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DYNAMIC LINE RATING THROUGH EXTRAPOLATION AT NEARBY SPANS IN COMPARABLE ENVIRONMENTS: PREDICTING WIND WITH MACHINE LEARNING MODELS TRAINED ON LOCAL WIND MEASUREMENTS

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Abstract: Due to increasing and variable power flows, many overhead lines approach their traditionally static or seasonal rating limits, which were established decades ago based on very conservative weather conditions for more stable flows. Since expanding infrastructure often entails lengthy delays and high costs, Dynamic Line Rating (DLR) of overhead lines (OHLs) is an alternative solution to leverage unexploited line capacity. In DLR, wind is the primary cooling factor. However, wind speed and direction vary greatly over short distances due to local environmental features like trees, buildings, terrain roughness, conductor level, turbulence, and the atmospheric boundary layer physics. Despite continued advancements, meteorological models still struggle to account for local disturbances, which are very complex in practice to be explicitly incorporated into digital models. Typically, the approach at Ampacimon involves adjusting weather provider wind values and forecasts according to local measurements from sensors installed on the conductor at critical spans. This paper examines the constraints and opportunities of a hybrid approach that employs Artificial Intelligence (AI) / Machine Learning (ML) techniques to extrapolate wind data from critical span locations to adjacent spans with comparable line and environmental conditions. Three conditions must be met: low distance and angle between spans (such as parallel circuits) and little wind obstruction around the span. This new approach improves the scalability of DLR systems with a more optimized number of sensors, reducing installation costs, yet still ensuring high accuracy. Despite the high variability of wind, satisfactory results, validated in the field against sensor measurements over one year of data at multiple locations, are presented. This study also highlights the critical need to include local sensor-based wind measurements in the process to avoid overestimating the real available capacity.

Keywords: Dynamic Line Rating, Line Rating Forecasting, Line Rating Extrapolation, Overhead Lines, Machine Learning

INTRODUCTION

Electrical flows have increased considerably and have become more complex, variable and volatile, making them harder to predict and control in recent times. These new constraints have also pressured system operators to be a lot more responsive to these multiple and simultaneous changes in the electrical flows. Under such conditions, it becomes critical that existing transport and distribution resources are fully exploited. A comparison of challenges and regulations for grid capacity optimization in Western Europe is described in [1]. Many overhead lines approach their traditional static or seasonal rating limits, which were established decades ago based on conservative weather conditions suitable for more stable flows. Since expanding infrastructure often entails lengthy delays and high costs, one of the solutions to adapt the system to those new dynamic constraints is the Dynamic Line Rating of overhead lines.

In operation, the capacity of OHLs is limited by two main factors: clearance under each span and/or maximum allowed conductor temperature [2, 3]. These are strongly influenced by the weather conditions around the line. Traditionally, operators rely on Static Line Rating (SLR) to estimate the maximum capacity under worst-case weather conditions: typically 0.6 m/s of effective wind speed, 1000 W/m² of solar radiation, and a statistically high ambient temperature in the region per season. To relax these conditions, alternative ratings such as Ambient Adjusted Rating (AAR) or Dynamic Line Rating can be computed following IEEE-738 [2] or CIGRE-TB-601 [3]. AAR offers interesting lower-bound gains compared to SLR but would not relieve all specific congestion cases nor prevent all topological or costly dispatch actions.

As a matter of fact, the best rating approach to unlock as much transport capacity gains as possible is achieved

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with DLR. A case study is described in [4] with photovoltaic plant integration to the grid in Japan where a significant curtailment reduction was achieved with DLR. DLR considers the most influential factor in terms of cooling, i.e. the wind, but minor wind overestimates can have big consequences in terms of rating. The effects of sheltering and wind overestimation are discussed in more details in CIGRE-TB-299 [5]. Even though certain weather features such as ambient temperature and solar radiation are well estimated by weather models, the high variability in space and time of wind calls for sensor measurements to ensure operational safety. Despite their constant improvements [6], numerical [7] or physical meteorological models still fail at capturing these local effects that are also too complex to be modelled explicitly in digital models [8].

To forecast meaningful ratings that relieve congestions, the focus must be set on low wind speeds, i.e. lower than 2-3 m/s. When considering safe grid operation, higher wind speeds would most likely bring volatile and useless capacity gains. Knowing that wind speed typically follows a Weibull distribution [9], low wind speeds are much more present than high ones. Unfortunately, model uncertainty is higher when forecasting low wind speeds. Indeed, low wind is a very local and highly dynamic feature that changes in the presence of trees or buildings and varies with terrain roughness, conductor level and the atmospheric boundary layer physics. This underlines the need for local sensor-based measurement in the process.

In fact, a reliable operation of the electrical infrastructure is of paramount importance for both utilities and consumers. The probability for the forecasted rating to be higher than the true rating should be very low, typically of 1-2% defining high confidence levels, respectively noted P99 and P98 for the 99th and 98th percentile. This was specifically discussed in [10] with a probabilistic framework for DLR that predicts wind and rating at a given percentile, i.e. at a given balance between overestimation risks and capacity gains. This study was entirely based on sensor measurements.

