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Ampacity forecasting using neural networks

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Abstract. Ampacity techniques have been used by Distributor System Operators (DSO) and Transport System Operators (TSO) in order to increase the static rate of transport and distribution infrastructures, especially those who are used for the grid integration of renewable energy. One of the main drawbacks of this technique is related with the fact that DSO and TSO need to do some planning tasks in advance. In order to perform a previous planning it is compulsory to forecast the weather conditions in the short-time. This paper analyses the application of the neural network to the estimation of the ampacity in order to increase the amount of power produced by wind farms that can be integrated into the grid.

Key words

Wind Energy, Ampacity, Neural Networks (NNs), Grid Integration, monitoring system.

1. Introduction

Ampacity techniques have been used by DSO and TSO in order to increase the static rate of transport and distribution infrastructures, especially those who are used for the grid integration of renewable energy. The ampacity of an overhead line is the maximum current that the line can carry depending on the weather conditions and the maximum conductor temperature. Ampacity computation can be performed using both IEEE and CIGRE. On the other hand, DSO needs a large enough period of time to handle the lines safely and optimally. To obtain a future ampacity with an acceptable level of accuracy is required good weather predictions, especially for the wind, considering that it is the most important parameter in ampacity calculation and at the same time it is difficult to predict.

Artificial neural networks (ANN) have been widely used in electrical applications like load forecasting and wind generation during the last decade. From a general point of view, ANN are useful because their ability to model unknown nonlinear relationship between electrical and non-electrical variables. In addition, the use of ANN in load modelling requires the computation of weather forecast. In this paper ANN are used to estimate a forecast of the ampacity by using meteorological data.

2. Weather prediction

Weather prediction is not an easy task. From a general point of view, the weather can be considered a chaotic system. This means that small errors at the beginning of the estimation process of a forecast can increase in a rapid way affecting the predictability accuracy. Depending on the estimation process the error is related with model simplifications of atmospheric processes.
One way to deal with this problem is by the time evolution of a probability density function in the atmosphere's phase space.

Weather forecast can be studied mainly two approaches:

- Atmospheric models.
- Time series models.

In this paper, models based on time series are used to predict meteorological data.

These models can be fed based on two types of methods:

- Univariate time series model: consider the past values of the variable itself to predict.
- Multivariate time series model: consist in performing predictions of a variable over the past values of the variable itself and past values of other exogenous variables.

Among these methods are found different techniques such as ARIMA or Box-Jenkins models, ANN and Fuzzy Inference Systems (FIS). In this case, ANN will be used to predict ampacity.

3. Artificial Neural Network

The main reasons for using ANN to predict meteorological data are: i) it is not necessary to know the nature of the data series; ii) the model is adaptable to non-linear functions and iii) it fits the evolution of the data series just going to train it.

The ANN used in this paper is a Multiple Multilayer Perceptron network with majority voting technique. This architecture has been trained using Levenberg Marquardt (LM). This kind of ANN has an output layer, an input layer and one or more hidden layer. From a practical point of view, the number of hidden layers depends on the degree of complexity of the problem.

The population data for training includes wind speed and direction, ambient temperature, solar irradiance and ampacity data computed according both CIGRE and IEEE methods.

In the first part of the study is important to analyse the integrity of the meteorological data. Weather stations provide data sets. To obtain accuracy predictions, data series must to have an appropriate length and not have discontinuities. The study system consists of one weather station located on a tower. Weather station has a GPRS modem which sends data to a server. In this server there is a PC that computes the weather prediction algorithm and the ampacity calculation engine. Ampacity forecast values are sent to the DSO or TSO control centre to enable them to take appropriate operational decisions. Fig. 1 shows the basic block diagram of the ampacity system.

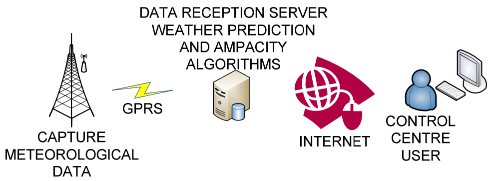

Figure 1. System Diagram.

The next stage is to create and train the neural network model with selected data series. Inputs and targets are necessary to train the network. The inputs include four data series (ambient temperature, wind speed and direction and solar irradiance), the forecast variable and the variable to be predicted considering the prediction horizon. The ANN has 10 hidden layers and 1 output layer.

The generated model is fed by values of variable to be predicted and the exogenous variables. Results are compared with real value of data series to obtain the errors in the forecast. Table I represents the data model populations.

Table I. Population Data for the neural network.

