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Improvement of safety operating conditions in overhead conductors based on ampacity modeling using artificial neural networks

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Abstract— **Thermal ratings are usually considered for planning the operating conditions for overhead lines and are usually obtained with static parameters. These conditions can be improved using dynamic ratings based on the region weather forecasts, and this improvement can be ever higher when a local prediction is performed at the point where the line is located. In this work, a model based on artificial neural networks techniques is applied to predict the ampacity property of a transmission overhead line, in order to adjust and optimize the operation point of the grid under safety conditions. These predictions are calculated for a time horizon of 24 hours and are validated with actual conditions of a real overhead line monitored by sensors. With the conclusion that applying the selected model, the operational security of the conductor can be improved, passing from a 17.82% of overheating conditions to only a 3.91%.**

Index Terms—**ampacity prediction; artificial neural networks; line rating; overhead line; safety operating conditions**

I. INTRODUCTION

Overhead conductors must be able to transmit large amount of energy without overheating. This point has a huge influence in the decision-making for power conductor engineering and operation. For this reason, knowing in advance the information about the maximum current capacity that a conductor can tolerate on its working conditions, without risking deterioration or damage, can be really helpful [1]. This limitation, property that defines the maximum acceptable electric current that can be transmitted without damaging the conductor due to its physical properties, is defined as ampacity [2, 3].

The classical Static Line Rating (SLR) based on fixed conservative weather assumptions, used by many power system operators, is starting to be substituted by new Dynamic Line Rating (DLR), new approaches that modify overhead line current-carrying capacity based on more realistic weather assumptions, obtained from mathematical models [4-6]. These models can predict weather conditions that help to calculate the ampacity or directly can predict the ampacity obtained according to the thermal rating obtained with the weather conditions [7, 8].

The potential benefits of consider DLR over SLR are multiple and have been discussed in many studies [9, 10], although in this work the focus is paid in reducing the deterioration or damage of the conductor, extending its working life, making a combination of both line ratings. For this purpose, a dynamic line-rating model is selected based on its prediction capacity from a proposed group of machine-learning algorithms based on Artificial Neural Networks (ANN). And the final model is applied to predict the ampacity up to 24 hours ahead in an overhead line located in the Basque Country, Spain.

The use of mathematical modelling has been studied to improve operating conditions in overhead lines previously in the literature, but always using different techniques and focused on improvements of other operation conditions aspects. For example, [11] and [12] applied some machine learning algorithms to obtain dynamic line ratings but based on another kind of variables. [13] and [14] based the prediction on the use of time series techniques. And [15] worked applying statistical prediction.

In the proposed approach, 18 variables were computed based on past information of the ampacity [16]. These 18 variables were selected due to the knowledge obtained from the trend and seasonality in the time series data gathered from the monitoring of the line [17]. Later, a multivariate analysis of these variables was performed to understand better the information provided by them and its relation with the predicted

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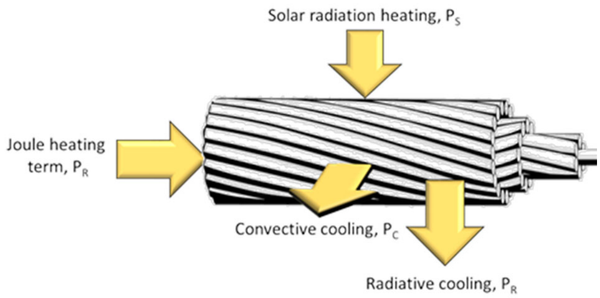

Figure 1. Steady state heat balance in the conductor

variable, ampacity 24 hours ahead. Then the most significant variables to perform the most accurate models to solve the proposed problem were selected [18, 19].

Then, several ANN algorithms were applied to build accurate models: extreme learning feedforward neural networks, model averaged multi-layer perceptron neural network, Bayesian regularized neural networks and quantile regression neural network. During the building and training, parameters of ANN algorithms were fully tuned trying to reduce the prediction error. Also, and to demonstrate the efficiency of the model, the resulting models were tested and validated with instances not previously used in the training stage, showing in this way the real prediction capacity of the models [20].

And finally, the selected ANN model and the static rating were combined to obtain the ampacity prediction that optimize the safety conditions of the conductor.