DLR sensor installation, although an order of magnitude cheaper than line reconductoring, entails a certain cost that hinders broad adoption. The main contribution of this new paper is a hybrid approach between sensor-less and sensor-based DLR to extrapolate wind data from sensor-equipped spans to nearby spans with comparable line and environmental conditions. This new framework should contribute to broader DLR adoption without compromising on operational safety. The paper will cover the measurement method of Ampacimon sensors, different conditions that affect the extrapolation of wind at other spans, the nearby span extrapolation approach applied in different scenarios to illustrate its benefits and limitations, and empirical conditions required for nearby span extrapolation.

1. AMPACIMON MEASUREMENT METHOD

As mentioned before, maximum conductor temperature and clearance under each span are the principal limitations in power line transportation capacity. Both are influenced by the main external cooling factor of a conductor, wind [5]. However, wind is also the most local, dynamic and volatile weather parameter when computing DLR.

The patented Ampacimon [11] technology offers a complete plug-and-play solution to measure both sag and the perpendicular component of the wind speed relative to the span orientation through frequency spectrum analysis [12, 13, 14, 15] in order to compute accurately the DLR of a line.

The benefits of this technology are further explored for extrapolation purposes in comparable environments in the next sections.

2. WIND CORRELATION FACTORS BETWEEN SPANS