Population Data	8,379
Training Data	5,859
Validation Data	1,256
Testing Data (model)	1,256

Fig. 2 summarizes the architecture of the ANN.

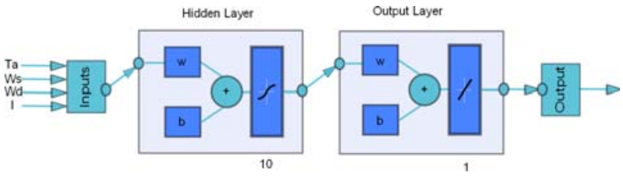

Figure 2. Neural Network diagram.

4. Results

Fig. 3 shows the histogram of the absolute error of the ambient temperature as the variable to predict and the cumulative occurrence curve. The population data for model verification is 8,017 values.

Firstly, ambient temperature has been selected as a variable to predict wind speed, wind direction and solar radiation as exogenous variables.

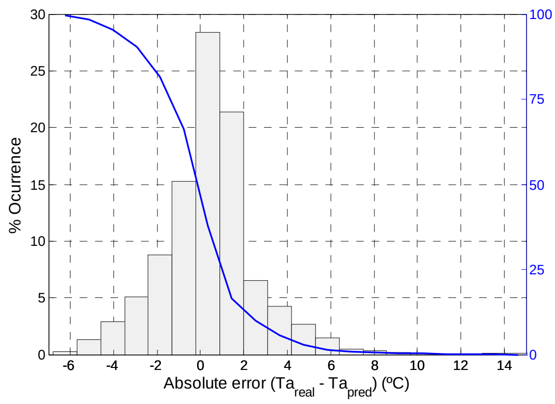

Figure 3. Probability density function and cumulative density function of ambient temperature prediction error.

The absolute error shows values between -4.1 and 5.6 ºC with a confidence interval of 95%. The 83.1% of the results are from -3 to 3 ºC.

Fig. 4 shows the histogram of the absolute error of the wind speed as the variable to predict and the cumulative occurrence curve.

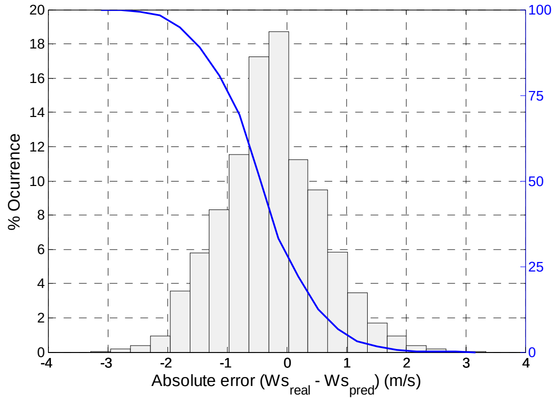

Figure 4. Probability density function and cumulative density function of wind speed prediction error.

In the case of wind speed, the absolute error is between -1.2 and 3.2 m/s with a confidence interval of 95%. The 64.5% of the results are from -1 to 1 m/s.

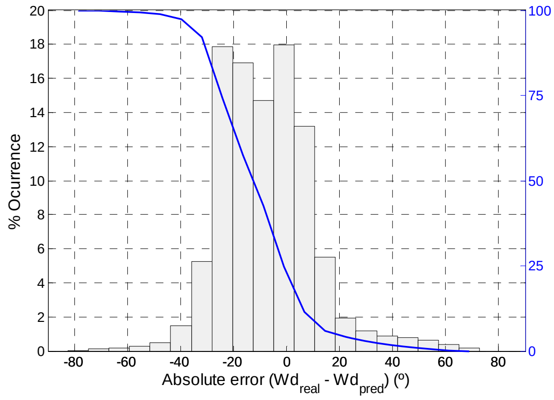

Figure 5. Probability density function and cumulative density function of wind direction prediction error.

Fig. 5 shows the histogram of the absolute error of the wind direction. The absolute error is between -36.1º and 37.7 º with a confidence interval of 95%. The 54.5% of the results are from -15 to 15 º, an acceptable error interval.

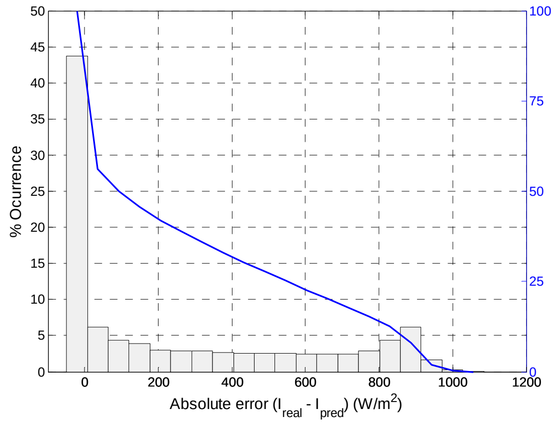

Figure 6. Probability density function and cumulative density function of solar radiation prediction error.

