Overhead line ampacity forecasting with a focus on safety

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***Abstract*—Predictions of the ampacity of overhead lines can be framed in a general context that aims to make electric grids highly efficient and reliable. In this paper, a methodology is presented that provides ampacity forecasts, which are valid for both the very short term, such as a few minutes or hours, and longer terms, up to 24 hours ahead. The former can be useful for grid operations, while the latter may be valuable in electricity markets. A time series methodology and mesoscale weather forecasts have been combined in machine learning algorithms for producing reliable ampacity forecasts for a span located in complex terrain. In a prior step, the developed algorithms made point forecasts, but finally, a computationally inexpensive algorithm produces probabilistic forecasts. These probabilistic forecasts are nonparametric, as they are not based on predefined probability distributions, and they demonstrate how a low risk in overhead lines is closely related to the reliability of ampacity forecasts.**

***Index Terms*—Energy efficiency, power distribution, power system management, smart grids, wind energy integration.**

I. Introduction

NOWADAYS, most electric grids are still operated under the supposition of a constant ampacity of their lines, as measured by the so-called static thermal rating. The same weather conditions are assumed for every hour of the day, every day of the year or season, and for entire regions where multiple overhead lines are located. This static rating may be seen as a conservative estimation whose calculation is based on the assumption of low-convective cooling due to wind, high air temperatures and solar radiation [1]. If the current and weather conditions are steady, the conductor is supposed to be in thermal equilibrium, and thus, its thermal state can be defined [2] [3] as in (1), where P_J stands for Joule effect heating, P_S represents solar radiation heating, P_C denotes convection cooling, and P_R represents radiative cooling. Evaporative cooling is usually neglected due to its small weight in the overall thermal balance, although it was analyzed in [4].

$$P_J + P_S = P_C + P_R \tag{1}$$

However, if the thermal capacity of overhead lines must be used efficiently, it is necessary to account for variations in the weather conditions, leading to the concept of the dynamic thermal rating (also called the dynamic line rating). The dynamic rating varies over time and over space. Thus, it varies along a line and may be different for lines with similar characteristics. Therefore, a large portion of the thermal capacity of lines can be made available when the weather conditions are favorable, and they can be operated safely when the conditions are unfavorable.

The methods for the dynamic calculation of ampacity can be divided into two main categories. The ambient-adjusted dynamic line rating (DLR-AA), which is only based on air temperature variations, enables the dynamic adjustment of multiple lines in a region for the same temperature when air temperature gradients are small [5]. On the other hand, for dynamic line ratings with real-time monitoring (DLR-RTM), variations in other weather magnitudes are also considered, and a larger portion of the thermal capacity of the lines is made available because of the important impact of forced convection cooling on conductor ampacity [1] [5]. In the latter case, ampacity is estimated at particular line locations, but the total thermal capacity of a line is limited each time by a different span and can be calculated as the minimum along the line [6]. There are different approaches for real-time ampacity calculation (DLR-RTM) [7] [8]:

1) *Direct measurement of weather conditions*
2) *Conductor temperature measurement*
   The current, conductor temperature, solar radiation, and air temperature are measured, and then, the perpendicular effective (PE) wind speed is calculated.
3) *Sag or tension measurement*
   Sag can be related to the average temperature of the conductors along a line section or span.

The dynamic rating of a line can be estimated in real time from the measurements obtained by devices distributed along it or predicted for different time horizons. Ampacity predictions are useful for grid operations, but such calculations must rely on a real-time monitoring system, which ensures that the maximum allowable conductor temperature (MACT) is not exceeded [5]. If it is exceeded, this situation may lead to risk due to insufficient clearances along a line, premature aging of conductors, or the annealing of the aluminum conductor strands. In recent years, a few companies have made their grid operations dynamic [9] [10] [11], although only the company in [11] makes ampacity forecasts.

When ampacity is forecasted more than a few hours ahead, weather forecasts are needed. However, the resolution of

This work was supported by the Ministerio de Economía, Industria y Competitividad, under the Project DPI2016-77215-R(AEI/FEDER, UE).
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mesoscale wind forecasts makes their adaptation to the orography and conditions of overhead lines necessary. This paper proposes a methodology for forecasting the ampacity of overhead lines that explores time horizons short enough for grid operations and horizons long enough for day-ahead electricity markets. This demonstrates how, even though they reduce errors to a minimum, point forecasts lead to risks. Otherwise, high-reliability probabilistic forecasts ensure that when a probability level is selected, safety is guaranteed up to this level while the potential thermal capacity of overhead lines is unlocked beyond the static rating.