In order to extrapolate from one span to another, it is insightful to understand how wind varies between spans in different conditions. Figures 1, 2, 3 and 5 are produced over two years of data between January 2022 and December 2023. Wind speed [m/s] and wind direction [°] are retrieved from a weather provider while the perpendicular component of the wind speed is retrieved from Ampacimon sensor. For this analysis, all wind data are resampled to a 10-min frequency. To focus on the most relevant wind speeds in terms of rating, i.e. low wind speeds, only periods when the sensor perpendicular wind speeds are lower than 3 m/s are kept. This analysis focuses mainly on Western Europe.

Three principal factors that may affect wind correlation between two nearby spans have been identified: the distance between both spans, the angle between both spans $\in [0°, 180°)$ and the wind obstruction along either span (due to trees, buildings, …).

2.1. Distance Between Spans

In Figure 1, each wind rose compares the weather provider wind direction at different pairs of spans increasingly distant. A focus in the charts is here made on the frequency of each wind direction bin which is encoded in the radial axis. The span orientation of each pair of spans compared is also plotted to remind that the resulting perpendicular wind speed will differ depending on the span orientation. A first observation across all wind roses is that some dominant winds remain present across all graphs, though with some variations. Being limited by the number of weather stations available, a second observation is that the weather provider data has a limited resolution in space. Wind remains similar up to 10's km between spans. More noticeable differences may appear around 15 km.

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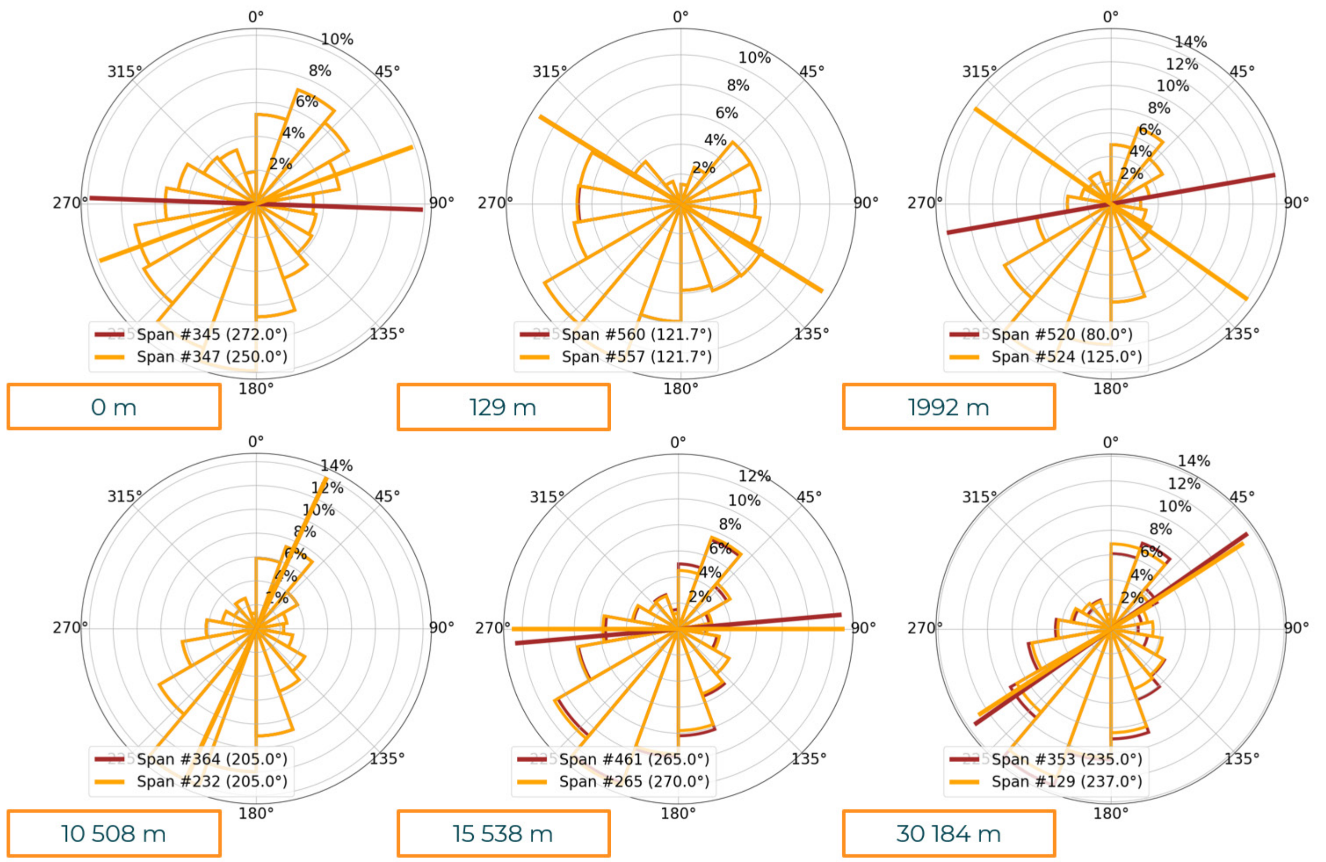
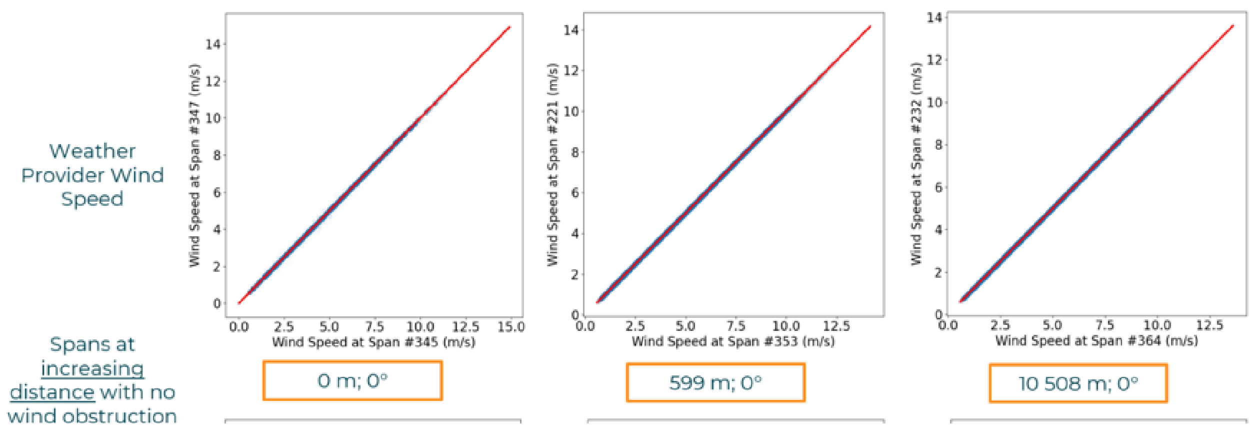