II. Materials and Methods

A. Line rating calculation

Thermal conditions of overhead transmission lines limit the amount of energy that can be transported by a conductor. These thermal conditions are not fixed and change due to the conductor heat balance and determinate the possible limits of conductor current. Hence real time monitoring of electrical and environmental conditions can help to optimize line capacity

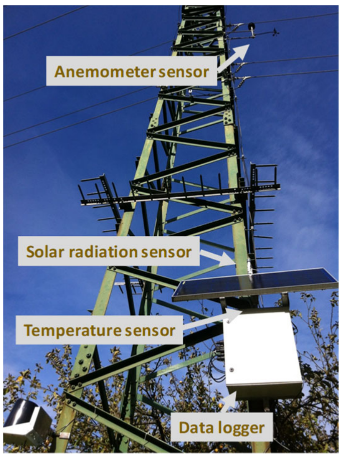

Figure 2. Implementation of the measurement system in the transmission line structure

utilization, and the deterioration risk and damage. Although this optimization is a complex task due to the complexity of monitoring this system, thus it is usually applied the steady state heat balance in the conductor following IEEE and CIGRE models (Fig. 1) (Eq. 1).

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

where P_J is the Joule effect heating term, P_S solar heating term, P_C convective cooling term due to wind conditions, and P_R radiative cooling condition [5, 21].

Many electric companies, in addition to use this steady state heat balance, fix values of solar radiation, temperature and wind speed and direction throughout the whole year in this balance. These values are fixed with a high margin of safety to protect the conductors, even reducing the transport capacity of the line below of its possible admissible values.

But this heat balance can be optimized by knowing the environmental conditions at the line location. And in this way, improve transport capacity and reduce risk of damage on the conductors. Wind speed, wind direction, ambient temperature, and solar radiation are the variables that usually are analyzed to obtain the ampacity value of a line. Based on these parameters, ampacity was calculated in a pilot line, to subsequently built models to predict this property 24 hours ahead.

B. Test pilot line description

The studied pilot line site is located in the Basque Country, northern area of Spain, and consists of one transmission corridor with a north-south distribution line segment. The test grid is owned by Iberdrola, one of the biggest electric utilities companies in Spain. The segment under study is designed based on a conductor wire type ACSR-LA-180 to deliver 25.06 MVA in summer and 28.25 MVA in winter.

The study focus in this distribution line allows to make a dynamic heat balance in the conductor based on readings of temporal variation of local weather condition. A measurement system (Fig. 2) was placed on the distribution line to gather ambient temperature and solar radiation at 4 m height, and wind speed and direction at 10 m height.

These data were collected with 1-minute frequency for nearly three years (July 25, 2010 to June 30, 2013). Based on these data a dynamic value of ampacity was obtained and subsequently compared with the static values used by Iberdrola.

C. Data processing

The measurements gathered from the pilot line were preprocessed [21] to obtain an ampacity time series with 10 minutes steps based on the average value of the instances gathered during each period. Since some missing data were collected, an interpolation for gaps shorter than 1 hour was performed.

Then and based on the resulting ampacity time series, the 18 variables used as inputs in the models were calculated:

- Ampacity at studied actual time.

- Measured ampacity with several periods lagged on time (10 minutes, 20 minutes, 30 minutes, 60 minutes, 120 minutes, 240 minutes and 1440 minutes).

- Average ampacity during the several periods (last 30 minutes, last 1 hour, last 2 hours, last 4 hours and last 24 hours).

- Several forecasts of the Spanish State Meteorological Agency (AEMET) (30 minutes ahead, 1 hour ahead, 2 hours ahead, 4 hours ahead and 24 hours ahead).

D. *Multivariate analysis*

To compute and study these variables and its relations with the prediction feature, several techniques like data pre-processing, outlier detection, analysis of variance, analysis of covariance, analysis of correlation, multivariate data visualization, and principal components analysis were applied. The final dataset was normalized between 0 and 1 to balance the weight of all variables and improve the statistical-analysis quality.

In this study, the statistical software tool R v3.4.1 [22] was used to conduct the multivariate analysis tasks and the ampacity modelling process.

E. *Artificial Neural Networks*

There is a diverse range of techniques that can be applied for the prediction of a quantitative feature of nonlinear behavior. Among them, ANN [23, 24] are a widely used technique. Based on biological neural networks, this technique interconnects neurons through dendrites, generating an output signal that is sent to another neuron using an axon. This biological system is modified to predict a quantitative value, assigning numeric bias and weights to the neurons interconnection, and generating neuron output signals according to an activation function inside of each neuron.

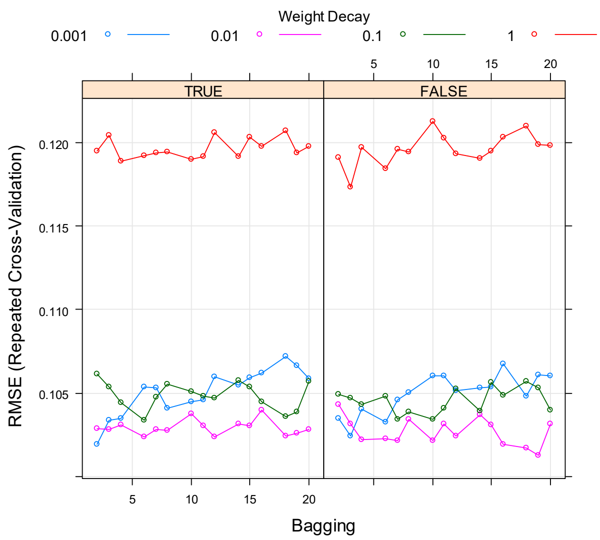

Figure 3. Results obtained from training period (50 times repeated 10 fold cross-validation) using AMPNN to predict ampacity. Values of the most accurate configuration: weight decay = 0.01, hidden neurons = 19, and bagging method not applied.

