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Dynamic Line Rating Using Numerical Weather Predictions and Machine Learning: a Case Study

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***Abstract*—In this paper a dynamic line rating experiment is presented in which four machine learning algorithms (Generalized Linear Models, Multivariate Adaptive Regression Splines, Random Forests and Quantile Random Forests) are used in conjunction with numerical weather predictions to model and predict the ampacity up to 27 hours ahead in two conductor lines located in Northern Ireland.**

The results are evaluated against reference models and show a significant improvement in performance for point and probabilistic forecasts. The usefulness of probabilistic forecasts in this field is shown through the computation of a safety-margin forecast which can be used to avoid risk situations.

With respect to the state of the art, the main contributions of this paper are: an in depth look at explanatory variables and their relation to ampacity, the use of machine learning with numerical weather predictions to model ampacity, the development of a probabilistic forecast from standard point forecasts and a favourable comparison to standard reference models.

These results are directly applicable to protect and monitor transmission and distribution infrastructures, especially if renewable energy sources and/or distributed power generation systems are present.

***Index Terms*—dynamic line rating, forecasting, machine learning, time series**

I. Introduction

The growth in the penetration of renewable energy sources in the European electrical system (with 90GW wind farm installed capacity and more than 10% annual growth [1]) has implied that transmission and distribution (T&D) networks need to adapt to the variable nature of these sources, increasing their capacities. Moreover, it is widely expected that much of the future growth of renewables may be based on distributed power generation systems (DG), which also raise issues concerning the T&D networks: changes in the power flows pattern or voltage and fault current levels, for example. Although the deployment of DG units in convenient locations can alleviate some of the effects of intermittent power sources on T&D networks, in case of customers not close enough to the DG location, the effect might be an increase of losses and congestions [2].

Replacing T&D line infrastructure is seen as an important bottleneck towards the EU 20/20/20 objectives [3], due to the complexity of the task and its financial and environmental requirements. Dynamic line rating (DLR) is seen as an effective solution to a more efficient exploitation of the existing infrastructure, by estimating a dynamic value for the ampacity instead of using the traditional fixed seasonal limits. The use of DLR is especially useful in the framework of wind power, as the cooling effect of wind on the cables is highly and conveniently correlated in time with wind power production.

Studies indicate that DLR is a key tool to enhance the penetration of distributed generation and smart grids [4], [5], as it helps to ensure optimal operation increasing visibility through monitoring and allowing for reliable, automated and integrated control systems which imply a safer and more reliable operation of the infrastructure. More importantly, the multiplication of data sources and the complexity of the required SCADA systems suggest the use of big data/computational intelligence techniques in their treatment [6].

This paper presents an application of such techniques to the DLR problem through a case study on ampacity forecasting for two conductor lines in Northern Ireland. The main objective of the study is to investigate the feasibility of providing automatic forecasts of line ampacity up to 27 hours ahead that can be used to protect the power system and to increase its operation flexibility. Given the fact that the described forecasting method can also be readily used to predict actual values of the dynamic ratings, the presented proposal is also a tool which not only can be used to predict future limits of a line, but which can also be used for real time monitoring or *nowcasting*.

The rest of the paper is as follows: Section II reviews the state of the art in dynamic line rating forecasting while in Section III, the problem and the data on which the study will be based are described. Section IV describes the forecasting approaches used in the study, while the performance of these models is analyzed in Section V. Conclusions are finally drawn in Section VI.

II. State of the Art

Over the last 40 years, research on overhead dynamic line ratings, a relatively narrow field in electrical engineering, has seen an exponential growth. Since the seminal series of papers by Davis in the late 70s [7], where Box-Jenkins stochastic models were first applied to predict future ratings, many different experiments have been put forward and several technical solutions have been tested. Amongst the fist attempts, across the late 80s, [8] developed a forecasting system using

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a probabilistic approach which took into account previous line loading and weather history. Approximately at the same time, a study on the effect of variability in weather conditions on conductor temperature [9] lead into another forecasting system [10], [11] which compared a weather-based model with a conductor temperature-based one. Dynamic line rating forecasts constitute an important input to network management solutions, as described in [4], [12].

According to [13], [14], the technologies for the exploitation of overhead dynamic line ratings can be categorized into sag-based techniques (which monitor the sag of the conductors through optical means) [1], [15], tension-based techniques (use physical means to determine the tension of the conductor) [16], [17], temperature-based (monitor the operating temperature of the conductor through sensors installed in the line) [18], [10], [11] and current rating-based (calculate the maximum current rating by monitoring or estimating the weather conditions and feeding them into one of the standard models). In this paper, we will center our attention in the last category, which has seen a bloom in the last two decades.