II. State of the Art Forecasting Methods

The existing studies on overhead line ampacity forecasting are based on direct measurements or forecasts of weather conditions from numerical weather prediction (NWP) models. In many of them, algorithms for the individual prediction of each weather magnitude (wind speed and direction, air temperature, and solar radiation) are described. These individual predictions are used as inputs for a thermal model to calculate ampacity forecasts for different time horizons.

Nevertheless, the various weather magnitudes are mutually correlated, and sometimes their effects on overhead conductors cancel each other. The magnitudes with the largest influence on the temperatures of conductors is wind speed, followed by air temperature and solar radiation; and other factors, such as rain and moisture, are usually neglected [3]. At high wind speeds, the cooling of conductors is dominant, while at low wind speeds, air temperatures and solar radiation can raise conductor temperatures considerably [1]. Therefore, in a different approach [12] [13], the thermal model for the conductor can be directly used to produce ampacity "observations" from local measurements of the weather magnitudes or raw ampacity "forecasts" from NWP model outputs, which are inputs for statistical models used to forecast ampacity.

Many of the methods found in the literature make point forecasts and produce a single value as the ampacity forecast for each time point in the future. They try to minimize the error independent of its sign; the sign is positive for ampacity forecasts above observational values, which means that the MACT is exceeded, or negative. However, there is always uncertainty inherent to each forecast, and it can be expressed as a probability, in the form of prediction intervals, or as prediction quantiles. Therefore, probabilistic ampacity forecasts allow for the selection of a particular risk level and thus the heating level of conductors.

Probabilistic forecasts can be parametric or nonparametric (empiric). The parametric approach is based on the assumption of a certain probability distribution and defined by the parameters of its probability density function (PDF). In some cases, a Gaussian distribution is assumed, but wind speed is usually modeled as an asymmetric Weibull distribution, and wind direction is modeled with the Von Mises distribution. Ampacity forecasts are then estimated from the forecasts of the weather magnitudes via simulations based on the Monte Carlo method [14] [15] [16]. Otherwise, in nonparametric approaches, no assumptions about the shape of the probability distributions are made beforehand, and empiric prediction intervals or quantiles are calculated [12] [13].

On the other hand, the prediction of wind speed or the power output of wind turbines [17] can be classified based on the following:

1) *Statistics of local measurements*
2) *Weather forecasts (NWP models)*
3) *Physical approach (NWP models + terrain model)*
4) *Statistical approach (NWP models + local measurements)*
5) *Combination of the physical and statistical approaches*

Despite some aspects that must be taken into account [18], there is a correlation between line ampacity and wind power output; the closer an overhead line is from a wind farm, the higher the correlation [19]. Therefore, ampacity prediction can be similarly classified based only on local measurements or based on NWP models.

A. Measurement-based ampacity prediction

Most of these prediction models use series of past measurements of various weather magnitudes to forecast each of these magnitudes individually; however, solar radiation is usually modeled with a Fourier series as a function of the position of the sun. Typically, measurement-based forecasts have a time horizon of one hour, and longer horizons have yielded poor results [20] [21]. Ampacity forecasts based on an autoregressive (AR) air temperature model, considering a low, constant PE wind speed, are described in [21], whereas AR models for air temperature and wind direction and transfer function models for wind speed and the Nusselt number are preferred in [20]. A different approach is proposed in [14], where AR models with Bayesian inference are used to estimate the parameters of the probability distribution of the forecast for each weather variable. All these individual probabilistic forecasts are combined to make probabilistic forecasts of conductor temperatures. In [22], air temperature and wind speed are decomposed in the north and east directions and forecasted by AR and VAR (vector autoregressive) models and their heteroscedastic counterparts, AR-CH and VAR-CH.

There are also some cases based on artificial neural networks (ANNs), which make point forecasts, and these include a finite impulse response neural network trained with the back-propagation algorithm [23], a multilayer perceptron trained with the Levenberg Marquardt algorithm [24], and a gated recurrent unit network [25]. On the other hand, a different methodology, not based on time series, is presented in [26] [27], where the uncertainty of the forecasts is quantified as empiric quantiles calculated by using quantile regression and quantile regression forests (QRFs) with a set of weather measurements.

B. NWP-based ampacity prediction

NWP-based ampacity forecasts have a typical time horizon of 24 to 48 hours imposed by the scale of the NWP model. Although mesoscale resolution weather forecasts are directly used in some proposals [28], some kinds of physical or statistical adjustments are necessary to achieve a reduced risk of exceeding the MACT. This is due, at least in part, to the resolution of mesoscale models, which are not enough to account for the local effects of wind [17]. To avoid this issue,

The final version of record is available at http://dx.doi.org/10.1109/TPWRD.2021.3059804

in [29], a conservative ampacity prediction is made that takes air temperature forecasts into account but uses static values for wind and solar radiation. Thus, a reduced risk is achieved, but in return, only a minor portion of the thermal capacity of overhead lines is made available when small convective cooling is considered.

