasibility of implementing Dynamic Line Rating (DLR) in power distribution systems without physical field devices. The study focuses on Iberdrola's distribution lines, evaluating the potential of replacing physical sensors with third-party meteorological services for estimating essential environmental variables. The research assesses the accuracy of data from three selected providers (Copernicus, MeteoFlow, and Open-Meteo) against measurements from sensors installed on six power lines. Python-based tools were developed to normalize electrical lines, facilitating accurate DLR calculations.**

The analysis includes statistical techniques to evaluate dispersion, correlation, error metrics, and uncertainty, alongside a global and regional sensitivity analysis of meteorological variables according to IEEE-738 and CIGRE-TB 601 standards. Sensitivity analyses, including Delta, PWAN, and Sobol methods, were conducted to assess the impact of these variables on DLR calculations.

Results indicate that while meteorological data can effectively replace temperature and solar radiation sensors, challenges remain in accurately estimating wind speed and direction, the most influential variables for DLR. The study concludes that while full sensor replacement is not feasible in all scenarios, a hybrid approach combining physical measurements with advanced meteorological modeling can enhance grid reliability and efficiency.

***Index Terms*—Smart Grids, Dynamic Line Rating, Meteorological Services, Sensor Replacement, Sensitivity Analysis, Uncertainty Analysis, Power Grid Reliability**

I. Introduction

The electric sector is currently undergoing a significant transformation driven by the urgent need to reduce greenhouse gas emissions and mitigate the impacts of climate change. The revised Renewable Energy Directive of 2023 sets a binding target to achieve at least 42.5% renewable energy by 2030, with an aspiration to reach 45% [4]. This transition presents considerable challenges to traditional power grids, originally designed for a centralized and stable supply model, where electricity was distributed from large power plants to end users through transmission and distribution networks.

The increasing integration of renewable energy sources, such as wind and solar, along with the adoption of electric vehicles and battery storage, is shifting the power generation model from centralized to distributed (DERs). These non-dispatchable energy sources introduce variability and uncertainty in generation, complicating network planning and operation, and potentially compromising system reliability [10]. Moreover, aging infrastructure, which was not designed to handle current and future demands, coupled with increasingly frequent and severe extreme weather events, poses significant challenges to grid resilience [5]. As a result, there is an urgent need for the expansion and modernization of power grids to meet growing demand, driven by the electrification of various sectors and the new energy flows resulting from DERs.

To address these challenges, the adoption of smart grids is emerging as a promising solution. Smart grids, characterized by digitalization and automation, enable more efficient energy management, facilitate the integration of renewable sources, and enhance the reliability of power supply. These advancements allow for greater visibility and control of the network, supporting the identification and resolution of issues, and leading to a more efficient and secure power grid [10].

Iberdrola, one of the world's leading power companies, is at the forefront of this transition, managing a vast distribution network in Spain through its subsidiary i-DE, which spans 270,000 kilometers and serves over 11 million customers [7]. The company faces significant challenges, including the aging infrastructure, high costs, long lead times for traditional investments, and growing energy demand. To optimize the use of existing resources and improve network flexibility and efficiency, Iberdrola is exploring innovative solutions such as the implementation of Dynamic Line Rating (DLR).

DLR is a technology that allows the real-time calculation of the thermal capacity of power lines based on actual environmental conditions, rather than relying on static seasonal ratings. Preliminary results from DLR deployment projects and studies like Beatriz Morales' Master's Thesis [13], have demonstrated the potential of DLR to optimize network capacity and improve efficiency. However, challenges remain, such as the significant variability of DLR calculations over time and the complexity of installing and maintaining field devices in remote locations.

In response to these challenges, this study proposes to evaluate the feasibility of replacing physical field sensors with third-party meteorological data for DLR calculations. By comparing data from selected meteorological services against physical sensor measurements on six distribution lines, the study aims to assess whether these services can provide reliable estimates of the environmental variables needed for DLR, such as ambient temperature, wind speed and direction, and solar radiation. Additionally, this work will explore sensitivity analysis to evaluate the impact of these variables on DLR calculations, using standards like CIGRE-TB 601 and IEEE-738, and examine forecasting techniques to predict DLR based on short-term weather forecasts.

II. State of the Art

A. Line Rating

Line Rating refers to the maximum electrical current that a power line can safely transport without causing overheating of the conductor. Traditionally, this limit was determined using conservative and constant environmental conditions, known as Static Line Rating (SLR). While SLR ensures safety, it often leads to underutilization of line capacity because it does not account for real-time variations in weather conditions. With the advent of advanced information and communication technologies, DLR has emerged, allowing the real-time adjustment of line capacity based on actual weather conditions, thereby optimizing the use of the existing infrastructure [8, 9].

B. Dynamic Line Rating (DLR)

DLR dynamically determines the maximum current a power line can carry by considering real-time weather conditions. The calculation of DLR involves a detailed thermal model of the conductor, taking into account factors such as wind speed, wind direction, ambient temperature, solar radiation, and the conductor's material properties. These factors can be measured directly using sensors installed along the line or estimated using mathematical models [9, 15].

One of the primary advantages of DLR is its ability to fully exploit line capacity under favorable weather conditions, reducing the need for building new transmission lines and optimizing energy flow within the grid. Moreover, DLR enables greater integration of renewable energy sources, which are often variable and dependent on weather conditions. However, challenges such as dependency on data quality, complexity in implementation, potential network instability, and possible premature aging of conductors must be managed [8, 15].

C. Methods and Techniques for DLR Calculation

The precise determination of a power line's load capacity, crucial for the implementation of DLR systems, is based on various measurement and calculation methods that can be classified into two main categories:

1) Direct Methods: Direct methods provide accurate measurements of physical parameters of the conductor but are usually more expensive and complex to implement. These include the use of infrared thermometers, thermocouples for temperature measurement, load cells for measuring the mechanical tension of the conductor, and optical or ultrasonic sensors for sag and clearance measurement. While these methods offer high precision, they require physical contact or proximity to the conductor, which can be a limitation in certain scenarios [15].

2) Indirect Methods: Estimate the conductor's temperature and other relevant parameters using mathematical models and data analysis, without requiring direct physical measurements. These methods are generally more flexible and can be implemented over larger areas.

Thermal Models: Fundamental to the calculation of DLR, as they simulate the heat balance of the conductor by considering the heat generated by the current (Joule effect) and the heat exchanged with the environment. The balance of these forces is mathematically expressed as:

$$P_J + P_S = P_c + P_r \tag{1}$$

Where:

- P_J is the power dissipated by the Joule effect ($I^2 \cdot R$), where I is the current and R is the conductor's resistance.
- P_S is the power gained from solar radiation.
- P_c is the heat loss by convection to the surrounding air.
- P_r is the heat loss by radiation.

From this equation, the maximum allowable current I for a given conductor temperature can be calculated as:

$$I = \sqrt{\frac{P_c + P_r - P_S}{R(T_{cond})}} \tag{2}$$

This calculation is influenced by meteorological variables such as ambient temperature, wind speed, wind direction, and solar radiation, which affect the thermal balance of the conductor. The IEEE-738 and CIGRE-TB 601 standards provide detailed guidelines for these calculations, with each standard using slightly different approaches and assumptions [8, 9].