Amongst previous current rating-based works, [19] applies an expert system to predict DLR in what is one of the first applications of knowledge engineering techniques to this problem. In [20], a statistical risk analysis of the ratings of Polish overhead lines is performed and compared successfully against static line rating. In [21], a simple example of DLR modeling (using CIGRE equations) complemented with a protection relay for back-up is presented. In [22], a rather shallow experiment establishes a comparison between the CIGRE model and a proposed partial least squares model. Lange and Focken [23] investigate the gain in ampacity in situations of high wind power production, concluding that there is a strong and useful correlation. Another study of the correlation between wind farm output and line rating of key overhead lines can be found in [24]. In [25], [26], Monte Carlo methods are used to forecast DLR. Artificial Neural Networks are used in [27] to model and forecast ampacity and temperature whereas authors in [28] use weather forecast ensembles to produce probabilistic ampacity forecasts which allow for uncertainty estimation. Finally, [29] develops an alternative model to the CIGRE standard. The model, linear in its formulation, is based on direct measures of meteorological variables and line current, eliminating the need for inclusion of the mechanical and electrical properties of the conductor.

Two comments can be made about this bibliographic review on the state of the art in DLR modeling and forecasting. On the one hand, some of the aforementioned studies are especially relevant in our case as they are based on the same Northern Ireland Electricity transport network considered in this work [22], [30], [24], [27], [29]. On the other hand, it is remarkable that there are only a few studies considering machine learning models or other artificial intelligence-related approaches. Having proven its suitability for modeling and forecasting in complex numerical problems, as is DLR, this fact highlights the relevance of the study presented in this paper.

With respect to the state of the art, the main contributions of this paper are: an in depth look at explanatory variables and their relation to ampacity, the use of machine learning with numerical weather predictions, the development of a probabilistic forecast from standard point forecasts and a comparison to baseline persistence and a ”physical” approach.

III. Description of the data

This study concerns two 110 kV conductor lines between the Northern Irish cities of Omagh and Dungannon, of 10 km each. These lines are selected because they connect the recently installed wind farm power stations of the west to the highly populated areas to the east. The lines are equipped with meteorological stations on selected poles (5 on each line). These poles are located in an area between latitudes $54.53°$N and $54.61°$N and longitudes $7.24°$E and $6.80°$E. The poles equipped with meteorological stations will be referred to as reference poles. The two lines will be referred to as line A and line B. The poles are numbered from 1 to 5 and for short they will be referred to with the letter of the line and the number of the pole in a single code, i.e. $\mathsf{A1}$.

Three datasets were considered in this work: the instantaneous meteorological measures of each reference pole on each of the two lines (hereafter called “the measures”), the numerical weather predictions (hereafter referred to as “the NWP”) and the computed rating at each pole, which are calculated using the NIE-adapted CIGRE standard [31].

The measures dataset contains, for each pole, the values of the following variables sampled every 5 minutes: ambient temperature (in °C), instantaneous wind speed, average wind speed over 10 minutes (both in m s^{-1}), instantaneous wind direction (in degrees), solar radiation (in J m^{-2}), current (in A), conductor temperature and internal temperature (both in °C). There is a particularity on the measures dataset. At some point of the period of study, some of the Lynx conductors (109 MVA) were replaced by INVAR conductors (200 MVA) in order to increase the capacity of different sections of the lines. This was of course taken into account in the study.

The NWP dataset comes from the deterministic meteorological model of the European Centre for Medium-Range Weather Forecasts (ECMWF), and its value lies on the the assumption that NWP are a valuable source of information in order to compute future ratings of the lines. The model produces four variables: 2 m temperature (in K), surface solar radiation downwards (in W m^{-2} s) and 10 m U and V components for wind (in m s^{-1}). For each variable, we have predictions made at 00:00 and 12:00 UTC spanning 48 hours with a 3 hour time step.

The NWP are obtained for a grid of 9x13 points covering the latitudes between $53.5°$N and $55.5°$N and the longitudes $8.25°$E and $5.25°$E with a horizontal resolution of $0.25°$. In order to obtain forecast values for each reference pole of the line, we interpolated the values from the 4 closest grid points to each pole.

A. Explorative analysis of the data

In order to make this analysis comprehensible, we will be confining it to a single pole of the 20 under study whenever the differences with the rest are not significant.