As stated before, a physical model accounts for the effects of orography. Weather forecasts can be interpolated as functions of distance and wind speed corrected for terrain rugosity by a "wind profile power law", as in [15] [30]. Probabilistic forecasts (average, standard deviation, maximum, and minimum), which are calculated from weather point forecasts of each weather magnitude, are also possible [15]. In addition, by using computational fluid dynamics (CFD) software, a resolution of a few meters for wind forecasts can be achieved [31].

The statistical approach, on the other hand, is intended to adjust mesoscale weather predictions to different locations of an overhead line. In [11] [32], mesoscale weather forecasts are processed with statistical tools and reinforcement learning that use input measurements from Ampacimon devices and weather stations. In [33] [34], weather forecasts are adapted to local measurements by different types of interpolation. In [35], past measurements and weather forecasts are used as inputs for a multivariate regression model, whose features are selected by principal component analysis. In [16], 20 scenarios of a weather forecast ensemble are processed. Probabilistic forecasts are made for each weather variable, where the model parameters are estimated by the expectation maximization algorithm, with local measurement training data. In [36], hourly ampacity forecasts are made for selected spans, and these are considered critical for determining the overall ampacity of a line. Weather point forecasts and measurements are used as inputs for an extended Kalman filter-based ANN to make probabilistic forecasts of the weather variables. Ampacity averages and standard deviations are calculated by Taylor´s expansion series.

In [12], interpolated weather forecasts and measurements are used to make ampacity forecasts up to 27 hours ahead. One-year series are used to train several forecasting models: generalized linear models, multivariate adaptive regression splines, random forests, and quantile regression forests, with the latter being the only one that produces probabilistic forecasts. In [13], probabilistic ampacity forecasts, up to 24 hours in advance, are made for several locations on a line. This work centers on the selection of a forecast's optimal quantile, which minimizes power generation costs due to a reduced transmission capacity. Forecasts are generated by a model based on a QRF, with recent observations and interpolated weather forecasts as inputs. In [37], the forecasts are extended up to 42 hours ahead with additional models: a quantile linear regression, mixture density neural network, and kernel density estimator.

III. Case Study

The methodology for the prediction of ampacity proposed in this paper uses local weather measurements and forecasts. To develop this methodology, available measurements from a pilot line property of the Iberdrola utility and weather forecasts for the location of the line are used.

A. *Pilot line*

The pilot line is a 30-kV distribution line across complex terrain located in Basque Country in Spain, with aluminum core steel reinforced (ACSR) conductors of type 147-AL1/34-ST1A (LA-180). The MACT assumed by Iberdrola for this line is 75 °C. The measurement instruments, including cup and ultrasonic anemometers, an air temperature sensor, and a solar radiation sensor, were installed on one of the supports of the line for almost three years. A datalogger registered these measurements each minute and sent them by GPRS to a server.

Weather forecasts for the region where the line is located were produced from a high-resolution limited-area model (HIRLAM) with 0.05° spatial resolution. At this latitude, the distance between mesh nodes is 4 km (longitude) and 5.5 km (latitude). The model forecasts wind speed and direction at a 10 m height, air temperature at 2 m, and solar radiation at surface level. The forecasts for nodes near the pilot installation were interpolated to obtain forecasts for this location by the Spanish National Weather Agency (Agencia Estatal de Meteorología, AEMET). The model runs every 6 hours (at 00:00, 06:00, 12:00, and 18:00 hours), with forecasts up to 36 hours ahead and a resolution of 3 hours.

B. *Data analysis and preprocessing*

Prior to use, the data were processed as follows:

1) Calculation of perpendicular effective wind speed (both measured and forecasted wind)

2) Time interpolation of the weather forecasts (3-hour to 1-minute resolution; each run interpolated between the forecasts for different amounts of times in advance)

3) Calculation of 10-minute average measurements and weather forecasts

4) Calculation of the "observed" and "forecasted" ampacity time series with CIGRE´s steady-state thermal model

5) Splitting of data into training (1 year) and test (2 years) datasets

It was also considered that NWP models run at a certain hour, with all data available until that time, but the models require several hours for computation. In the case of the HIRLAM model run by AEMET, forecasts are available after 4 hours. Thus, the most recent run available was selected. This can be seen in the example of Fig. 1, where the 4-hour delays are marked in red, in-time available data in green, and data used for 24-hour-ahead ampacity forecasts starting at 12:00 in blue.