Figure 1: Weather station wind speed and direction over 2022-2023 at pairs of spans distant of about 0, 150, 2000, 10 000, 15 000, 30 000 m

Looking now at the wind speeds, a correlation analysis can be made for the weather provider wind speeds at pairs of spans and for the Ampacimon sensor perpendicular wind speeds at the same pairs (see Figure Figure 2, Figure 3 and Figure 5).

In Figure 2, the angle between spans and wind obstruction at both spans are each time very low. In this ideal scenario, when the weather provider's perpendicular wind speed remains linearly correlated between both spans, so does the Ampacimon sensor's perpendicular wind speed. However, as the distance increases to 14+ km, the linear correlation at the weather provider data level and at the Ampacimon sensor level has more variance. This justifies the need for two sensors to estimate the wind properly.



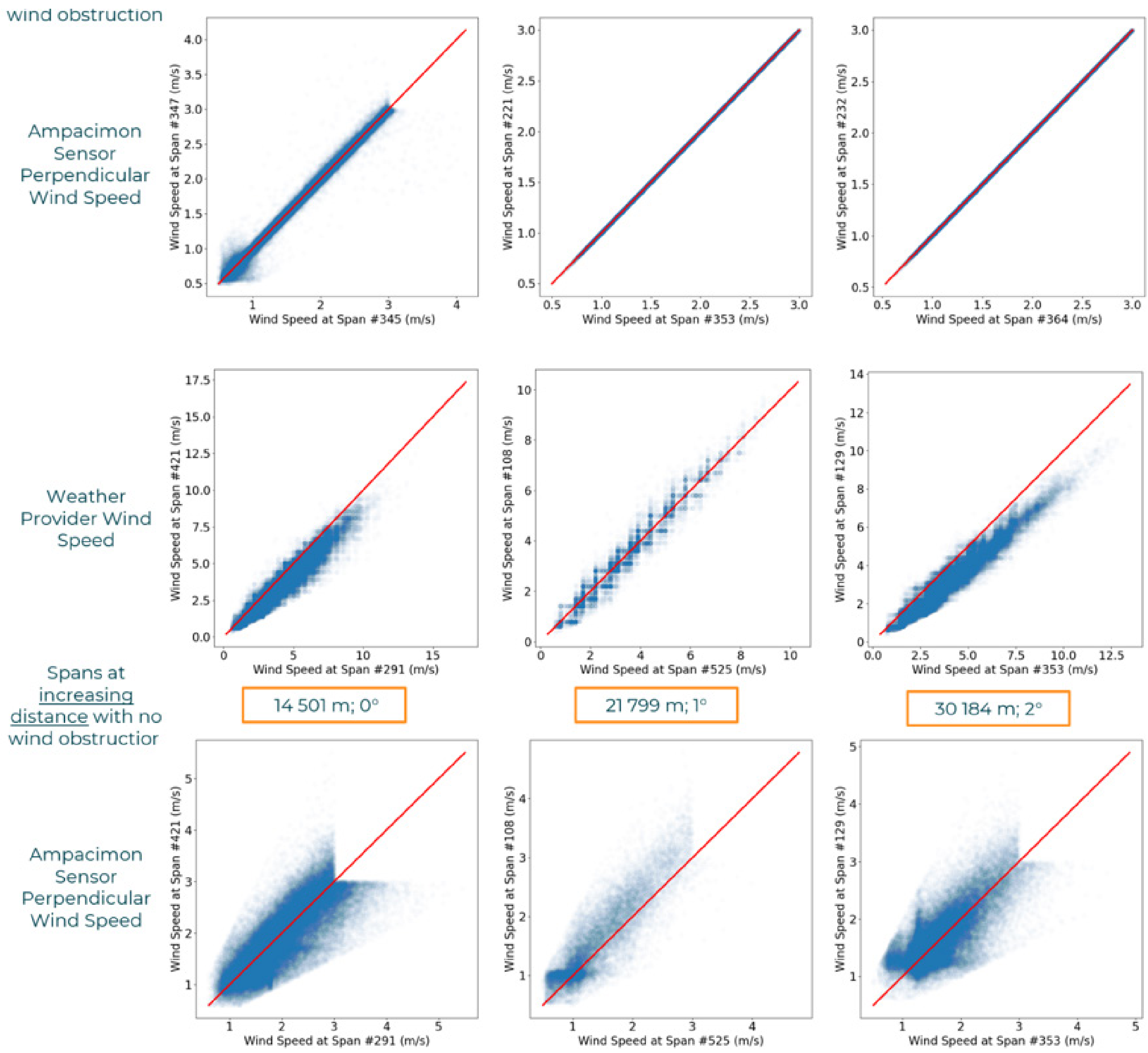


Figure 2: Wind speed from the weather provider and perpendicular wind speed from Ampacimon sensors - Correlation analysis between pairs of spans at different distances with low relative orientation angles and little wind obstruction conditions

2.2. Angle Between Spans

In Figure 3, two examples of higher angle but with low distance between spans and low wind obstruction show that an increasing angle deteriorates the correlation for the perpendicular wind speed. When two spans are not parallel, i.e. do not have an angle close to 0° between them, their span orientations are different and impact the measure of the perpendicular wind speed. As such, it is expected that the closer to 90° the angle between two spans is, the more their sensor perpendicular wind speeds should differ. The weather provider wind speed correlation is however not impacted as the information of direction is not included here.

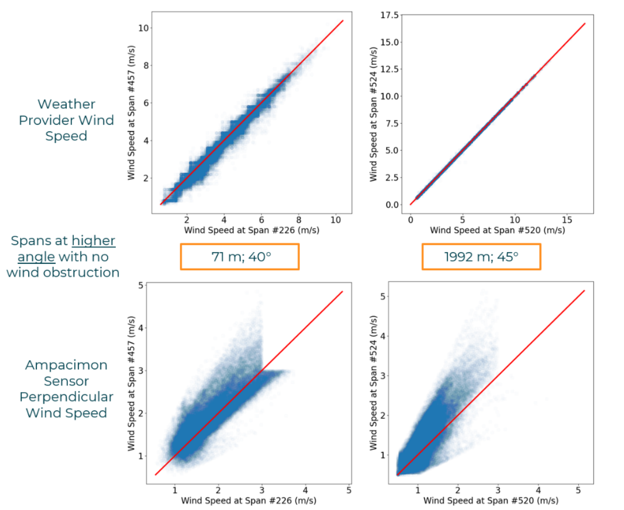


Figure 3: Wind speed from the weather provider and perpendicular wind speed from Ampacimon sensors - Correlation analysis between pairs of spans with medium angles and little wind obstruction conditions

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2.3. Wind Obstruction Along the Spans

The environment along each span, as seen in Google Map satellite images, is here classified into 3 categories: low, medium and high wind obstruction. This classification considers whether the environment is rural or urban; open field or obstructed by trees or buildings; and how dense the obstacles are. An example of such classification is shown in Figure 4.

Wind obstruction is a factor difficult to isolate in the pool of sensors. Furthermore, wind obstruction can only have an impact if two sensors are not too close to each other, otherwise both sensors may see the same wind. Therefore, in Figure 5, spans with medium to high wind obstruction at distances greater than 15 km between spans are shown. On the one hand, the weather provider wind speeds remain similar between pairs of spans. It can be deduced that wind obstruction is not accounted for by the weather provider. Moreover, weather models often suffer from a lack of resolution and weather stations are not measuring the wind at the altitude of the line. On the other hand, the pairs of Ampacimon sensors directly placed at the spans see a difference in perpendicular wind speeds. For instance, the sensor at the #461 (resp. #528; #168) span sees most of the time a higher perpendicular wind speed than the sensor at the #265 (resp. #519, #221) span.