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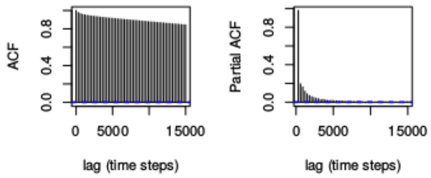

Fig. 1. Autocorrelation and partial autocorrelation functions for the ratings of pole A1.

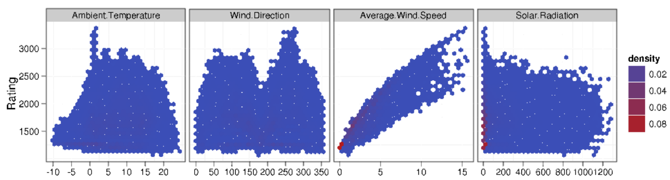

Fig. 2. Dispersion of line rating with respect to measured meteorological variables for pole A1.

1) Data quality assessment: In order to overcome short gaps in the time series, we applied the procedure known as *last observation carried forward*, i.e. when a missing datum is found, it is considered to have the same value of its immediate predecessor. We applied this process for gaps of up to 3 data, which results in failures of up to 15 minutes being estimated with past values.

2) Rating and measures: We examined how the rating relates to the other meteorological variables. In Figure 1 we can see the autocorrelation function and the partial autocorrelation function for one pole. The autocorrelation pattern suggests that any statistical modeling of this series can benefit from the use of autoregressive terms. Also, it shows that differencing the series could lead to more accurate models.

Figure 2 shows how the rating relates to the measured meteorological variables. Unsurprisingly, wind has a clear effect on rating. Wind direction shows a two-peak pattern which indicates that the cooling effect of the wind is the same for orthogonal wind directions with respect to the line.

3) Relations between measures and NWP: In order to make the NWP data comparable with the measures, we interpolated them both in space and time. In space, for each pole of the line, we found the four closest points of the NWP grid and applied bi-linear interpolation to estimate the value of the forecast variables at the coordinates of the pole. In time, we needed to have values every 15 minutes, so we resampled by interpolating linearly from the 3 hour horizons found in the NWP data.

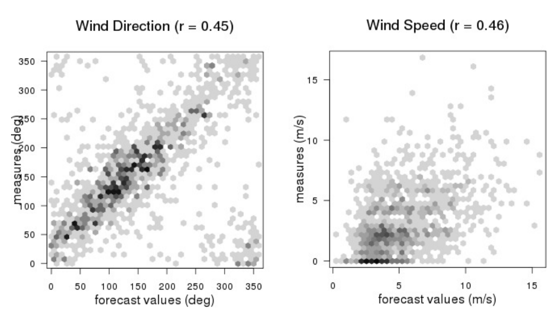

Fig. 3. Scatterplots of measured variables versus NWP predicted variables at pole A1.

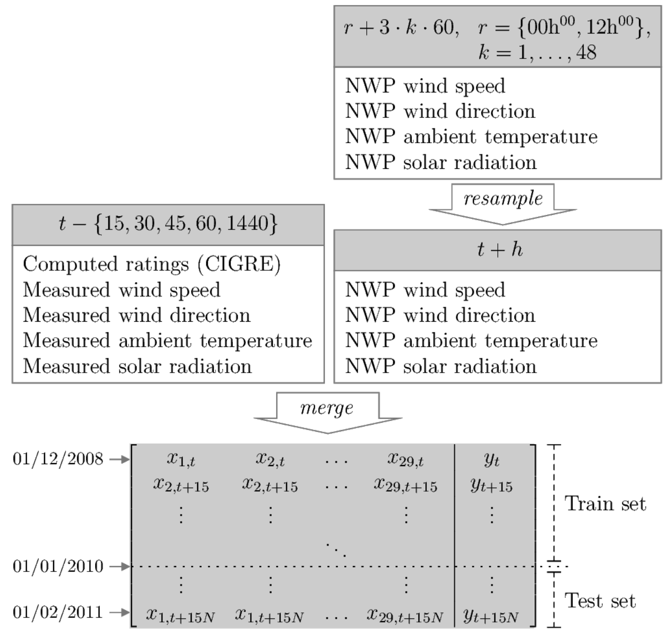

Fig. 4. Summary of the data preparation process depending on h, the forecasting horizon.

We can show how these interpolated NWP data relate to the actual measured variables at the poles. Figure 3 shows scatterplots for wind speed and direction against the NWP predictions.