Methods Based on Wide Area Measurement Systems (WAMS): Utilize data from phasor measurement units (PMUs) to estimate line impedance, which correlates with conductor temperature. This method, particularly useful for long transmission lines, enhances the accuracy of DLR calculations by integrating real-time data from multiple sources [10].

D. Standards for DLR Calculation

The methods for calculating DLR are guided by international standards, which provide frameworks and mathematical models for assessing the thermal capacity of conductors. The most widely used standards are IEEE-738 and CIGRE-TB 601. These standards have evolved to incorporate more sophisticated models and consider a broader range of variables, reflecting the complex and dynamic nature of power line operations.

Both standards perform a thermal balance of the conductor, ensuring that the heat gained from the current and solar radiation is equal to the heat lost through convection and radiation. However, there are key differences between the two:

- IEEE-738: Tends to use simpler, more empirical formulas, focusing on practical, easy-to-apply methods for real-time operations.
- CIGRE-TB 601: Offers a more detailed analysis, incorporating factors like conductor albedo and specific wind effects, which can provide more accurate results but require more complex calculations [1, 18].

These differences can lead to variations in the calculated thermal limits, which are crucial for determining the DLR. Comparative studies have shown that the CIGRE standard often provides more conservative temperature estimates, particularly under low wind speed conditions, making it more suitable for regions with highly variable weather conditions [3].

E. Meteorological Estimates and Prediction Models

Accurate meteorological data is essential for reliable DLR calculations. Meteorological models are categorized by scale:

1) Macroscale models: Cover large geographic areas and predict broad weather patterns. Examples include the ECMWF and GFS models, which operate on a global scale and provide long-term forecasts.

2) Mesoscale models: Focus on smaller regions, with higher resolution, often used to predict local weather events such as storms or fronts. Models like HARMONIE-AROME and WRF fall into this category.

3) Microscale models: Provide very high-resolution data, crucial for predicting conditions in complex terrains. These models, such as those used in CFD simulations, are essential for refining wind predictions and are often coupled with mesoscale models for enhanced accuracy [12].

The combination of these models allows for accurate short-term predictions. Statistical and dynamic downscaling techniques further enhance the precision of these models by adjusting them to local conditions.

F. DLR Implementations and Use Cases

DLR technology has been implemented in various regions, with significant benefits for grid efficiency and renewable energy integration. Below are some notable examples:

- Slovenia (ELES, 2019): ELES, the Slovenian transmission operator, introduced the SUMO system, an indirect DLR approach based on mesoscale weather models. This system provided a 48-hour forecast capability, significantly improving grid reliability during critical weather events by preventing conductor icing and optimizing line flows [11].
- China (State Grid, 2017): State Grid implemented a DLR system using Monte Carlo simulation techniques to evaluate line capacity reliability. This system reported a 30% increase in line capacity under optimal conditions, utilizing real-time data and high-resolution weather models, demonstrating the potential for significant operational improvements [6].
- Norway (Statnett, 2021): Statnett, the Norwegian transmission system operator, implemented a DLR system incorporating machine learning algorithms to predict line capacity based on real-time weather data. This system has been crucial in managing the integration of wind power into the grid, particularly during periods of high variability in weather conditions [17].

These cases underscore DLR's role as a critical tool for enhancing grid efficiency and integrating renewable energy, aligning with global sustainability goals.

III. Methodology

This section outlines the methodological approach taken to assess the feasibility of implementing DLR using meteorological data from third-party providers, in comparison to traditional physical sensors. The methodology covers data collection, normalization, comparative analysis, DLR calculation, sensitivity analysis, and error propagation studies. The developed tool for the study is depicted visually in Figure 1.

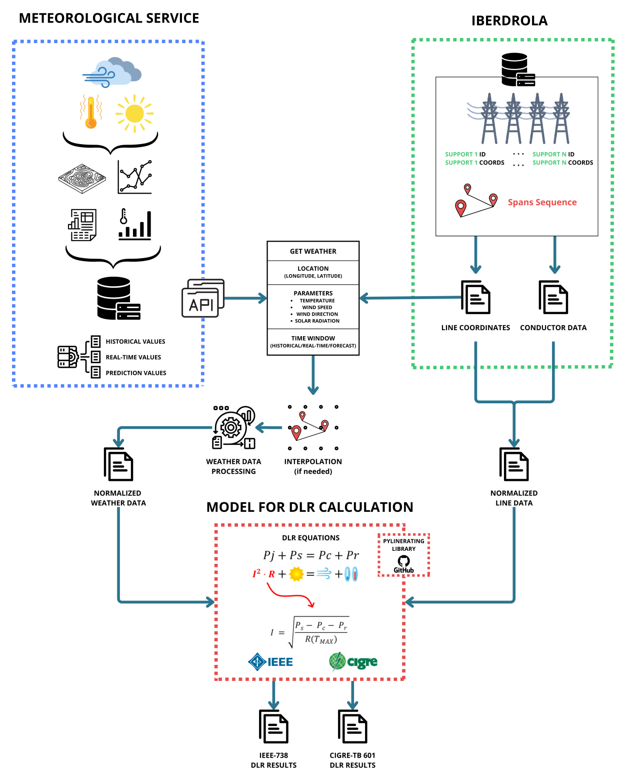

Fig. 1: Workflow of the tool developed for DLR calculation using meteorological data and field data.

A. Data Collection and Normalization

The methodology began by gathering meteorological data from three external services: Copernicus, MeteoFlow, and Open-Meteo. These services were selected based on their ability to provide essential meteorological variables, including ambient temperature, wind speed, wind direction, and solar radiation, across diverse geographic locations. Concurrently, historical weather data was retrieved from sensors installed on six distribution lines within Iberdrola's network.

To enable a reliable comparative analysis, a normalization process was applied to the collected data. This process involved standardizing the meteorological data to ensure consistency across different service providers. The weather data was acquired through API requests at consistent time intervals, which allowed for the comparison of real-time sensor data with forecasted values. To address missing data points and outliers, time filtering and interpolation techniques were applied, which facilitated the reconstruction of temporal resolution gaps in the datasets.

Electrical power line data was also normalized by collecting detailed information on pylon coordinates, span sequence, and conductor characteristics. This normalization ensured that the meteorological data could be accurately associated with each span of the power line for subsequent DLR calculations.

B. Comparative Analysis of Meteorological Data

The accuracy of meteorological data provided by external services was evaluated by performing a comparative analysis against sensor-based measurements from the selected distribution lines. The comparison employed several statistical methods and metrics, including boxplot comparison, scatter plots, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Pearson correlation coefficient, to quantify the agreement between service estimates and sensor data.

To facilitate this comparison, a resampling process was employed to ensure consistent timestamps across the various datasets, thereby enabling a reliable comparison of time series data.