Figure 4: Wind obstruction categories (view from maps.google.com). Line route is highlighted in red

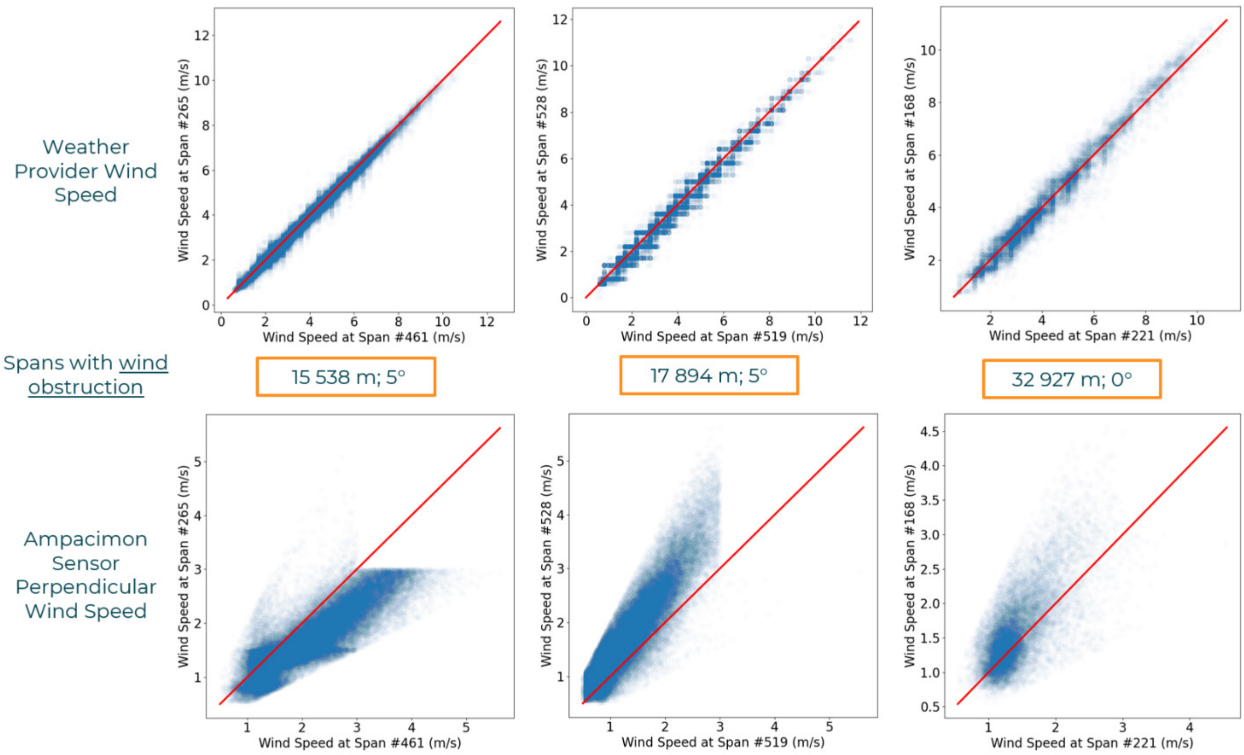

Figure 5: Wind speed from the weather provider and perpendicular wind speed from Ampacimon sensors - Correlation analysis between pairs of spans at different distances with low angles and high wind obstruction conditions

3. NEARBY SPAN EXTRAPOLATION

As described in [10], a usual approach to predict the wind, either in real-time or at a given horizon, is to train a proprietary neural network model per span that is first fed with the wind speed and direction of the weather provider and fit the output to the measured perpendicular wind speed at the Ampacimon sensor. At the end of the training, the model is able to correct the weather provider data to match the sensor data, learning thus to take the environment along the span into account.

To extrapolate this at another span, the main contribution of this paper is to define a nearby span extrapolation approach which consists in training a model on a first span and then run an inference on the trained model with the data of the weather service provider extracted at another span location close by. In the following, the year 2022 is set as the training period and the year 2023 as the inference period.

3.1. Ideal Scenario: Parallel Spans Connected to the Same Towers

In the scenario shown in Figure 6, a neural network model is trained at one span and runs at a parallel span just next to it (distance: 0m).

Figure 6: Two parallel spans next to each other equipped with Ampacimon sensors, both installed on the lowest phase (view from maps.google.com)

One predicted percentile, the P98, of the real-time perpendicular wind speed is plotted and can be compared to the true perpendicular wind speed measured at the sensor on the same span. Operators tend to manage lines in a very safe way and usually opt for the P99 or P98 curve that respectively targets a 1 and 2% of periods where the true wind is overestimated. With 3 months of inference data plotted, Figure 7 already shows encouraging results as the P98 follows closely the sensor wind curve without overestimating it most of the time.

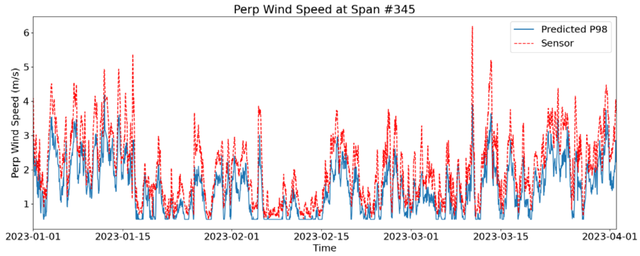

Figure 7: Perpendicular wind speed at the sensor and at P98 when extrapolating at the neighbouring span (0 m) in a parallel circuit

Figure 8 shows, for the P98, the number of consecutive hours of overestimation on the abscissa axis, the wind overestimates on the left ordinate axis and the number of overestimation sequences on the right ordinate axis. Looking at the red stars, most overestimates are below 0.5 m/s. Note that the model generates a rating prediction every hour. Out of a total of 7219 hours in 2023, very few hours of overestimation can be seen. As an example, there was only one overestimation sequence of 4h. This happened only 1 / 7219 < 0.02% of the time and the overestimates did not exceed 0.25 m/s during that sequence. Similarly, 74 overestimation sequences of 1 hour occurred during 2023. The biggest overestimate was of about 0.6 m/s but most were actually below 0.25 m/s. In fact, the empirical percentile computed on the data in 2023 is a P98.8, close to the theoretical target of a P98, ensuring here that only 100 – 98.8 = 1.2% of the time periods have seen overestimations. In this case, the extrapolation is thus a success confirmed by identical environment, weather and span orientation conditions. For perpendicular wind speed estimation, only a single sensor for both spans is here needed.