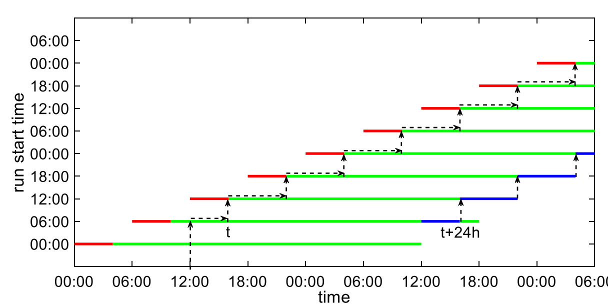

Fig. 1. Example of the NWP model output for each run.

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Data were analyzed before and after being processed. Currently, most overhead lines are operated with regard to a static rating, which was used as a reference. In the region where the pilot line is located, 0.6 m/s PE wind speed, 26 °C air temperature, and 1000 W/m^2 solar radiation were considered. In such conditions, the static rating for the pilot line was calculated as 482.3 A. Despite being a conservative rating, it exceeds the MACT of the pilot line 11.6 % of time. This value is much larger than the 1 % recommended by CIGRE [1]. In the same document, it is also recommended to not exceed the MACT by 20 °C, and this is not achieved. The percentage of time that the static rating exceeds the ampacity observations is represented in red in Fig. 2. For other times, represented in light yellow, there is no risk, but most of the capacity of the pilot line is wasted.

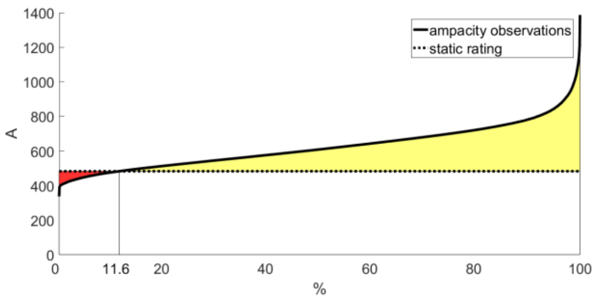

Fig. 2. Static rating of the pilot line.

The relationship between ampacity and each of the weather variables was analyzed. In each case, no simple linear relationship, which could lead to the construction of simple models for forecasting ampacity, could be observed. The dependency of ampacity on recent observations and weather forecasts was also analyzed. In Fig. 3, the autocorrelation function (ACF) of the ampacity training series (10-minute lags) is demonstrated. A certain daily periodicity and an important autocorrelation with respect to the most recent hours can be observed. The cross-correlation of the observed ampacity for the forecasted ampacity training series was 0.53.

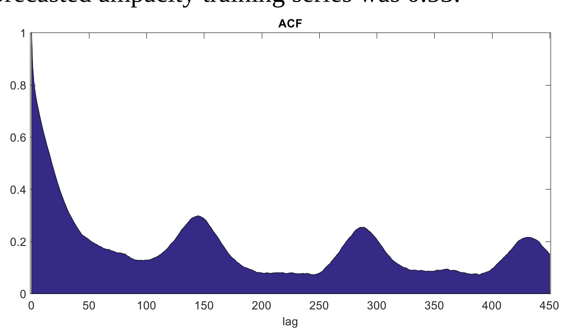

Fig. 3. Autocorrelation of ampacity observations.

IV. Point Forecasting

As stated above, a methodology for the prediction of ampacity for time horizons that is useful both for grid operations and for electricity markets is proposed in this paper. Although it was expected that weather forecasts would be needed for 24-hour-ahead ampacity forecasts, an autoregressive integrative moving average (ARIMA) model, based only on measurements, was also used for comparison purposes. Different algorithms were developed based on linear regression (LR) and an ANN, both of which produce point forecasts. In a further step, explained in the next chapter, an algorithm for producing probabilistic forecasts from point forecasts, used to reduce the risk of the forecasts, is also proposed.

A. Measurement-based ampacity forecasting

ARIMA models allow for the prediction of the evolution of a process from recent observations of related magnitudes. The observations can be measurements of physical magnitudes such as wind speed, air temperature, or solar radiation, or they can be derived magnitudes such as ampacity. In this work, the latter approach was taken; thus, the ampacity calculated from recent weather measurements was used to forecast its future outcomes. A model was obtained from the training dataset after a procedure of identification, parameter estimation, and checking. Once the model was obtained, ampacity was forecasted for the test period while keeping the model parameters constant over this period.

