Chapter 7
Optimization of Windspeed Prediction Using an Artificial Neural Network Compared With a Genetic Programming Model

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ABSTRACT

The precise prediction of windspeed is essential in order to improve and optimize wind power prediction. However, due to the sporadic and inherent complexity of weather parameters, the prediction of windspeed data using different patterns is difficult. Machine learning (ML) is a powerful tool to deal with uncertainty and has been widely discussed and applied in renewable energy forecasting. In this chapter, the authors present and compare an artificial neural network (ANN) and genetic programming (GP) model as a tool to predict windspeed of 15 locations in Queensland, Australia. After performing feature selection using neighborhood component analysis (NCA) from 11 different metrological parameters, seven of the most important predictor variables were chosen for 85 Queensland locations, 60 of which were used for training the model, 10 locations for model validation, and 15 locations for the model testing. For all 15 target sites, the testing performance of ANN was significantly superior to the GP model.

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1. INTRODUCTION

The fluctuation of the wind heavily affects wind power generation. Therefore, accurate wind forecasting models are very important for effective wind power systems management. Among all the renewable energy sources, windspeed needs more forecasting approaches than currently implemented due to its higher intermittency rate (Masrur, Nimol, Faisal, & Mostafa, 2016). In the literature, three different methods have been introduced for windspeed (Ws) forecasting: physical, statistical and hybrid (Foley, Leahy, Marvuglia, & McKeogh, 2012). Physical methods are based on principles of physics such as the numerical weather prediction (NWP) models. Statistical models can be as simple as persistence to more complicated models such as Artificial Neural Networks (ANN) (Blonbou, 2011) or Markov chains. Hybrid methods combine physical and statistical models like the Autoregressive Integrated Moving Average Model (ARIMA) and ANN, which can generate non-linear functions to create an accurate model capable of predicting time series of windspeed and wind power output.

Many studies with several different models were done for diverse regions around the world. The ARIMA model was proposed by Benth and Benth (Benth & Benth, 2010) for forecasting the windspeed for three different wind farms in New York state. Zhu and Genton (Zhu & Genton, 2012) reviewed statistical short-term windspeed forecasting models, including autoregressive models and traditional time series approaches used in wind power developments to determine which model provided the most accurate forecasts. Due to the nonlinearity pattern of wind data, the forecasts using ARIMA may have inaccuracies because the ARIMA model is a linear series model (Cadenas & Rivera, 2010). Therefore, ANN has been applied to handle the nonlinear nature of windspeed data in previous research. A comparison of ANN and ARIMA was presented by Cadenas and Rivera (Cadenas & Rivera, 2007) using seven years of windspeed data. Six years of this dataset were used for the training, and one year for the validation, using performance metrics like Mean Square Error (MSE) and Mean Absolute Error (MAE). These were found to be lower for ANN when compared with ARIMA. Similarly, daily, weekly and monthly windspeed was forecasted using data from four different measuring stations in the Aegean and Marmara regions of Turkey by Bilgili and Sahin (Bilgili & Sahin, 2013). The results show that the ANN forecast was superior. In addition to this, recently Zameer et al. (Zameer, Arshad, Khan, & Raja, 2017), proposed the Genetic Programming (GP) model for the short term prediction of wind for five different wind farms in Europe, the average root MSE was 0.1176 ms^{-1}.

A challenge for the machine learning (ML) models is the requirement of the input data that must be related to the target variable. These input variables are not often available easily due to the remoteness of potential sites and the cost and maintenance associated with the experimental apparatus. Fortunately, Meteorological reanalysis have arisen as an important data source for renewable energy modeling studies over the past few years for several reasons: reanalysis data are usually available globally; they provide several decades of coverage; and they are usually freely available. Commonly used global reanalysis of the most recent generation include MERRA (Modern-Era Retrospective Analysis for Research and Applications), re-analysis proposed by NASA's (National Aeronautics and Space Administration) Global Modeling and Assimilation Office (Rienecker, Suarez, Gelaro, Todling, Bacmeister, Liu, & . . . Kim, 2011), the ERA-Interim re-analysis of the ECMWF (European Centre for Medium-range Weather Forecasts) (Dee et al., 2011) and the Japanese 55-year reanalysis (JRA-55) (Kobayashi, Ota, Harada, Ebita, Moriya, Onoda, & . . . Takahashi, 2015). There is a wide range of recent work done by using reanalysis data for wind power simulation (e.g. Refs. (Staffell & Green, 2014).

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