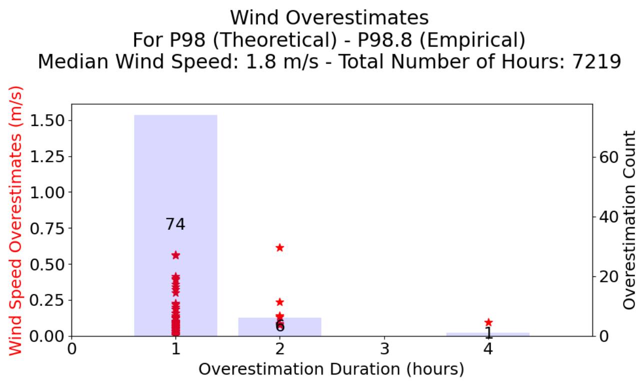

Figure 8: Perpendicular wind speed overestimation analysis at the 98th percentile when extrapolating at the neighbouring span (0 m) in a parallel circuit

Nevertheless, two sensors make sense in terms of operational safety as both spans may not see the same amount of current and as such would be in different thermal conditions despite being affected by the same weather conditions. It is likely that both spans would thus have different sag values, and this should be individually monitored to ensure that a safe clearance under each span is met.

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3.2. Acceptable Scenarios: Middle Distance, Low Angle and Little Wind Obstruction

In Figure 9, two spans are next to each other (140 m) on the same line with an angle of 10° and little wind obstruction disparity between both. Once again, a model is trained on 2022 data of the first span then an inference is run with this model at the second span on 2023 data. In Figure 10, an empirical percentile of P98.5 is obtained for a theoretical target of P98. Most overestimates (red stars) are moreover below 0.3 m/s. This yields very good extrapolation results.

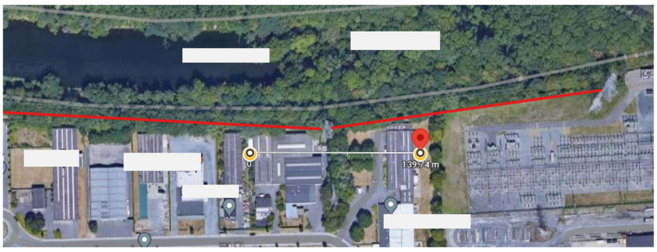

Figure 9: Two spans, highlighted in red, of the same line, next to each other (140 m) with an angle of 10° between each other and little wind obstruction disparity (view from maps.google.com)

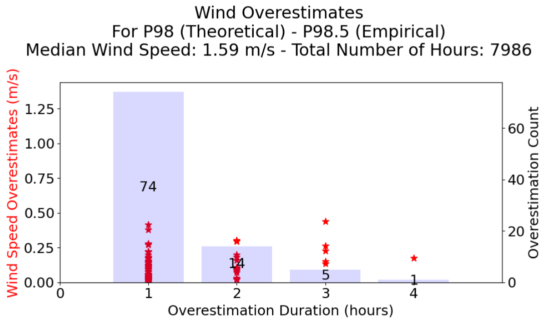

Figure 10: Perpendicular wind speed overestimation analysis at the 98th percentile when extrapolating at the next span (140 m) in a line with small span orientation change (10°) and medium wind obstruction

The same analysis can be made for the scenario of two spans yet distant of 10 508 m but still parallel (0°) and in a rural environment with low wind obstruction. In Figure 11, the theoretical P98 trained on 2022 data from the first span translates to an empirical P96.5 on 2023 data of the second span. The model is slightly underperforming with a 100 - 96.5 = 3.5% instead of 2% of time periods in overestimation. Despite moderately favorable conditions, this is still a very acceptable extrapolation scenario as most overestimates are below 0.3 m/s.

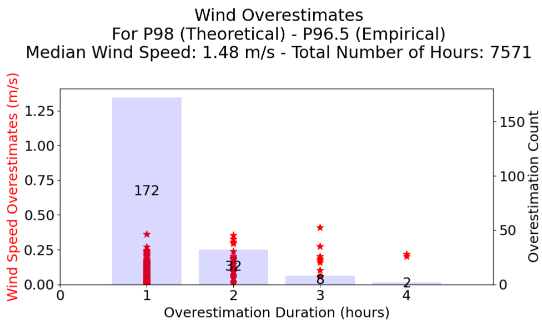

Figure 11: Perpendicular wind speed overestimation analysis at the 98th percentile when extrapolating at a parallel (0°), distant (10 508 m) span with low wind obstruction

3.3. Bad Scenarios: High Distance, Angle Close to 90° and/or High Wind Obstruction

The following scenarios would, however, not allow to safely extrapolate the perpendicular wind speeds.

