to draw the conclusion that the increase in forecasting difficulty also increases the importance of the ability of the simulation routine to adapt to different forecasting requirements.

About the best number of units in the hidden layer of the ANN models there is one fact that should be evidenced. There were three possible numbers of hidden units, according to the criteria set in Section 4.2. Both in CS#1 and CS#2, the number of hidden units that delivered the best results was the number of units in the input layer. However, to conclude that this choice delivers better results, more simulations should be ran.

6. Conclusions

This paper intends to present the basics on forecasting wind speed with ARMA and ANN, define similar criteria to adjust the required settings in both models and compare their performance under similar forecasting conditions. However, due to the inherent differences between the models, conclusions from the performance comparison should be drawn with care.

A general conclusion that may be drawn from the obtained results is that both ARMA and ANN do perform better than the reference persistence model. In what relates to the comparison between ARMA and ANN, one may conclude that, in general, ARMA models achieve slightly better forecasts, but they are more time consuming than the ANN models.

The predicted wind speed is much more accurate when the forecasts are performed with an hour in advance than when they are done with four to nine hours in advance, as it is the case of the MIBEL case. This worsening is thus expected, since short-term wind power forecasting models present a better performance for forecasting horizons of a few hours. The forecasts performed for the MIBEL case are not acceptable for any model employed, since all of them present high errors. This is a known limitation of the statistical forecasting models.

This work focuses on the forecast of wind speed with ARMA and ANN models, employing only wind speed hourly means time series. However, ARMA models allow one to utilize them with an exogenous time series and ANN models may have as input several kinds of data. This opens the possibility to train the models not only with wind speed data, but also with other variables of interest, such as wind power, temperature, atmospheric pressure and humidity. The combination of these data, as long as it is measured simultaneously in the same site, might conduct to better results, since the explanation of the input wind speed becomes more complete, thus the forecast is expected to be more accurate.

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