C. Dynamic Line Rating Calculation

DLR calculations were conducted following the standards outlined in IEEE-738 and CIGRE-TB 601. Python-based subroutines were developed and integrated into a tool designed for this purpose. These subroutines incorporated environmental variables—such as ambient temperature, wind speed, wind direction, solar radiation, and conductor constraints that directly influence the ampacity of overhead conductors.

The tool can calculate the DLR for each span of the power lines, considering the time conditions of each span and the conductor characteristics used for the construction of the line. This approach allowed for the calculation of the DLR at any span, with any kind of weather conditions. With this tool, all the analysis and comparisons could be done.

D. Sensitivity Analysis

To assess the impact of individual meteorological variables on DLR calculations, a comprehensive sensitivity analysis was conducted using both local and global methods. A Latin Hypercube Sampling (LHS) approach was employed to generate 100,000 samples of the input variables, ensuring a thorough exploration of the input space [14]. The distributions used for these variables are summarized in Table I.

Variable	Dist Type	Parameters
Ambient Temp	Beta	a=10.8, b=6.7, loc=-19.3, scale=63.7
Wind Speed	Weibull	shape=1.7, loc=1.32, scale=2.8
Wind Direct	Uniform	Range = [0, 90]
Solar Radiation	Dirac + Unif	Dirac at 0 + Range [0, 1000]
Altitude	Uniform	Range = [0, 1000]
Conductor Type	Uniform	Discrete: LA 175, 180, 280, 300
Conductor Temp	Uniform	Range = [60, 90]
Absorptivity	Uniform	Range = [0.5, 1]
Emissivity	Uniform	Range = [0.5, 1]

TABLE I: Distributions used for LHS in Sensitivity and Error Propagation Analyses

The following techniques were utilized:

- Sobol Analysis [19]: This method decomposed the variance in the DLR results to quantify the contribution of each input variable. Sobol indices were used to measure the sensitivity of DLR to each meteorological variable and their interactions.
- PAWN Analysis [16]: PAWN, a global sensitivity analysis method, was used to evaluate the influence of each input variable by analyzing the differences in cumulative distribution functions (CDFs). The Kolmogorov-Smirnov statistic was applied to quantify the distance between conditional and unconditional CDFs, providing insight into the distributional effects of each variable on DLR.
- Delta Analysis [2]: This non-parametric method focused on measuring the variability in the output distribution due to the variability in each input variable. The Delta index provided a clear understanding of how uncertainties in the input variables propagate through the DLR model.

These analyses highlighted the relative importance of different variables needed for the DLR calculation with the weather conditions approach.

E. Error Propagation and DLR Prediction Simulation

An error propagation study was conducted to quantify the impact of uncertainties in meteorological data on DLR calculations. Similar to the sensitivity analysis, 100,000 samples were generated using LHS to ensure extreme scenarios coverage. Various error magnitudes were then applied independently to each variable, simulating both positive and negative deviations to reflect more favorable environmental conditions than actual ones, resulting in an overestimated DLR.

Subsequently, DLR was calculated for both the base case and the altered scenarios. The differences between the overestimated DLR and the base case DLR were measured, and error values were determined for different confidence levels.

For the DLR prediction simulation, a specific example was conducted using Open-Meteo data for the location of Device 1 on Line 2. Error margins were applied to each predicted variable, with 50% and 95% confidence intervals calculated to simulate the most and least favorable environmental conditions. The DLR was then calculated for these scenarios, providing a robust framework for understanding the potential range of DLR values under varying conditions.

IV. Results

A. Comparative Analysis of Meteorological Services and Line Sensors

1) Methods and Statistical Comparisons: This subsection details the statistical methods and metrics used to compare data from meteorological services with line-installed sensors. Box plots were employed to visualize the distribution of each variable provided by the meteorological services, comparing these with the distributions from the sensors. The correlation between external service data and sensor measurements was evaluated using scatter plots, distribution functions, and the correlation coefficient, helping to quantify the similarity between the datasets.

Error metrics, including Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), were calculated to identify which services provided the most accurate data relative to actual sensor measurements. Finally, the error range of each service was determined, allowing for the calculation of the 95% confidence interval and establishing the reliability of each service's data.

2) Comparison between Service Estimates and Sensor Measurements:

a) Data Box Plot Analysis:

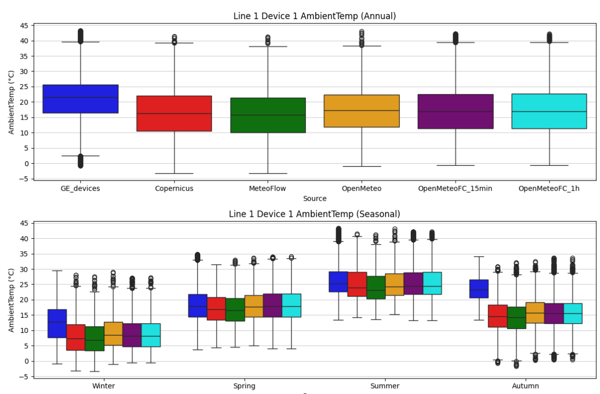

Fig. 2: Ambient Temperature Box Plot for Device 1 Location on Line 1

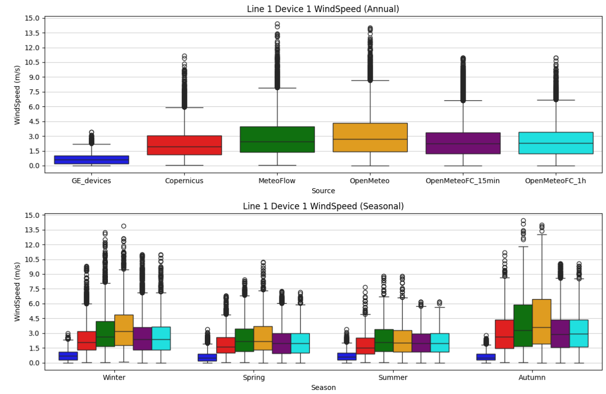

Fig. 3: Wind Speed Box Plot for Device 1 Location on Line 1

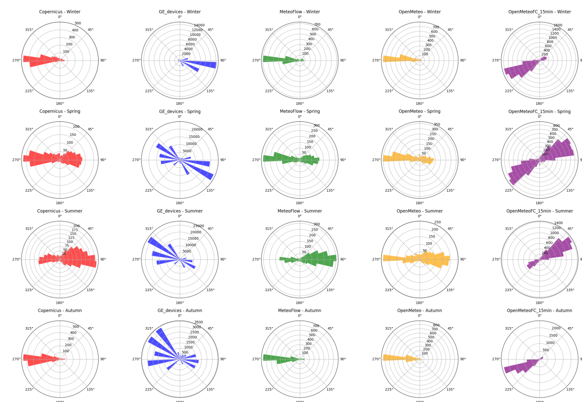

Fig. 4: Wind Roses for Device 1 Location on Line 1

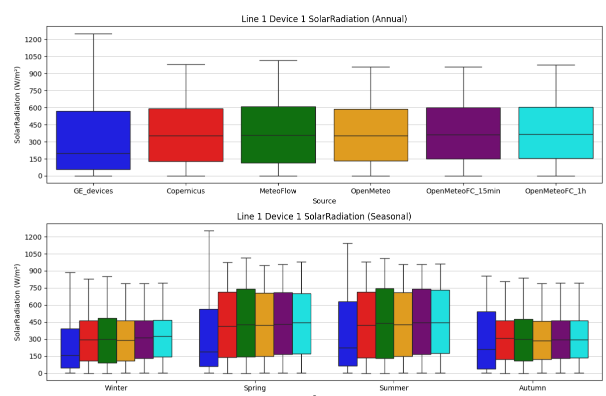

Fig. 5: Solar Radiation Box Plot for Device 1 Location on Line 1

b) Correlation, Scattering and Distribution Analysis:

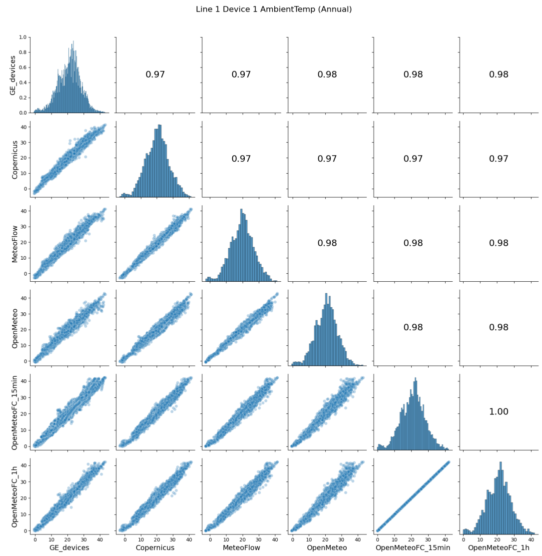

Fig. 6: Ambient Temperature Device 1 on Line 1

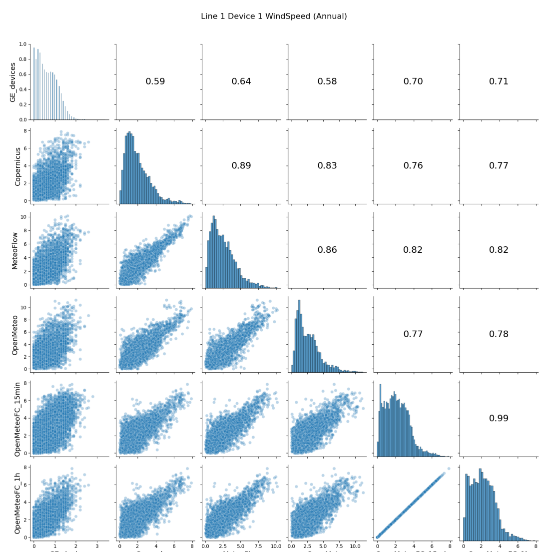

Fig. 7: Wind Speed Device 1 on Line 1

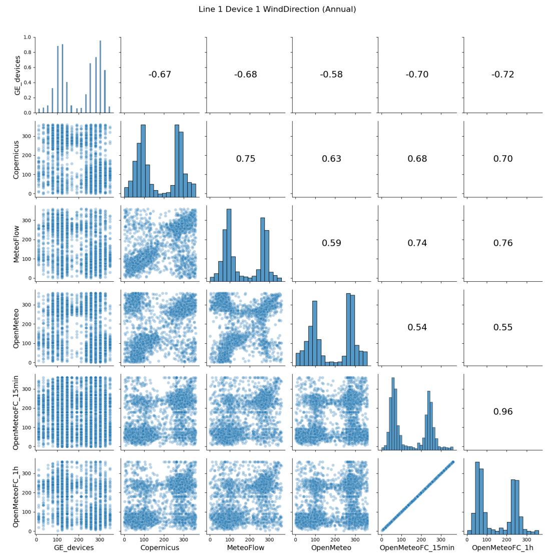

Fig. 8: Wind Direction Device 1 on Line 1

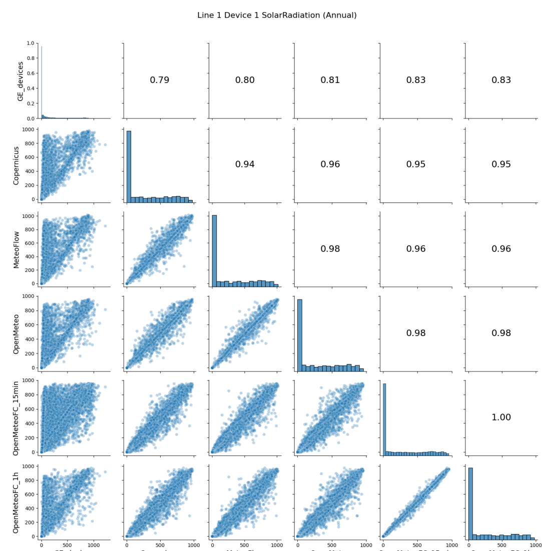

Fig. 9: Solar Radiation Device 1 on Line 1

c) Error Metrics between Services and Sensors:

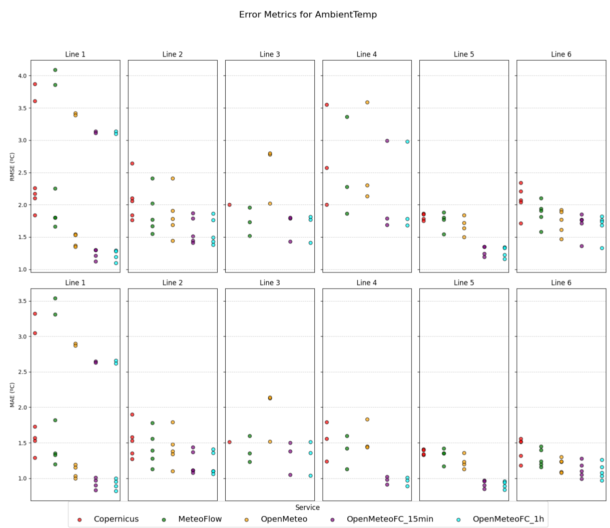

Fig. 10: Error Metrics for Ambient Temperature per Line and Service

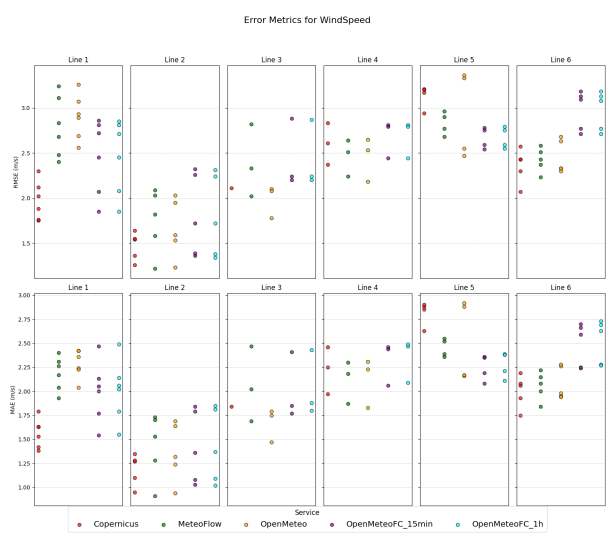

Fig. 11: Error Metrics for Wind Speed per Line and Service

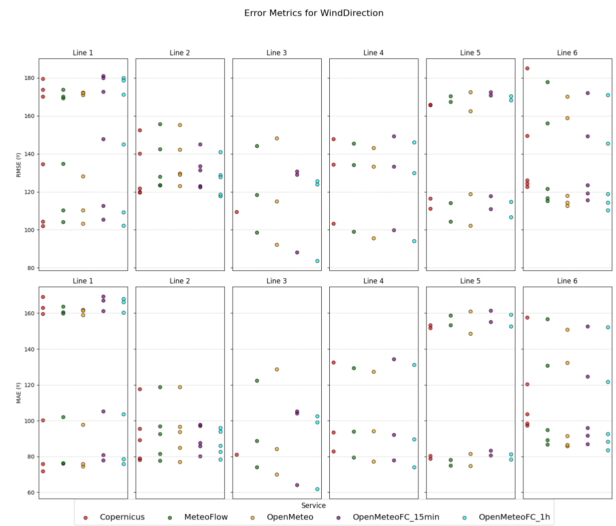

Fig. 12: Error Metrics for Wind Direction per Line and Service

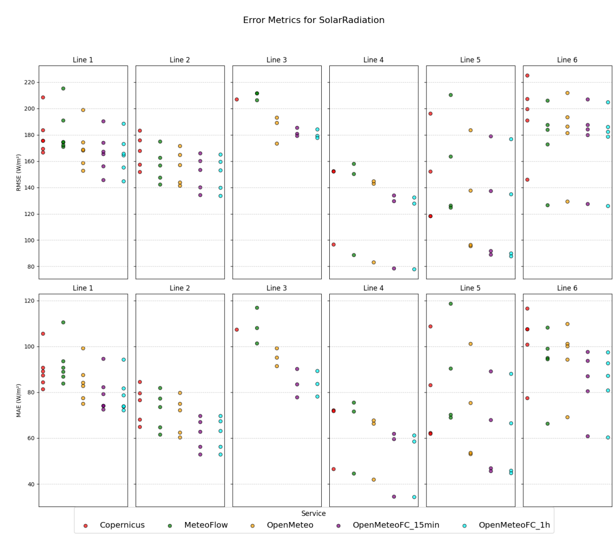

Fig. 13: Error Metrics for Solar Radiation per Line and Service

d) Uncertainty of Meteorological Services:

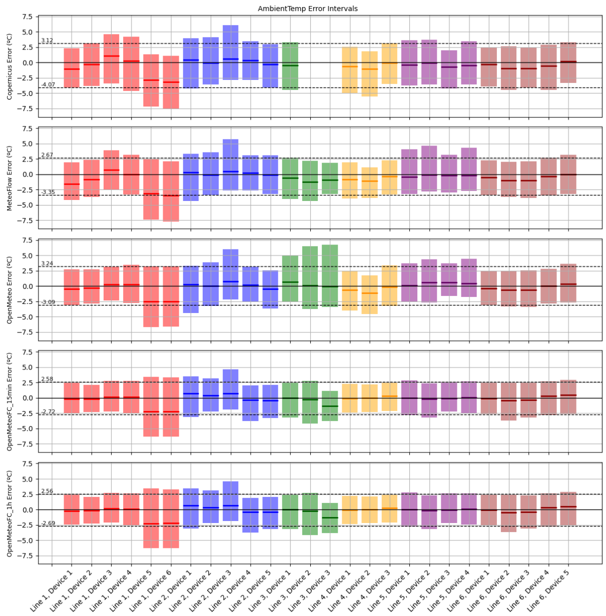

Fig. 14: Error Intervals for Ambient Temperature

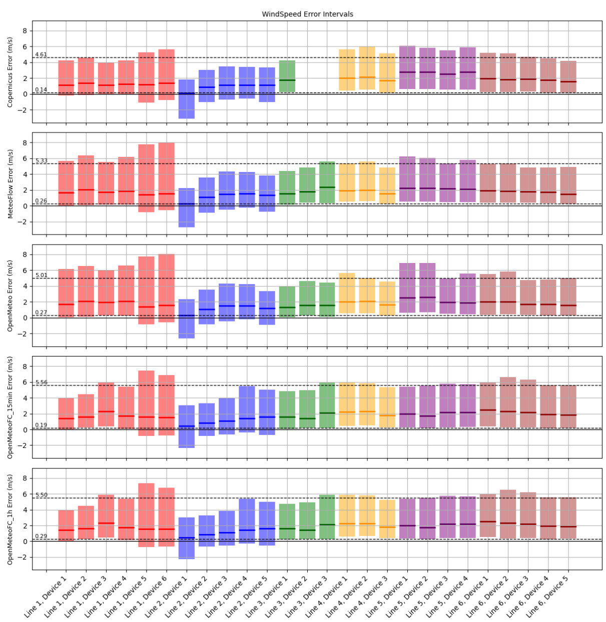

Fig. 15: Error Intervals for Wind Speed

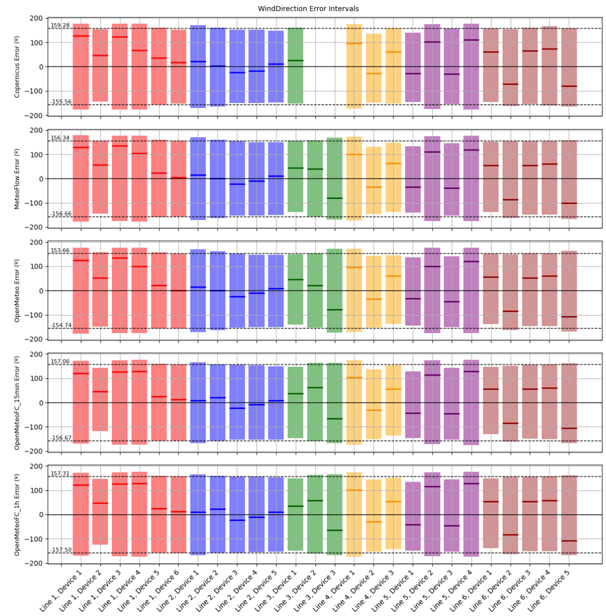

Fig. 16: Error Intervals for Wind Direction

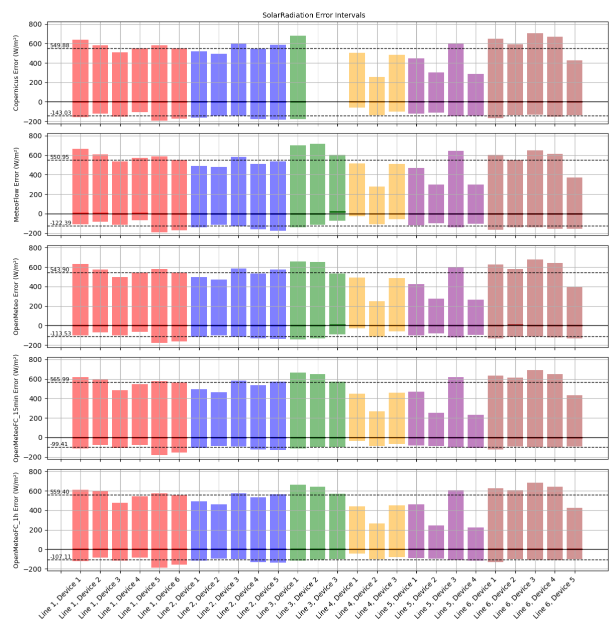

Fig. 17: Error Intervals for Solar Radiation

B. Analysis of DLR Calculation for IEEE and CIGRE Standards

1) Sensitivity Analysis of DLR Calculation:

a) PAWN Analysis: The PAWN analysis results are shown in Tables II and III for the CIGRE-TB 601 and IEEE-738 standards. These tables summarize the minimum, maximum, mean, median, and coefficient of variation (CV) of the PAWN index for each variable.