We can see that the predicted wind direction is correlated to the actual measures. However, the low correlation coefficient is due to the circular nature of this variable for which the linear correlation coefficient is not well suited. With respect to wind speed this correlation is much less evident.

These correlation values provide an a priori estimate of the achievable performance of medium term line rating forecasts. The fact that wind direction is well predicted is very positive. However the low correlation observed for wind speed indicates that obtaining accurate forecasts using a straightforward approach is unlikely.

IV. Methodology

In order to apply automatic learning on a dataset, it is necessary to divide it into, at least, two subsets: a part of the data that will be used strictly for learning (the *train set*) and another part that will be used to evaluate the performance of the trained model (the *test set*). In our case, we decided to fix 2010-01-01 as the split point, thus having an approximate 50% split.

Furthermore, to make the comparison fair, the same set of input variables and lags has to be used for all the models (except for persistence and downscaling). The selected set of input variables can be divided into three groups:

- Lagged values of the computed rating series: lags $t - 15$, $t - 30$, $t - 45$, $t - 60$ and $t - 1140$ minutes (= 24 h).

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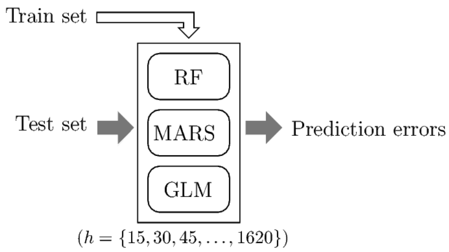

Fig. 5. Flowchart for the point forecasting process. Train and test sets come from the data preparation process outlined in Fig. 4. First the models are trained using the train set and then used to predict the test set for different values of the horizon h (in minutes).

- Lagged values of the measured meteorological variables (wind speed, wind direction, solar radiation and ambient temperature), using the same set of lags as above.
- NWP values for wind speed, wind direction, solar radiation and ambient temperature, downscaled as explained in Section IV-A and resampled to a 15 minute frequency.

Therefore, a set of 29 explanatory variables was used as input to the statistical models, as shown in Figure 4.

The forecasting requirements stated by NIE were to have predictions for the 15, 30, 45 minutes and 1, 2, 3, 4 hour horizons. However, to increase the generality of this study, we decided to forecast up to 27 hours ahead with 15 minute time steps, in a rolling window approach. Given that the NWP produced by the ECMWF are updated every 12 hours and that they are provided with at most a 7 hour delay, the width of the rolling window was set to 27 hours to always provide forecasts for the same number of horizons. This is outlined in Figure 5

The forecasting procedure used in the experiments was based on the idea of producing a forecast every 15 minutes with all the information available at that point in time. For example, at an instant t, we know the value of the past meteorological measures up to instant t, and hence we know the computed rating up that instant t. We also have the most recently produced NWPs, which, in the worst case, were produced 12 hours ago. We use all this information to produce a forecast for the time $t + k \cdot 15\mathrm{min}$ where $k = 1 \ldots 108$, i.e. for every 15 minutes up to 27 hours.

A. Basic models: persistence and downscaling NWP

Before going into deeper considerations about the statistical forecasting models that we will use, we consider two basic approaches that will serve as benchmarks for the comparison.

The persistence model (also called the *naive predictor*) is the simplest trivial predictor and predicts that future values will be the same as the current value. It is a good ground for evaluation of other algorithms. Any noteworthy algorithm must perform at least as well or better than the naive predictor, and we will use it here as the basis for comparison.

Thanks to the NWP we have a good source of information about what is expected to happen in the future. This information is ignored in the persistence model (a fact that renders the comparison with persistence not entirely fair) but can be used to build simple and robust predictors. On the one hand, we could compute the rating directly out of the meteorological values forecast by the NWP. This, however, has the disadvantage that NWP come from a global model covering a much wider area than the area of interest, and hence local effects are not accounted for. As well, the values predicted for each pole would not be very different from one another, as the coarse grid of the NWP model would mean that two poles could share the same set of NWP data.

On the other hand, given the fact that, apart from the NWP (interpolated both temporally and spatially as described in Section III-A3, page 3), we have locally measured meteorological values, we could think of applying a simple statistical *downscaling* procedure to the NWP data. This procedure is based on the idea that the values predicted by a NWP model for a single point are constantly proportional to what really happens at that point. This stems from the fact that the local conditions and spatial configuration affects the meteorological values in a more or less constant manner (see figure 3).