Several ARIMA models were identified, and then, the model with the lowest Bayesian information criterion (BIC) was selected: (1,1,1) x (0,0,0). Their parameters were estimated by the maximum likelihood method, leading to (2), where x_t is the ampacity to be forecasted at time t; x_{t-1} and x_{t-2} are ampacity observed for the previous 10 and 20 minutes, respectively; and a_t and a_{t-1} are the current and 10-minute lagged forecasting errors.

$$x_t = 0.62\, x_{t-1} - 0.38\, x_{t-2} + a_t + 0.74\, a_{t-1} \qquad (2)$$

In the forecasting procedure, ampacity is sequentially forecasted from the start of the test dataset by using (2) until the series is depleted. If at any given time there is not enough available data, no forecast is made.

B. Weather forecast- and measurement-based ampacity forecasting

To reduce the error of the ampacity forecasts that can be directly calculated from the NWP model output, a methodology with a statistical approach that combines this output with observations based on local measurements is proposed. Two different models based on machine learning are proposed, although both use the same predictors and data. The first model is based on LR, and the second is based on a single-layer perceptron ANN (SLP-ANN, or SLP).

The features of both models were selected while taking into account, among other factors, the autocorrelations of the ampacity observations. The data were normalized between 0 and 1 and ordered in a matrix used for all time-ahead forecasts, thereby providing all necessary data. The following features were checked, resulting in 17 out of 18 being significant:

1) *Observations at the current time, and for the previous 10, 20, and 30 minutes and 1, 2, 4, and 24 hours*
2) *Average of observations for the previous 30 minutes and 1, 2, 4, and 24 hours*
3) *AEMET-based forecasts for the next 30 minutes and 1, 2, 4, and 24 hours*

A different LR model was trained for each time horizon to find the most suitable coefficients. The selection of these coefficients was performed to minimize the error in a ten-fold cross-validation procedure. Thus, the training data were split into ten subsets, nine of which were used to train the model, and the remaining subset was used to calculate the root mean square error (RMSE). This procedure was repeated ten times to calculate the final error as the averaged RMSE.

The single-layer perceptron was trained with the back-propagation algorithm. The selection of this model was due to computational capacity limitations, which outweighed the necessity for highly complex models. Similar to the LR models, a different model was trained for each time horizon, and a cross-validation process was used to minimize the RMSE. The number of neurons in the hidden layer and the weight decay parameter that led to a minimum RMSE were also selected. The number of neurons was restricted to 20 due to computational capacity limitations, and the weight decay was 0.01.

C. Evaluation of point forecasts

To evaluate the proposed methods, each forecast for the time horizons ranging from 30 minutes to 24 hours using the entire test dataset was compared to the corresponding observation. The normalized root mean square error (NRMSE) was calculated as the RMSE divided by the range of observations. The normalized mean absolute error (NMAE) and normalized bias (NBias) were obtained by dividing each individual error by each individual observation, as in [12] [37].

The forecasts obtained by the proposed methods were also compared to reference values, such as the static rating or the ampacity directly calculated from raw NWP model outputs (AEMET). In Fig. 4 and Fig. 5, it can be observed how the LR and SLP models induced small errors for short time horizons, as they depend on recent observations, and outperformed the static rating and AEMET, even for long time horizons. It is worth mentioning that AEMET produced the same error level and a large positive bias for any amount of time ahead. In fact, this positive bias means that the ampacity forecasts were generally above the observations, and if NWP model forecasts were directly applied to forecast ampacity, it could potentially lead to large MACT exceedance. The LR and SLP models also outperformed the ARIMA model, mainly for the longest horizons, as they benefit from weather forecasts. The errors of the LR and SLP models were similar to those found in [23] [12] [37], with NMAEs close to 10 % for 1- or 2-hour-ahead time horizons and below 15 % for longer horizons. Although the single layer perceptron model is more complex and requires much more computational time than the LR model, the results obtained by both methods were similar, with comparable error levels.

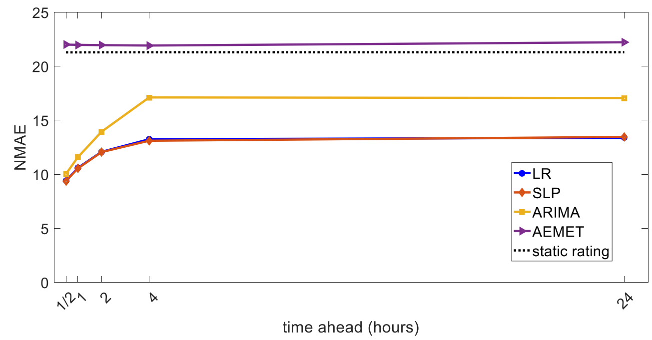

Fig. 4. NMAE of ampacity point forecasts.