Parameter	minimum	mean	median	maximum	CV
AmbientTemp	0.017	0.099	0.084	0.235	0.660
WindSpeed	0.090	0.270	0.238	0.525	0.515
AngleOfAttack	0.030	0.118	0.113	0.277	0.592
SolarRadiation	0.010	0.028	0.023	0.059	0.547
Altitude	0.006	0.014	0.013	0.021	0.327
ConductorType	0.220	0.227	0.224	0.239	0.036
MaxTempCond	0.008	0.051	0.050	0.091	0.560
Absorptivity	0.005	0.008	0.007	0.015	0.369
Emissivity	0.007	0.019	0.020	0.036	0.453

TABLE II: Sensitivity PAWN Results for CIGRE-TB 601

Parameter	minimum	mean	median	maximum	CV
AmbientTemp	0.017	0.105	0.088	0.248	0.667
WindSpeed	0.090	0.246	0.211	0.487	0.536
AngleOfAttack	0.026	0.124	0.114	0.311	0.625
SolarRadiation	0.012	0.029	0.023	0.059	0.528
Altitude	0.006	0.013	0.011	0.020	0.331
ConductorType	0.228	0.237	0.232	0.250	0.040
MaxTempCond	0.008	0.055	0.052	0.099	0.562
Absorptivity	0.005	0.009	0.008	0.017	0.407
Emissivity	0.007	0.019	0.019	0.036	0.458

TABLE III: Sensitivity PAWN Results for IEEE-738

b) Sobol Analysis: Figure 18 presents the first-order indices from the Sobol analysis for different combinations of ambient temperature, wind speed, and wind angle of attack.

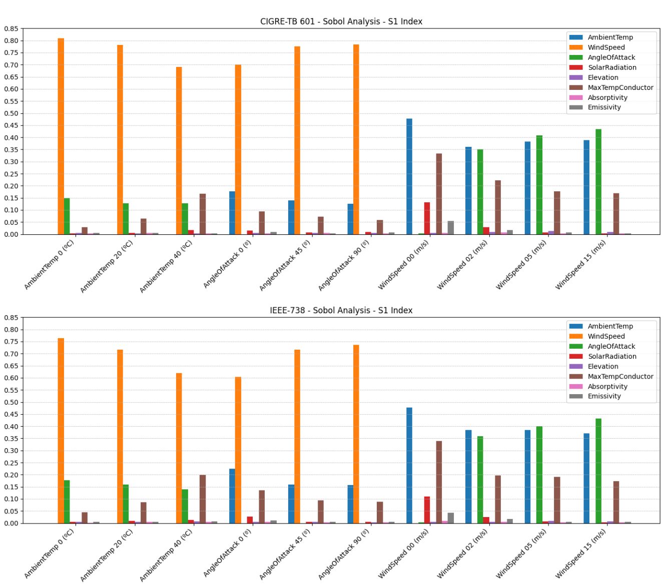

Fig. 18: Regional Sensitivity Analysis for CIGRE-TB 601 and IEEE738 Standards

C. Error Propagation Analysis of Meteorological Variables

The results of the error propagation analysis are summarized in Tables IV and V, showing the impact of errors in meteorological variables on the DLR calculation for both standards.

CIGRE-TB 601	50%		90%		95%		99%	
Amb Temp Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
-1 ºC	7	1.0	9	1.3	10	1.4	11	1.6
-2 ºC	15	2.0	18	2.5	19	2.7	21	3.2
-3 ºC	22	2.9	27	3.8	29	4.1	32	4.7
-4 ºC	29	3.9	36	5.0	38	5.4	42	6.2
Wind Speed Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
+0.5 m/s	31	4.3	40	5.4	42	5.6	46	6.0
+1 m/s	61	8.3	77	10.5	82	10.9	89	11.7
+3 m/s	165	22.4	207	27.9	218	28.9	236	31.0
+5 m/s	253	34.4	314	42.2	330	43.7	358	46.6
Wind Dir Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
±5º	0	0.0	24	3.9	28	4.5	34	5.1
±11º	0	0.0	51	8.1	60	9.8	73	11.2
±45º	0	0.0	160	26.0	187	31.0	228	35.8
±90º	0	0.0	212	34.6	245	40.8	298	46.7
Solar Rad Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
-100 W/m²	4	0.6	5	0.9	6	1.0	6	1.3
-300 W/m²	13	1.7	16	2.7	17	3.1	19	3.9
-500 W/m²	21	2.8	26	4.4	28	5.1	31	6.4
-800 W/m²	33	4.4	42	7.0	44	8.0	49	10.1

TABLE IV: DLR Errors for Different Cases. CIGRE-TB 601 Standard

IEEE-738	50%		90%		95%		99%	
Amb Temp Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
-1 ºC	7	1.0	9	1.2	9	1.4	10	1.6
-2 ºC	14	1.9	17	2.5	18	2.7	20	3.1
-3 ºC	21	2.8	26	3.7	27	4.0	30	4.6
-4 ºC	28	3.8	34	4.9	36	5.3	40	6.1
Wind Speed Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
+0.5 m/s	23	3.2	30	4.1	32	4.3	35	4.6
+1 m/s	45	6.1	58	7.8	61	8.2	67	8.8
+3 m/s	119	16.3	151	20.3	159	21.1	173	22.6
+ 5 m/s	180	24.6	226	30.2	237	31.3	258	33.4
Wind Dir Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
±5º	0	0.0	27	4.1	32	5.3	39	6.5
±11º	0	0.0	55	8.7	67	11.2	83	13.7
±45º	0	0.0	163	26.6	195	33.4	238	40.0
±90º	0	0.0	205	33.7	244	42.0	297	50.2
Solar Rad Err	(A)	(%)	(A)	(%)	(A)	(%)	(A)	(%)
-100 W/m²	4	0.6	5	0.9	6	1.0	6	1.3
-300 W/m²	13	1.7	16	2.7	17	3.1	19	3.9
-500 W/m²	21	2.8	26	4.4	28	5.1	32	6.5
-800 W/m²	33	4.5	42	7.0	44	8.0	50	10.2

TABLE V: DLR Errors for Different Cases. IEEE-738 Standard

D. Example of Use for DLR Predictions

Considering the inherent uncertainty in meteorological estimates, error margins were applied to each variable to assess their impact on conductor temperature. This approach sets maximum and minimum environmental limits, ensuring that the most unfavorable DLR prediction remains below the actual DLR, enabling safe and reliable operational decisions.