Thus, we can use the training set to compute a regression[1] for each meteorological variable to express the local measured values for that variable as a function of the NWP forecast values. Then, for the testing set, we use this learned relations between NWP and actual values to locally adapt each NWP variable for each pole. If we use these locally adapted NWP to compute the rating, we can expect to obtain better results than persistence, especially for longer term horizons.

B. Machine learning statistical models

Amongst the panoply of statistical and machine learning forecasting models, we chose models coming from three different paradigms: the multivariate adaptive regression splines (MARS), the generalized linear models (GLM) and random forests (RF).

1) Generalized linear models (GLM): The generalized linear model (GLM) [32], [33] is a flexible generalization of ordinary least squares regression. The GLM generalizes linear regression by employing a link function that defines the relationship between the systematic component of the data and the dependent variable and by allowing the magnitude of the variance of each measurement to be a function of its predicted value. Generalized linear models were formulated as a way of unifying various other statistical models, including linear regression, logistic regression and Poisson regression.

2) Multivariate adaptive regression splines (MARS): Multivariate adaptive regression splines (MARS) [34], [35] is a spline regression model that uses a specific class of basis functions as predictors in place of the original data. The MARS basis function transform makes it possible to selectively blank out certain regions of a variable by making them zero, allowing MARS to focus on specific sub-regions of the data. MARS excels at finding optimal variable transformations and interactions, as well as determining the complex data structure that often hides in high dimensional data.

[1]As a first approach, and given the strong linear component of the relation between measured and NWP variables (see figure 3), in this case a linear regression was used, but more complex alternatives could also be considered.

3) Random Forests (RF): An RF predictor is an ensemble of individual classification tree predictors [36]. For each observation, each individual tree votes for one class and the forest predicts the class that has the majority of votes. The user has to specify the number of randomly selected variables to be searched through for the best split at each node. The Gini index [37] is used as the splitting criterion. The largest tree possible is grown and is not pruned. The root node of each tree in the forest contains a bootstrap sample from the original data as the training set.

4) Quantile regression forests (QRF): The algorithm quantile regression forest (QRF) [38] is a generalization of the RF model which provides a non-parametric and accurate way of estimating conditional quantiles for high-dimensional predictor variables.

C. Evaluation criteria

The following evaluation criteria are routinely used in forecasting and are used here to asses the accuracy of the different forecasting approaches. In this section $\hat{y}_{t+h|t}$ represents the forecast value for time $t+h$ computed at time t while y_{t+h} represents the observed value at $t+h$. N is the number of predictions.

- Normalized mean absolute error (MAE), as used in the framework of the Twenties European Project [39] (with acceptable values fixed at below 35%):

$$\mathrm{NMAE_h} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_{t+h|t} - y_{t+h}}{y_{t+h}}\right| \quad (1)$$

- Normalized forecasting bias:

$$\mathrm{NBias_h} = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{y}_{t+h|t} - y_{t+h}}{y_{t+h}} \quad (2)$$

V. Results and discussion

In this section we will describe the results of the experiments carried out with the data. We can divide these experiments in three categories: a comparison between the different available models to decide if one is best suited to this problem, a comparison of the results amongst the 10 selected poles to detect if the results are consistent and an application of a probabilistic model and its evaluation.

A. Forecast model comparison

The first stage of the experiments was aimed at comparing the different models described in the previous section, to try to determine if one of them is better suited to our problem.

Figure 6 shows the results of the comparison of the different models for pole A1. It is clear from this figure that both RF and MARS produce the best results amongst the five models. The results for GLM are not bad either when compared to persistence and downscaling. Only during the first hour does persistence outperform the other models, which confirms that the series is stable on the short term. It is also remarkable that the acceptable value for the NMAE (equation (1)), set to 35% in the Twenties project, is actually beaten by persistence and

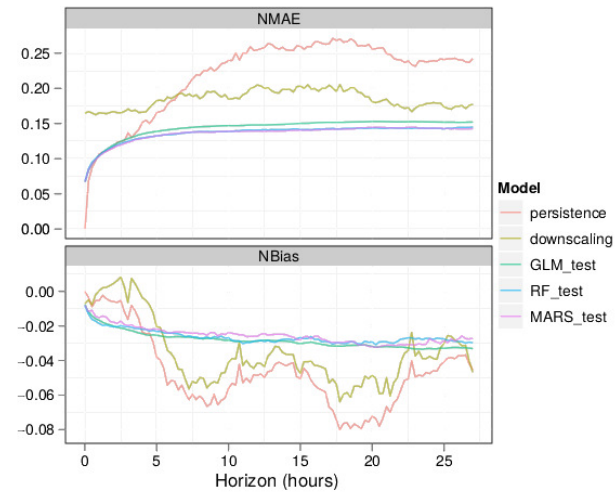

Fig. 6. Prediction errors for all the considered models over pole A1 (using testing data set).