Fig. 6 shows the histogram of the absolute error of the solar irradiation as the variable to predict and the cumulative occurrence curve.

The absolute error is between -26.8 and 909.1 W/m^2 with a confidence interval of 95%. The 38% of the results are from -20 to 20 W/m^2, an acceptable error interval.

In the case of solar radiation is important to compare these results with the option to predict solar radiation through technical equations based on day, hour and location, as is shown in Fig. 7.

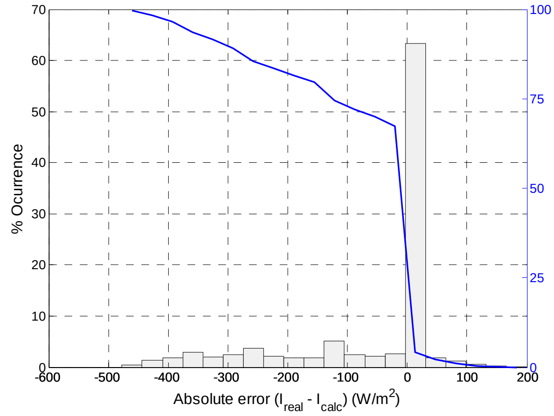

Figure 7. Probability density function and cumulative density function of solar radiation calculation error (theoretical computation).

In this case confidence interval of 95% is situated from -391.3 to 58.2 W/m^2 and 64.6% of the data are between -20 and 20 W/m^2.

Table II summarizes the MSE and the CC for all the weather parameters.

Table II. Mean Square Error and Correlation Coeficient.

Variable	MSE	CC
Ambient temperature	2.35	0.89
Wind speed	1.28	0.58
Wind direction	19.37	0.64
Solar radiation (ANN)	419.32	0.1
Solar radiation (calculation)	140.85	0.74

On the other hand, the set of predicted values is used to calculate ampacity. Errors values of ampacity are obtained by comparing calculate values with meteorological data measured and with meteorological data predicted.

Fig. 8 shows the histogram and the cumulative density function of the ampacity prediction.

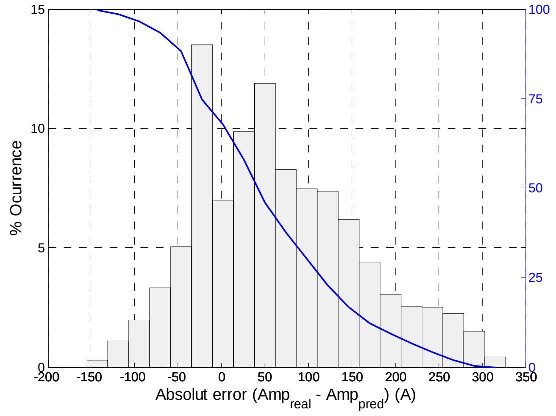

Figure 8. Probability density function and cumulative density function of ampacity prediction error

The absolute error is between -92.4 and 271.6 A with a confidence interval of 95%. The 40.7% of the results are from -50 to 50 A, an acceptable error interval. Fig. 9 shows a qualitative view of the time evolution of observed and predicted values of ampacity.

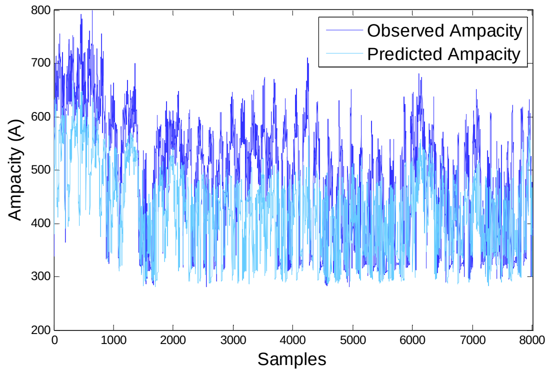

Figure 9. Observed ampacity vs. Predicted ampacity

5. Conclusion

ANN can be used as a method for weather forecast. The advantage of this method is related with the fact that it does not need complex computations and the mathematical model but only the meteorological data.

Results are highly dependent on the type of local climate, as there are more accurate in more stable climates. Another important factor is the continuity of data series to improve the model.

Finally it is observed that even though wind speed error is not very large, being the most significant variable, leads to a wider error in final ampacity prediction.

Acknowledgement

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