Figures 19 and 20 show DLR forecasting examples using the CIGRE-TB 601 and IEEE-738 standards, with confidence intervals (colored areas) representing the possible DLR ranges based on meteorological uncertainties.

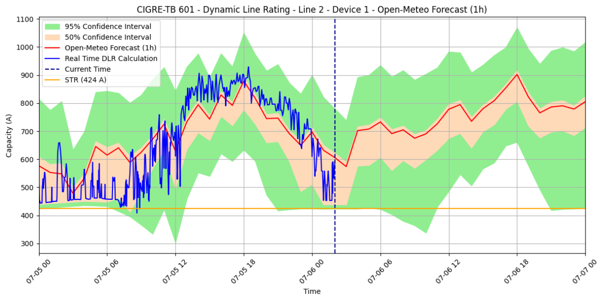

Fig. 19: DLR Forecasting Example using CIGRE-TB 601

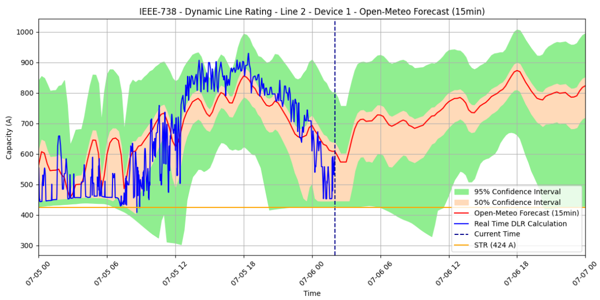

Fig. 20: DLR Forecasting Example using IEEE-738

V. Discussion

The discussion focuses on the implications and challenges identified in the comparative analysis between meteorological services and line sensors, along with insights from sensitivity and error propagation analyses, highlighting key factors that influence the accuracy and reliability of DLR calculations.

A. Ambient Temperature

The comparison between sensor measurements and meteorological service estimates for ambient temperature, reveals a consistent pattern where the temperatures recorded by the devices (GE devices) are generally higher than those estimated by meteorological services (Figure 2). This discrepancy is particularly evident during the winter and autumn seasons, where sensor measurements can be up to 5°C higher than the estimates.

An underestimation of ambient temperature by meteorological services could lead to assigning operational limits that are less restrictive than necessary, potentially compromising the safety of the lines by allowing for higher ampacities than the conductors can safely handle under actual conditions.

Further analysis across different lines (Figure 6) confirms that this discrepancy is not isolated to a single location. The same trend is observed across various locations, suggesting that the meteorological models used by these services may not fully capture the microclimatic conditions present along the distribution lines. While Open-Meteo shows slightly better alignment with sensor data, the overall trend of underestimation remains a concern (Figure 14.

B. Wind Speed

Wind speed shows an even more pronounced discrepancy between sensor data and meteorological service estimates. As shown in Figure 3, the wind speeds recorded by the sensors are consistently lower than those estimated by the services, with the most significant differences observed during periods of low wind speed. This is further corroborated by the correlation ana lysis (Figure 7), which reveals moderate positive correlations, suggesting that while the services can track the general trend of wind speed variations, they consistently overestimate the actual values.

Wind speed plays a vital role in the cooling of overhead conductors, and overestimation by meteorological services could result in DLR calculations that suggest higher line capacities than are safe. The tendency towards overestimation observed in all lines highlights the need to carry out more wind speed measurements with different sensors to guarantee the veracity of the study.

C. Wind Direction

Wind direction is another variable where discrepancies between sensor data and meteorological service estimates were observed. As shown in the wind roses (Figure 4), the direction measured by the sensors often differs significantly from the estimates provided by the services. This discrepancy differs depending on the location and season.

The orientation of wind relative to the conductor is crucial for calculating the effective cooling due to wind. Errors in wind direction estimates can thus lead to significant inaccuracies in DLR calculations. The negative correlations observed in the scatter plots (Figure 8) further indicate that the sensors may be oriented differently from the reference direction used by the meteorological models, complicating the veracity of the study.

The substantial uncertainty of wind direction estimates, as indicated by the wide error intervals (Figure 16), underscores that better wind models with spatial and temporal resolution are needed.

D. Solar Radiation

The boxplot analysis (Figure 5) shows that the peaks of solar radiation measured by the devices are consistently higher than those estimated by the meteorological services. This overestimation by the services, especially during periods of high cloud cover, could lead to more conservative DLR estimates, as seen in Figure **??**.

While conservative estimates can provide an additional safety margin, they also reduce the operational efficiency of the power lines by underutilizing their capacity. The error metrics (Figure 13) show that the services tend to overestimate solar radiation during low-radiation periods, leading to higher than necessary operational limits. The impact of these errors is most pronounced during summer months when the discrepancy between sensor data and service estimates is greatest.

E. Sensitivity Analysis of DLR Calculation

The PAWN analysis (Tables II and III) reveals significant insights into the influence of various parameters on the DLR calculations according to IEEE-738 and CIGRE-TB 601 standards. The analysis highlights that wind speed, ambient temperature, and wind angle of attack are the most influential factors, with wind speed showing the highest sensitivity across different scenarios (Figure 18). Particularly under high wind conditions, the cooling effect on the conductor significantly increases the DLR, consistent with both standards.

Interestingly, the type of conductor, while important, exhibits a relatively constant influence, as indicated by its low coefficient of variation. This suggests that once the conductor type is chosen, it does not lead to variations in DLR under varying environmental conditions, making it a less critical factor in sensitivity analysis compared to meteorological variables.

The analysis also indicates that as ambient temperature rises, the influence of wind speed diminishes, and the maximum conductor temperature becomes more critical. This shift emphasizes the need to consider temperature-related parameters more carefully in regions or scenarios where high ambient temperatures are expected. Solar radiation, while less influential than wind speed and ambient temperature, still plays a role in the DLR calculations, particularly in scenarios of zero wind speed, as reflected in Figure 18.

In comparing the two standards, the overall hierarchy of parameter importance remains similar, but specific sensitivity values differ slightly. The CIGRE-TB 601 standard places greater emphasis on wind speed, whereas the IEEE-738 standard gives more weight to ambient temperature, conductor temperature, and wind angle of attack. These differences imply that while both standards capture the essential effects of the variables, they do so with varying degrees of emphasis on certain factors, which could lead to different operational decisions depending on the standard used.

F. Error Propagation Analysis of Meteorological Variables

The error propagation analysis (Tables IV, V) provides valuable insights into the potential risks associated with inaccuracies in meteorological data when calculating DLR. For ambient temperature, the analysis indicates that underestimations of -4ºC can result in a maximum error of around 6.2% for both standards, which, while significant, is less severe than the errors associated with wind speed. This suggests that while temperature measurements are crucial, the impact of their inaccuracies may be more manageable compared to wind speed.