As can be seen in Figure 12, due to unfavorable wind obstruction, an important angle and a moderate distance between both spans, extrapolating from one span to the other yields an empirical P95.2 instead of the targeted P98 in Figure 13. It translates to 100 – 95.2 = 4.8% of time periods in overestimation in place of a 2%. In this scenario, the extrapolation is already a bit too risky, and it would be advised to install two sensors.

Figure 12: Two spans, highlighted in red, at moderate distance (1000 m) of each other with an angle of 120° and with medium wind obstruction at both spans due to few buildings and trees (view from maps.google.com)

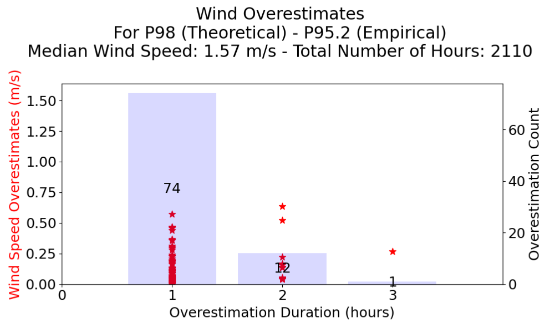

Figure 13: Perpendicular wind speed overestimation analysis at the 98th percentile when extrapolating at a moderate distance (1000 m) with some span orientation change (120°) and medium wind obstruction

If the distance between both spans is high (15 538 m) but the angle (5°) and wind obstruction are low, nearby span extrapolation starts to be risky. In Figure 14, the empirical percentile here is a P91.6 instead of a theoretical P98. This allows for 100 – 91.6 = 8.4% of time periods in overestimation instead of 2%.

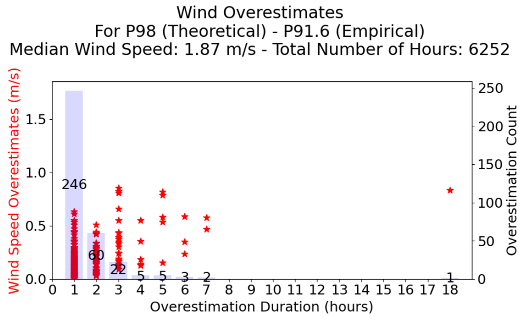

Figure 14: Perpendicular wind speed overestimation analysis at the 98th percentile when extrapolating at a high distance (15 538 m) with small span orientation change (5°) and low wind obstruction

It can be even worse if wind obstruction is important. In the next scenario, two spans are 17 894 m apart from each other and almost parallel (5°) but the wind obstruction is high because of a forest corridor at one span (see Figure 15).

Figure 15: One span, highlighted in red, in a forest corridor that shelters the wind (view from maps.google.com)

Training the model on one span and running an inference with it on the other span yield a dramatic wind estimation shown in Figure 16 with hundreds of overestimates that can sometimes jump well above 1 m/s. The empirical percentile on the year 2023 is estimated to be a P76.1

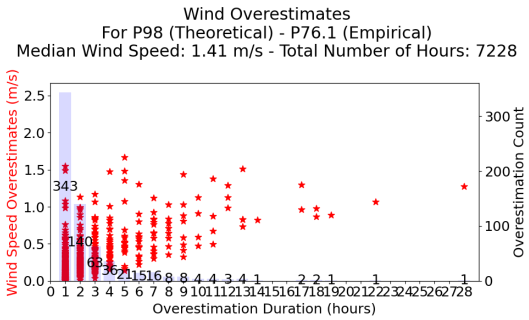

Figure 16: Perpendicular wind speed overestimation analysis at the 98th percentile when extrapolating at higher distance (17 894 m) with small span orientation change (5°) and high wind obstruction

instead of the targeted P98, which translates into 100 – 76.1 = 23.9 % of time periods in overestimation.

In this study, a choice was deliberately made to work with real-time values and at targeting the wind speed level instead of the rating level so as to limit the sources of uncertainty in the model to those that only come from the nearby span extrapolation approach. Moreover, rating is not a physical measure as opposed to wind speed and makes it harder to validate the results in the field.

The rating can however be computed by applying one of the thermal models defined in IEEE-738 [2] or CIGRE-TB-601 [3], feeding them with weather provider weather conditions (such as the solar radiation and ambient temperature), sensor-adjusted weather conditions (from the predicted perpendicular wind speed) and conductor parameters. Note that inputs such as ambient temperature, solar radiation, … though of much lesser influence than wind, would bring extra sources of uncertainty in the rating computation.

The methodology could also be reproduced at other time horizons than real-time. This will however factor in additional uncertainty that is external to the nearby span extrapolation approach. Indeed, the further the time horizons, the lesser the accuracy when the weather provider forecasts the wind.

4. EMPIRICAL CONDITIONS FOR NEARBY SPAN EXTRAPOLATION

Following an extended analysis, three main factors can prevent nearby span extrapolation:

- Very distant spans (> 15km)
- Perpendicular spans (90° +/- 35°)
- High wind obstruction (tall buildings, numerous trees, urban environment)

On a case-by-case basis, some factors can alter the nearby span extrapolation confidence:

- Distance ∈ (500m; 15 000m]
- Angle ∈ (5°, 65°] ∪ [125°, 175°)
- Medium wind obstruction (a few buildings, a few trees, ...)