The percentage of forecasts that exceeded observations was also counted, and this value can be viewed as the percentage of MACT exceedances over time if any precaution, such as a real-time monitoring system, is not taken. For all the time horizons evaluated, AEMET reaches a 78 % exceedance level, and this produces a high risk of the conductors overheating. With the LR, SLP, and ARIMA models, the observations exceeded the MACT 50 % to 55 %. This means that more than half the time, the MACT of conductors could be exceeded and this fact agrees with an NBias close to zero. However, it is shown below how with probabilistic forecasts, the level of overprediction can be selected, leading to safer ampacity forecasts.

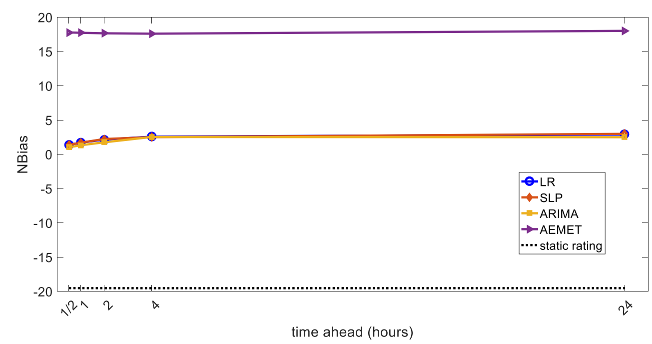

Fig. 5. NBias of ampacity point forecasts.

V. Probabilistic Forecasting

The uncertainty associated with forecasting can be expressed as probabilistic forecasts. In a parametric approach, a PDF for each ampacity forecast cannot be directly calculated from the forecasts of the weather magnitudes. This adds some difficulty, as computationally demanding simulations, such as those based on the Monte Carlo method, are necessary. Otherwise, in a nonparametric approach, ampacity forecasts are less computationally demanding. No assumptions about the shapes of probability distributions are made beforehand, and empiric prediction intervals can be calculated. These intervals may be asymmetric and not centered on point forecasts. It is possible to express probabilistic forecasts in the form of quantiles, defined as the probability τ that the forecasts $\hat{X}^{\tau}_{t+h|t}$ exceed the observations X_{t+h}, as in (3). This provides the grid operator with a direct evaluation and selection of the level of risk that each particular line exceeds the MACT, as opposed to the static rating or point forecasts with fixed risks that in some particular cases may be too high.

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$$P\left(\hat{X}^{\tau}_{t+h|t} > X_{t+h}\right) = \tau \qquad (3)$$

In this work, empiric quantiles of the errors of the ampacity point forecasts for the training dataset are proposed. The errors are assumed to be constant over time, so probabilistic forecasts can be easily calculated by subtracting the error quantiles from each point forecast in the test dataset. TABLE I and TABLE II show the error quantiles calculated for 1 h- and 24 h-ahead point forecasts, respectively.

TABLE I
ERROR PERCENTILES FOR 1 H-AHEAD POINT FORECASTS (A)

Percentile	LR	SLP	ARIMA	AEMET
25	57.5	55.6	59.0	187.1
10	102.8	99.5	114.2	264.4
5	129.6	125.9	152.6	310.9
2.5	154.2	148.6	186.2	349.0
1	184.8	180.2	229.8	391.6
0.5	206.6	203.9	263.9	415.8

TABLE II
ERROR PERCENTILES FOR 24 H-AHEAD POINT FORECASTS (A)

Percentile	LR	SLP	ARIMA	AEMET
25	74.6	70.8	85.9	183.9
10	126.3	120.3	175.7	264.4
5	155.8	149.3	235.3	315.7
2.5	180.8	174.4	297.0	361.1
1	208.3	204.4	385.5	412.5
0.5	227.7	227.5	451.4	447.6

Fig. 6 shows an example of 24 h-ahead forecasts produced from the LR model with empiric quantiles for a two-day period. It can be observed how the point forecasts try to match the observations and minimize the mean error but overpredict ampacity near half of the time. Probabilistic forecasts allow for the selection of quantiles that overpredict ampacity for a small fraction of the total points.

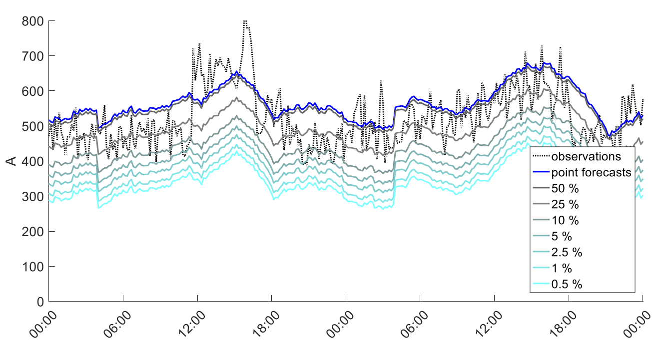

Fig. 6. 24 h-ahead probabilistic ampacity forecasts from the LR model.