There are many approaches of how artificial neural networks can make a prediction of a variable, feedforward ANN and recurrent or feedback ANN. In this work, four feedforward approaches, where signals travel one way from inputs to outputs, based on four of the most applied neural networks techniques are performed:

- Averaged Multi-layer Perceptron Neural Network (AMPNN) [24, 25].

- Bayesian Regularized Neural Networks (BRNN) [26, 27].

- Extreme Learning Feedforward Neural Networks (ELFNN) [28, 29].

- Quantile Regression Neural Network (QRNN) [30].

F. *Model selection criteria*

The neural networks models were trained based on the methodology 10 fold cross-validation and was repeated 50 times [31]. Also during the training stage, some of the most significant parameters of each algorithm were tuned to optimize the predictive performance of the models. The criterion to evaluate the accuracy of the predictions were the Root Mean Square Error (RMSE).

Then, the selected models from the training stage were validated on the testing stage. The RMSE was obtained again, but this time with new instances. And finally, it can be said that these new results give a real degree of generalization of the selected models.

III. Results

From the original 125547 instances under study, one year (From July 25, 2010 to July 24, 2011. 46790 instances) was selected to train the models, and the rest of the experiment time (78757 instances) to test and validate the models. Also, from the instances selected to train the models, a subsample of a random 10% of this dataset was performed to really train the models. This was due to the computational cost of using all the instances. For example, applying the methodology to the original problem with one of the algorithms costs around 168 hours, while using the reduced subsampled dataset, the computational cost was reduced to two and a half hours.

During the training stage, the RMSE was calculated based on 50 random repetitions of 10-fold cross-validation. In the same process, the most significant parameter of each of the algorithms under study were tuned, optimizing the prediction capability of each of the models. For example in Fig. 3 is shown the RMSE of the predicted variable during the training using AMPNN algorithm, when parameters like number of neurons or weight decay are varying in two cases, whether bagging sampling is applied or not. Table I shows the applied algorithms with the tuned parameters, and the final optimized value of these parameters. During this process, it was observed that the number of instances, even after subsampling, is high enough, since the use or not of the bagging method gives quite similar results.

TABLE I. TUNED PARAMETERS FOR EACH TECHNIQUE AND ITS OPTIMAL SELECTION

Method	Adjustments
BRNN	neurons = 2
ELFNN	neurons = 13; actfun = sig
AMPNN	neurons = 19; decay = 0.01; bag = FALSE
QRNN	neurons = 1, decay = 0.1; bag = FALSE

The models were trained and tested obtaining the results shown in Table II. Based on these results the most accurate model among the obtained was selected to predict the ampacity, in this case the one obtained with the AMPNN algorithm. In Fig. 4 this prediction 24 hours ahead can be observed (red dashed line) compared with the real values (black solid line) of ampacity during one week of the testing period.

TABLE II. RESULTS OBTAINED DURING TRAINING AND TESTING STAGE (VALUES IN %)

Method	Training RMSE	Testing RMSE
BRNN	10.35	9.87
ELFNN	10.36	9.97
AMPNN	10.12	9.84
QRNN	10.71	10.07

Once the model was selected, a study of the residuals was performed. This study was focused on statistically ensure that with a 95% of confidence the model was an accurate predictor and the prediction was under the real value. The residuals were considered Gaussian, even when it was verified that they show a small skewness (0.6244) to the left. Therefore, as the study zone was at the left of the distribution, or what is the same, the lower margin of the prediction, this value was applied to ensure statistically that the value of the ampacity was predicted lower to the real value with a 95% of security. In this case the margin was equal to 144.58 A for a 95% of confidence on the ampacity prediction.

The final prediction was the one obtained from the selected model minus the margin of error established by the lower 95% prediction interval (green dotted line in Fig. 4).

Once the final prediction model was selected, this model was combined with the static ampacity applied by Iberdrola (blue dotted-dashed line in Fig. 4). When the model prediction was lower than the static ampacity, the prediction of the model was taken. On the other hand, when the model prediction was higher than the static ampacity, the static ampacity was taken. This combination allows to optimize the safety scenario of an overhead line, goal of this study. Fig. 4 shows the effect of this combination (grey long-dashed line).