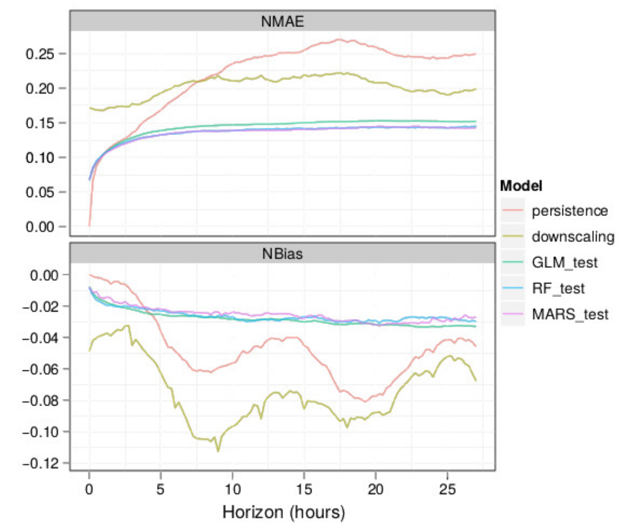

Fig. 7. Average pole prediction errors for all the considered models (using testing data set).

that RF, MARS and GLM manage to produce results that are around 15% maximum even for horizons over 20 hours.

To extend the conclusion from pole A1 to the whole set of reference poles, we computed the average error criteria obtained by each model for all poles. Figure 7 shows these averaged criteria. We verify that the results for pole A1 are representative for the set of poles, and hence the conclusion remains the same: RF and MARS obtain the best results.

Given these results, and considering that MARS is more computationally efficient than RF, we suggest to use MARS to compute the line rating forecasts.

B. Comparing results amongst poles

Once the best model has been selected, we wanted to compare the results amongst the different poles. Figure 8 shows the results of MARS for each pole.

It is clear that the model manages to capture the inherent behavior of all the series, showing good results for all of

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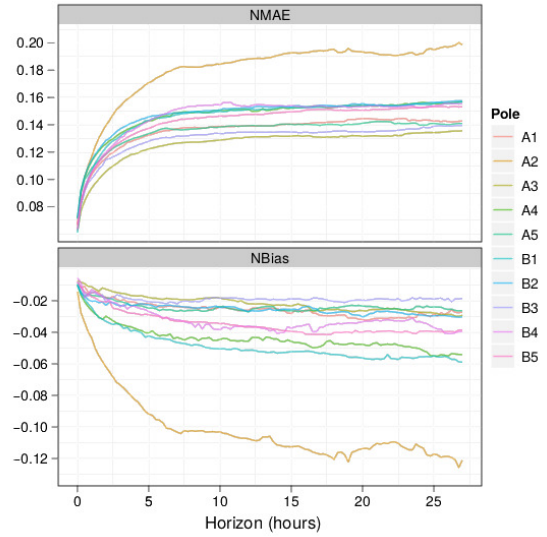

Fig. 8. Prediction errors for each pole using MARS.

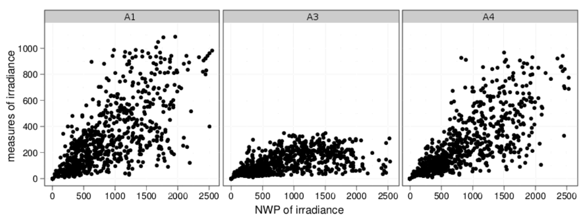

Fig. 9. Measures of irradiance against NWP forecasts of irradiance for poles A1, A3 and A4.

them (around 14% NMAE in the longest horizons). However, pole A3 seems to be an outlier with much worse forecast performances than the other poles.

We verified that the anomaly with A3 is consistent across the RF and GLM models and that it does not appears when, from the three groups of input variables defined in Section V-A, the NWP are not used as inputs to the model. This of course implies that the anomaly is related to these variables, either to the original data or to the downscaling process applied to them. To shed some light over this issue, we can compare the downscaled NWP for several poles.

Figure 9 shows evidence that the local measures for solar irradiance differ significantly between poles A3 and two other poles A1 and A4 (of which A4 is located very close to A3). Indeed, the measured irradiance at this pole is much lower than that observed for neighboring poles. This difference could be due to a shadowing effect on the irradiance sensor of A3 and would require further investigation. However, we assume that this evidence explains the difference in the forecasting performance of the models when applied to pole A3.