VI. RESULTS

Some recommendations about the safe operation of overhead lines are given in [1], and these are valid when the weather conditions (static or dynamic) are considered during ampacity calculations. Among these recommendations is that the average temperature of each line section should never exceed the MACT by 10 °C or more than 1 % of the time. Additionally, the local conductor temperature should never exceed the MACT by 20 °C. Safety criteria related to the conductor sag should also be considered.

The quality of the forecasts has been evaluated following some of these recommendations. Good reliability ensures that when a forecast quantile is selected, the percentage of temperature exceedances can be known beforehand. The sharpness of the ampacity forecasts is related to the efficiency of the lines, and this was also investigated. The sharper these forecasts are, the shorter the distance from each low percentile to the median is, and the larger the forecasted ampacity will be. Therefore, a large thermal capacity will be unlocked, provided that the forecasts are reliable enough to avoid unnecessary risk.

To quantify reliability, the percentage of forecasts that exceeded their corresponding observations over the whole test period was calculated for each quantile. The closer to the quantile this value is, the more reliable the forecasts are. In this manner, it is possible to quantify the risk of overprediction for each quantile and each time horizon. In Fig. 7 and Fig. 8, the quantiles are represented on the X axis, and the proportion of forecasts that exceed the observations is on the Y axis. Perfectly reliable forecasts are represented by the diagonal line, for which forecasts for the quantile τ exceed observations at the same proportion τ. The reliability of the probabilistic forecasts calculated from the point forecasts of the LR, SLP, ARIMA, and AEMET models are compared in Fig. 7 and Fig. 8. It can be observed how the reliability is better for smaller quantiles (0.5, 1, and 2.5), with values closer to the diagonal line. The reliability is worse for larger quantiles, independent of the time horizon chosen, although this tendency is clearer for longer time horizons. These results improve upon the results found in [36], with a frequency of 4.1 % for the 2nd percentile.

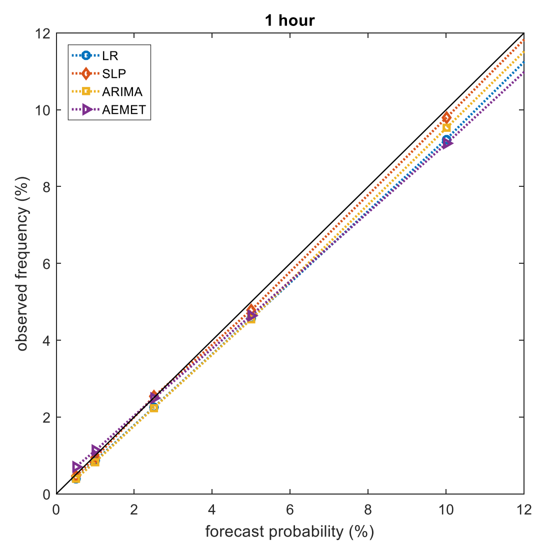

Fig. 7. Reliability of 1-hour-ahead ampacity forecasts.

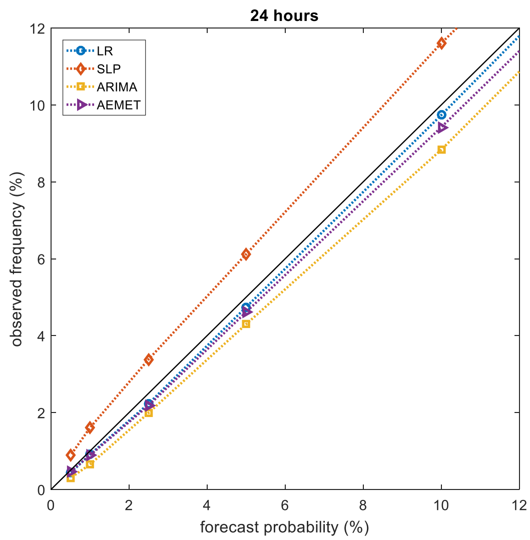

Fig. 8. Reliability of 24-hour-ahead ampacity forecasts.

In [12] [37], both reliability and sharpness, as well as measures of the quality of probabilistic forecasts, such as the continuous ranked probability score (CRPS) or quantile score (QS), are used. However, the forecasting algorithms do not specifically seek a good quality level for the lowest quantiles, which have the lowest risk and would probably be selected during grid operations or in electricity markets. On the other hand, indicators such as the CRPS evaluate the whole range of probability in the same manner and are given in amperes, and this makes comparisons to other lines of different thermal capacities difficult.