Some factors do not impact the nearby span extrapolation confidence:

- Distance ∈ [0m; 500m]
- Angle ∈ [0, 5°] ∪ [175°, 180°]
- Low wind obstruction (no building, no tree, open field, rural)

It is good to note that wind obstruction can vary with time. As such, tree pruning or growing vegetation should be checked at a regular time interval to safely extrapolate if the distance between both spans is typically higher than 500m.

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A final main contribution of this paper is the decision tree in Figure 17. To help decide on whether nearby span extrapolation can be considered, it is advised to refer to it.

5. CONCLUSION

To maximise power line usage and alleviate congestions, dynamic rating estimation based on variable weather conditions is an efficient solution that ensures safe line operation. This method has a proven track record worldwide with several years of successful implementations in SCADA systems. However, the widespread adoption of Dynamic Line Rating is impeded by the cost associated with sensor installation.

In this paper, a hybrid approach between sensor-less and sensor-based DLR has been explored by extrapolating the real-time perpendicular wind speed from sensor-equipped spans to other spans. As explained before, the results can be easily reproduced at further time horizons than real-time and at the rating level instead of wind speed level. It has been shown that perpendicular wind speed can be effectively extrapolated from one span to another depending on three important factors: distance between both spans, angle between both spans and wind obstruction along either span. A direct application of this study includes DLR estimation at all redundant lines (parallel spans) and at dense regions of overhead lines where low distance between spans is observed. Without losing accuracy, nearby span extrapolation will help to scale DLR cost-efficiently by optimizing the number of sensors needed while preserving access to trustworthy local wind measurements.

6. FUTURE WORK

In this study, extrapolating at nearby spans has proven to be a way to better scale sensor-based DLR. In many scenarios however, spans may not be close or parallel and the environment along them may drastically change. Furthermore, relying on the historic data of only one span to extrapolate at others can introduce some performance drift due to growing vegetation around either span. This must be carefully monitored over time.

To cope with the bias of relying on only one sensor-equipped span to extrapolate at other spans, another approach could be to rely on a multi-line model. This model could be trained on historic data from different lines scattered across a specific region. It should thus learn from different environment and span configurations. This regional model could then be used to run inferences on any other span in the same region. Further research must be undertaken to evaluate this methodology.

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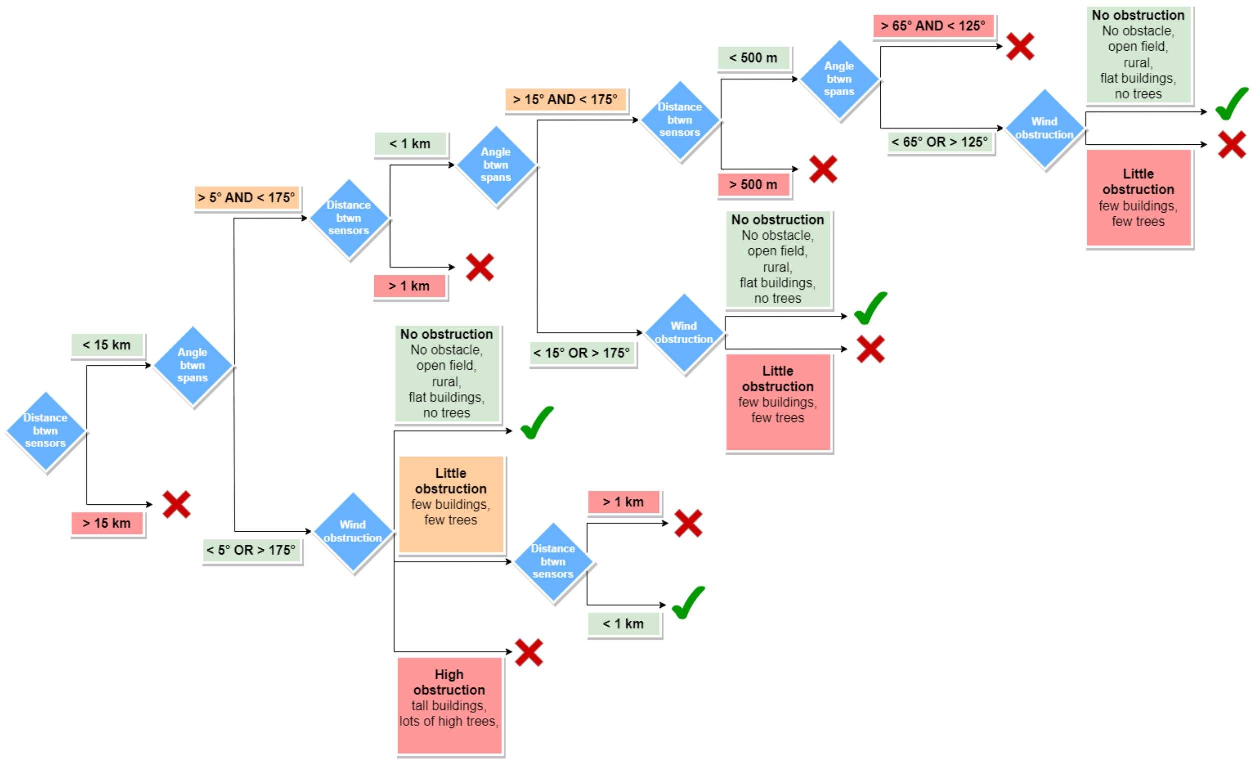

Figure 17: Nearby span extrapolation decision tree

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