C. Probabilistic forecasting

Finally, we applied QRF, a probabilistic model which estimates, instead of single (mean) predictions, the whole probability function for each time t.

Figure 10 shows an example of the output of QRF for pole A1 and some days of July 2010. As we can see, the

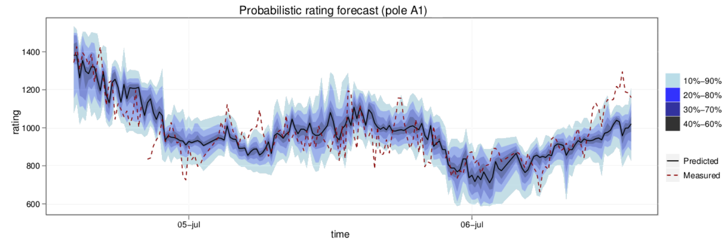

Fig. 10. Example of QRF probabilistic forecasts of the rating series (pole A1) for a period in July 2010.

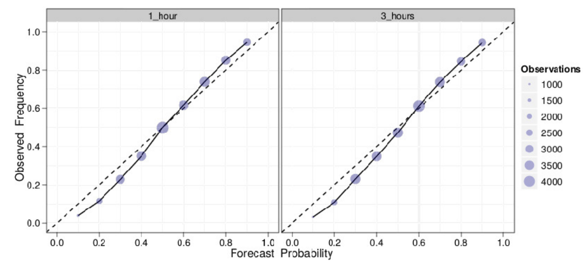

Fig. 11. Reliability of the probabilistic rating forecasts for 1, 2 and 3 hour ahead horizons of the rating series (for pole A1).

model is able to produce prediction intervals for each forecast horizon, which can be useful in the decision making process inside the control room. Observing the red dotted line, which corresponds to the actual computed rating values, we can see that it falls within the confidence intervals most of the time.

The evaluation of probabilistic forecasts is an open issue in the literature [40]. One of the most common tool to evaluate probabilistic forecasts is the reliability diagram. Reliability refers to the degree of similarity between the forecasts and the observations. For probabilistic forecasts, one might think of reliability as a measure of the bias of a probabilistic forecasting system. We expect that the empirical coverage achieved by each quantile forecast should equal the specified proportion.

In Figure 11, we see that the reliability obtained by the QRF model is satisfactory for the three shown horizons and all probabilities. We can however notice that the reliability is centered around the ideal values although the model slightly over-predicts for low probabilities and under-predicts for higher probabilities. The slight over-prediction for low quantiles is not necessarily negative in the frame of line rating forecasting. The model is slightly conservative which is positive since the rating should not to be exceeded.

However, reliability is not sufficient to characterize the quality of a probabilistic forecast since a forecast based on climatology is perfectly reliable and yet has no skill. A model is said to have no skill when it provides the same forecast distribution for all situations. A skillful model will provide sharper distributions for more certain situations and wider distribution when the uncertainty on the outcome is higher.

Sharpness refers to the degree of concentration of the distribution of the probabilistic forecast. If the density forecast takes the form of a Dirac delta function, this would have maximum sharpness in that it suggests that the forecaster believes that one particular value will occur with complete

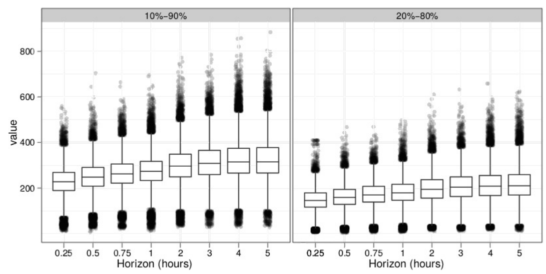

Fig. 12. Sharpness of the probabilistic forecasts for several horizons and three different intervals (for pole A1).

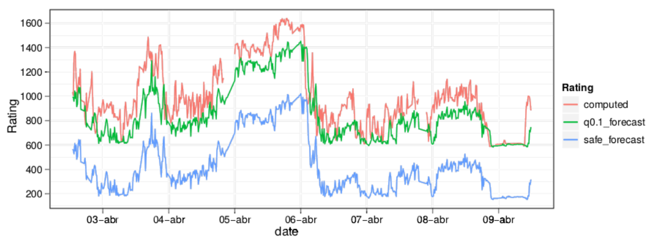

Fig. 13. Example of a possible operational forecast using a safety margin: 1 hour ahead 10% quantile and the same minus the maximum difference with the actual computed data in the last 6 months (for pole A1).

certainty. Reliability is related to sharpness in the same way bias is related to variance in deterministic forecast evaluation. That is, there is usually a sharpness-reliability performance trade-off in the same way that there is a bias-variance trade-off for point forecast models.