The results show that overestimation of wind speed can lead to significant errors in DLR, particularly under the CIGRE-TB 601 standard, where the error margin could reach up to 46.6% for overestimations of 5 m/s. This highlights the importance of precise wind speed measurements and the need for conservative safety margins when relying on wind predictions. Additionally, the analysis shows that reducing the error in wind speed measurements almost proportionally reduces the error in DLR calculations.

Wind direction errors, especially at higher wind speeds, introduce a significant challenge. The analysis indicates that even small errors in wind direction can lead to substantial overestimations of DLR, particularly under the IEEE standard, where a 90º error can result in up to a 50% error in DLR (Figure 18). For sensors with a resolution of 22º, the maximum error committed will be around 13%. However, it is important to note that the reduction in error for wind direction does not proportionally reduce the DLR error, except for very low angular errors below 22º.

Lastly, errors in solar radiation have a relatively minor impact on DLR calculations, with maximum errors not exceeding 10%. This reinforces the observation that while solar radiation is a factor, its influence is less critical compared to wind-related parameters. The reduction of errors in solar radiation leads to a proportional reduction in DLR error, similar to what is observed with temperature and wind speed.

G. Example of Use for DLR Predictions

The practical example of DLR prediction demonstrates the importance of incorporating safety margins to account for uncertainties in meteorological forecasts. The results, shown in Figure 19 and 20, underline that DLR values, when predicted with conservative margins, can still provide significant operational benefits over STR, particularly during periods of favorable weather conditions. However, the variability in predictions suggests that the reliability of DLR as an operational tool is highly dependent on the accuracy of meteorological data.

The analysis also shows that, despite the differences between the CIGRE and IEEE standards, the overall trends in DLR predictions remain consistent. This consistency suggests that either standard could be effectively used for operational purposes, provided that the appropriate margins for error are applied.

VI. Conclusions

This section provides a summary of the main conclusions of this study, grouped according to the objectives, along with recommendations and future work.

A. Evaluation of the Accuracy of Meteorological Estimates

Regarding the accuracy of meteorological estimates, the following conclusions can be drawn:

Ambient Temperature: Meteorological services generally provide similar temperature estimates. Open-Meteo offers the most accurate estimates, with an error range of [-2.7, +2.6] ºC at a 95% confidence level. In winter and autumn, services tend to systematically underestimate ambient temperature. Significant deviations were observed in certain locations, such as Devices 5 and 6 on Line 1, located in a residential area with the highest errors.

Wind Speed: Devices record maximum wind speeds of 4.5 m/s, with 50% of measurements below 1.5 m/s. This suggests installations in low-wind areas where DLR's contribution over SLR is moderate. The difference between device measurements and meteorological estimates results in error intervals between 0 and 5 m/s. Despite systematic differences in magnitude, the trends between services and sensors show reasonable correlations (0.5 to 0.7). The Copernicus service shows the lowest errors, with wind velocity errors ranging from [0.14, 4.61] m/s.

Wind Direction: Meteorological services agree on the predominant wind direction, but in situ measurements reveal deviations due to local factors like topography and obstacles. Meteorological services, with a $\pm 160°$ error range, fail to model these local influences effectively. Open-Meteo provides the lowest wind direction error, with an error range of $\pm 153°$.

Solar Radiation: Meteorological services underestimate maximum radiation, especially in spring, with Open-Meteo providing the most accurate estimates, with an error range of [-100, +570] W/m². Radiation patterns are consistent across locations, though with varying value ranges.

B. Impact of Variables on DLR Calculation

The variables most influential on DLR calculation are wind speed (27%) and conductor type (23%), followed by attack angle (12%) and ambient temperature (10%). The influence of these variables varies with weather conditions, and while conductor type consistently influences DLR, it is more a parameter than a variable for optimization. Local sensitivity analysis reveals wind speed and temperature as the most critical factors under varying scenarios.

Error Propagation: Errors in meteorological estimates propagate into DLR calculations. Open-Meteo's temperature error leads to a maximum DLR overestimation of 3.2% (CIGRE-TB 601) and 4% (IEEE-738). Copernicus' wind speed error could overestimate DLR by 46.6% (CIGRE) and 33.4% (IEEE). Wind direction errors cause significant overestimations, especially with Open-Meteo's $\pm 160°$ error. Improving the accuracy of these variables could reduce DLR estimation errors proportionally.

C. DLR Prediction

An example using Open-Meteo estimates shows that trends in DLR prediction are effectively captured, and even with wide confidence bands, DLR still offers operational advantages over the STR. Reducing uncertainty in the meteorological predictions would narrow these confidence bands, potentially improving the reliability of DLR predictions. However, it is important to note that no definitive conclusions can be drawn from this single example, and further studies are necessary.

D. Recommendations and Future Work

Improvement of Sensor Infrastructure: Address operational interruptions and improve measurement accuracy, particularly for wind direction. Conduct studies to verify current sensor measurements and optimize sensor placement to ensure accurate measurements in critical areas.

Development of a Hybrid System: Consider a cost-effective hybrid approach that combines high-precision sensors with meteorological data to minimize prediction errors and optimize grid operation. This hybrid system could also detect sensor failures early.

Microscale Model Development: Develop microscale models to improve local predictions, particularly for wind. Explore the use of AI to enhance these models with real-time sensor data. Assess the economic feasibility of deploying these models and additional sensors.

Improvement of DLR Calculation Accuracy: Verify and refine DLR calculation standards using modern simulation techniques. Apply smoothing techniques to DLR calculations to reduce erratic fluctuations and model cable capacity more accurately.

VII. Alignment With the Sustainable Development Goals (SDGs)

The master thesis "Evaluating the Feasibility of Replacing Physical Sensors with Meteorological Services for DLR in Power Systems" represents a significant step towards smarter, more efficient, and sustainable electrical grids. It aligns with the United Nations' SDGs, demonstrating how innovation can drive the transition to a cleaner, more resilient, and equitable energy future [20].

This work particularly supports SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure). These goals are part of a global agenda to address critical challenges, and this thesis contributes to these efforts by advancing DLR technology.

SDG 7: Affordable and Clean Energy [21]: DLR directly supports this goal by optimising the capacity of existing electrical infrastructure, enabling the more efficient integration of renewable energy sources into the grid. By reducing the necessity for new infrastructure construction, DLR decreases the carbon footprint of the electrical system, contributing to a cleaner and more sustainable energy supply. Additionally, by improving energy flow management, DLR minimizes transmission and distribution losses, leading to lower energy costs for consumers and broader access to affordable energy.

SDG 9: Industry, Innovation, and Infrastructure [22]: DLR fosters innovation by applying advanced solutions to the management of electrical grids, enhancing the resilience and capacity of distribution networks. This technology contributes to the development of more robust and reliable infrastructure that can withstand extreme weather events and ensure a continuous electricity supply. By maximising the use of existing infrastructure, DLR also supports economic efficiency and sustainable industrialisation, aligning with the goals of sustainable industry and innovation.

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