Using this prediction, the time when the conductor can suffer damage or deterioration pass from a 17.82% (14040 instances out of 78757) of the validation time to a 3.91% (3081 instances out of 78757). Also the number of consecutive periods where the real ampacity is lower than the predicted is reduced considerably (Fig. 5). The benefits of this optimization in the safety condition of the system affects to the power that the line can transport. The line reduce the capacity to deliver power in a 9.69% during summer, from 25.06 MVA based on a fix ampacity to 22.63 MVA using the proposed ampacity model. In the same way, during winter the capacity is reduced in a 10.17%, from 28.25 to 25.38 MVA.

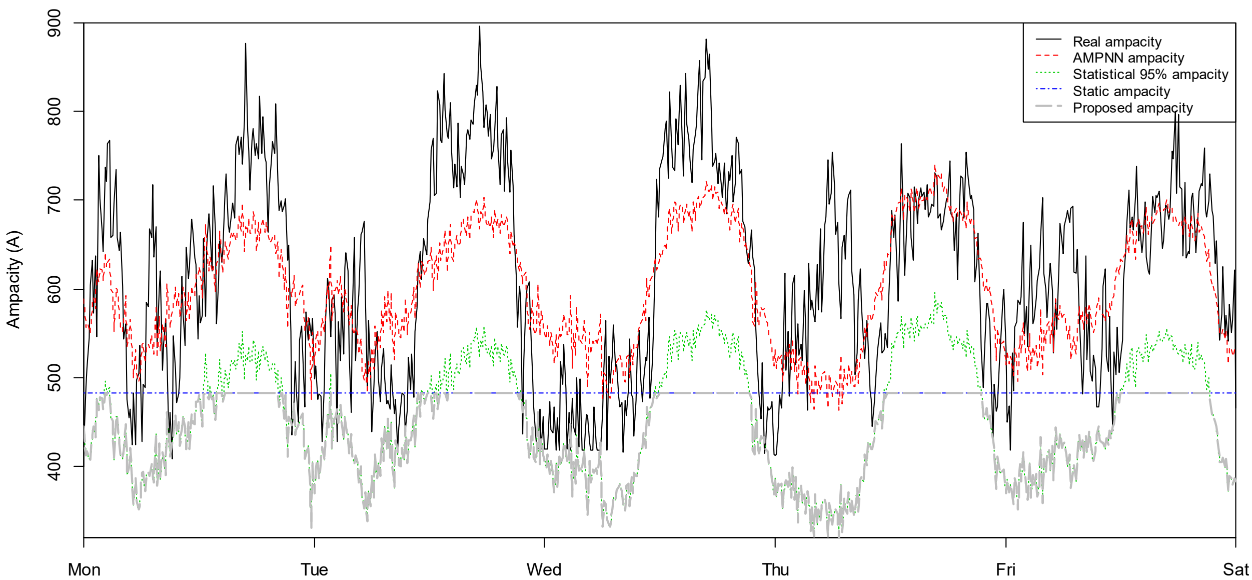

Figure 4. Comparison of the different ampacity values under study (from 2013-06-24 to 2013-06-29). The original value (black solid line), the predicted value from AMPNN (red dashed line), the predicted value with a 95% of prediction interval (green dotted line), the static model used by Iberdrola (blue dotted-dashed line), and the combined final model (grey long-dashed line).

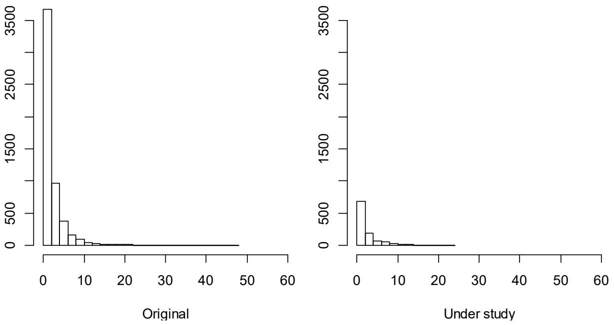

Figure 5. Histograms of consecutive periods where the real ampacity is under the predicted ampacity. Comparison between the real case and the study case.

IV. CONCLUSIONS

This work proves that machine learning algorithms can be useful in the prediction of electrical variables, such as ampacity. More specifically, algorithms based on artificial neural networks allow obtaining models with reduced prediction errors working with non-linear variables complex to predict. In addition, combining the results of the trained models with statistical analysis, it is possible to obtain a final prediction with a prediction interval of 95%, assuring the accuracy within the lower margin of ampacity levels in the prediction. All this process allows obtaining a dynamic ampacity model that reduces the periods in which the conductor of an overhead line is exposed to possible deterioration and damage by approximately 14%, reducing at the same time the number and duration of these periods.

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