The sharpness of the forecasts provided by QRF is assessed by determining the inter-quantile ranges of the forecast distributions. The idea behind inter-quantile ranges is to examine the size of representative quantile intervals, i.e. the distance between the rating values provided for given forecast quantiles. The distribution of inter-quantile ranges is presented in box plots with the minimum, maximum, the Q1, Q2, Q3 quartiles and mean of the distribution for different coverage rates. We consider $\delta(\beta) = q(1-\beta/2) - q(\beta/2)$ the size of the interval, where $1-\beta$ is the nominal coverage rate of the interval, and $q(\alpha)$ are quantiles such that $P(X \leq x) = \alpha$, where X is the variable of interest.

In figure 12 the sharpness for three coverage rates, 80%, 60% and 40%, is presented. As can be expected the median inter-quantile range decreases with the coverage rate. For all coverage rates the inter-quantile range increases with forecast horizon due to the increasing forecast uncertainty. Also, the forecast can be said to be skillful since the minimum and especially the maximum observed inter-quantile distances are significantly different from the median values.

Finally, to illustrate the operational usefulness of this approach, figure 13 shows the actual computed rating together with the predicted values of the 10% quantile of a probabilistic forecast for 1 hour ahead (green line). This means that the computed values will be above the forecast 10% of the time. We see that, at some points, the forecasts are higher than the actual computed values. To ensure the safety of the lines, we can substract from the forecasts a safety margin of, for example, the maximum difference between the 10% quantile and the computed rating over the last 6 months. Such a "safe" forecast is shown in blue, and gives an idea of what could be achieved with this approach. Note that the safety margin taken here is very conservative. A smaller safety margin could be chosen or the safety margin could be set dynamically by analyzing the NWP data to determine which situations have higher than usual uncertainty and require large safety margins. Having a probabilistic forecast can allow the operator to choose the quantile that provides an acceptable level of risk.

VI. Conclusions and perspectives

In this document we describe a dynamic line rating forecasting (DLR) study. We have presented an accurate application to predict future values of the rating for two conductor lines. This procedure is based on data transformations and the results suggest to use multivariate adaptive regression splines (MARS) as the core regression method. Our approach obtains good error results which rank far below the key project indicators defined in the Twenties Project for the DLR problem.

These results prove the feasability of computing line rating forecasts that can be used in the daily operation of the power system to lift some constraints while maintaining safe and reliable operating conditions. Moreover, together with its prediction abilites, the presented method can also be used to compute the actual values of the dynamic ratings (or *nowcasts*). Thus, it is expected that this approach can be used to permit a better use of DLR as a tool to protect and monitor, in real time, T&D infrastructures with high penetration of distributed generation and microgrids.

However, before line rating forecasts can enter the control room, further analysis and refinement should be carried out both from a purely forecasting perspective and from a network operation perspective. From a forecasting perspective several points should be addressed. In the present study, a fixed set of reasonable explanatory variables were used as inputs to the forecasting models. Further analysis of the input variables through computational intelligence feature selection methods could lead to the selection of a variable subset that leads to even more accurate forecasts. Also, the forecast ratings were provided for a subset of reference poles. The next step would be to compute line rating forecast for all reference poles and then derive the rating forecast for non-reference poles using a speed-up ratio approach. In this way a more precise total line rating forecast could be obtained. Once the complete line rating has been computed, the behavior of the forecast errors should be further investigated in order to better understand the possible situations when the models over-estimate the line rating. Such an investigation would be necessary in order to define appropriate safety margins around the rating forecasts. These safety margins should ensure that the lines are not overloaded while allowing more capacity to be exploited than the fixed seasonal ratings. An evident further refinement would be to provide weather dependent safety margins that dynamically asses the risk of over-estimating the line rating.

From a network operation perspective the infrastructure protection and capacity gains that can be obtained from using the forecasts provided in this study are clear, and an operational rating forecasting tool can be readily implemented. This tool will provide a capacity forecast that integrates a satisfactory safety margin, as well as nowcasts with risk level alarms. Both products will be provided to control room operators in a consultative capacity in order to undergo an initial operational assessment and allow for user feedback to be collected, finally allowing for the inclusion of these forecasts in the standard network operating procedures.

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