In this paper, only the ampacity forecasts for low percentiles were calculated because they are the safest, and the distribution of the calculated nonparametric forecasts is not symmetric. Therefore, an indicator that accounts for the sharpness of forecasts in the form of the average distance from each percentile forecast to the median is defined as in (4), which evaluates this distance as a percentage of the low half distribution of observations. In contrast with the literature, in this paper, it is calculated as a percentage, and this allows for the comparison of the results to those of different lines.

$$\text{width} = \frac{\sum_{i=1}^{N}\left(\hat{x}_{P50,i} - \hat{x}_{Pn,i}\right)}{N \cdot \left(x_{P50\ train} - x_{P0.5\ train}\right)} \cdot 100 \qquad (4)$$

In Fig. 9 and Fig. 10, it can be observed how forecasts from the proposed methods, LR and SLP, are much sharper than forecasts from the ARIMA and AEMET models and how 1-hour-ahead forecasts are sharper than forecasts for longer time horizons. Although the point forecasts obtained from raw weather forecasts, without any statistical adjustment (AEMET), are biased and lead to an important risk of ampacity overprediction, the proposed methodology for the calculation of empiric quantiles compensates for this bias and produces probabilistic forecasts with a reliability comparable to the those of the forecasts based on the LR and SLP models. However, as their sharpness is much smaller (larger distances from the lowest quantiles to the median) than those of the LR and SLP models, only a small portion of the thermal capacity of overhead lines can be unlocked.

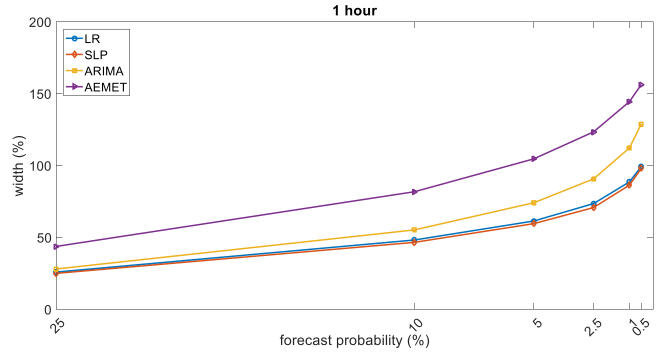

Fig. 9. Sharpness of 1-hour-ahead ampacity forecasts.

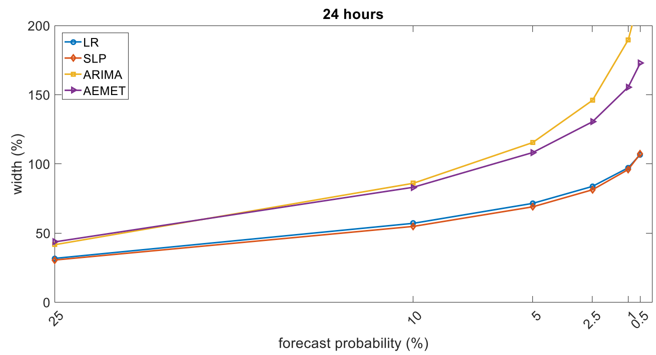

Fig. 10. Sharpness of 24-hour-ahead ampacity forecasts.

VII. Conclusion

Among the main contributions of this paper with respect to the literature is the development of a methodology and the comparison of several models used for producing ampacity point forecasts. Some of the models are based on weather measurements, while others are based on the adjustment of NWP model outputs to the scales of overhead lines. The latter approach uses machine learning and compares favorably to the literature while making efficient use of computational resources.

Second, but not less importantly, is the contribution to the development of a simple method that produces probabilistic forecasts from point forecasts. Probabilistic ampacity forecasts allow grid operators to select the thermal risk level for a particular line and make a more efficient use of the thermal capacity of lines than when using the static rating. However, it is demonstrated in this paper that the reliability of probabilistic forecasts plays a major role in the assessment of risk levels, and the methods developed here also compare favorably to the literature. This can be of particular importance for critical segments of lines in complex terrain, where the wind speed is usually low across some spans, leading to large sags.

Therefore, the main contribution of this paper is the development of a methodology that allows day-ahead probabilistic forecasts with high reliability for the lowest percentiles without compromising efficiency. Additionally, it must also be remarked that the proposed methodology was tested for time horizons from 30 minutes to 24 hours, and this makes it useful not only for grid operation but also for electricity markets.

ACKNOWLEDGMENT

The authors would like to thank the Iberdrola utility for the help provided with regard to the development of this project.

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