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Influence of Neural Network Training Parameters on Short-term Wind Forecasting

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Abstract

This paper investigates factors which can affect the accuracy of short-term wind speed prediction when done over long periods spanning different seasons. Two types of Neural Networks are used to forecast power generated via specific horizontal axis wind turbines. Meteorological data used is for a specific Western Australian location.

Results reveal that seasonal variations affect the prediction accuracy of the wind resource, but the magnitude of this influence strongly depends on the details of the Neural Network deployed. Factors investigated include the span of the time series needed to initially train the networks, the temporal resolution of this data, the length of training pattern within the overall span which are used to implement the predictions and whether the inclusion of solar irradiance data can appreciably affect wind speed prediction accuracy. There appears to be a relatively complex relationship between these factors and the accuracy of wind speed prediction via Neural Networks. Predicting wind speed based on Neural Networks trained using wind speed and solar irradiance data also increases the prediction accuracy of wind power generated, as can the type of network selected.

1. INTRODUCTION

Wind represents a clean and sustainable energy source which makes it a promising alternative to fossil fuels. On average, global wind power generation capacity has increased by 25% over the last years to reach 238 Gigawatts (GW), but is expected to grow by another 255 GW by 2016 (Global Wind Energy Council 2011). Combining wind with other renewable energy resources, such as solar energy and an energy storage means like hydrogen, can help build a 100 precent renewable energy system for small applications (Lund 2005, Lund and Mathiesen 2009). However, increasing wind power penetration requires a number of major challenges to be addressed, including the use of realistic models to determine techno-economic feasibility as well as utilising accurate wind speed predictions to better assess overall viability and the impacts on ancillary service requirements (Haque and Meng 2011). As with other renewable sources such as solar irradiance, the intermittent and seasonal nature of wind speed is a major hurdle against the utilisation of wind energy systems. For these reasons, wind speed prediction can play an important role in determining the overall feasibility of a renewable energy system and the scale of energy storage media such as batteries or hydrogen (Deshmukh and Deshmukh 2008, Abdel-Karim *et al.* 2009, Soman *et al.* 2010, Xiaomei *et al.* 2011). In this regard, wind power forecasts can be classified based on the prediction timescale into four categories, namely: very short-term (few seconds to 30 minutes ahead); short-term (30 minutes to 6 hours ahead); medium-term (from 6 hours to one day ahead); and long-term (one day to one week ahead) (Soman *et al.* 2010).

Among several methods, Neural Networks (NN) are excellent for predicting variables which are nonlinear or stochastic in nature and have therefore been used to forecast wind speed. The advantage of Neural Networks is that there is no need to base the predictions on preconceived mathematical models. Instead, the methodology relies on samples of training data (historical records of wind speed) to predict patterns of future wind power availability using an "intelligent" self-iterating numerical process which is presented as data intensive. The literature cites numerous investigations into the use of Neural Networks for wind speed prediction (More and Deo 2003, Reikard 2008, Wu *et al.* 2009, Hong *et al.* 2010, Anvari Moghaddam and Seifi 2011, De Giorgi *et al.* 2011, Shi *et al.* 2011, Sideratos and Hatziargyriou 2012) but the majority of the work done to date uses historical wind speed data as the only (meteorological) parameter to train the networks. Very few exceptions exist to this with some adding other parameters such as ambient temperature and humidity when predicting wind speed (Cali *et al.* 2008).

When basing predictions (largely) on wind speed data, several attempts have been made to perform very short-term wind energy forecasting using "intelligent" techniques such as Neural Networks (Kariniotakis *et al.* 1996, Li *et al.* 2001, Ricalde *et al.* 2011, Shi *et al.* 2011). Ricalde et al. used Neural Networks for wind speed forecasting and compared between different networks (Ricalde *et al.* 2011). However, limited wind speed data covering five hours (only) was used to train and test the networks which raise questions on the sensitivity of this methodology in predicting wind speed over longer periods of time. The current study will show that deploying networks over longer periods (like one year) is paramount in order to capture seasonal variations which have an impact on the accuracy and will address this shortfall by applying short-term predictions (1 hour ahead) over an extended period spanning multiple seasons. Welch, Ruffing and Venayagamoorthy similarly trained three types of Neural Networks to predict (fifteen minutes ahead) wind speed using wind speed, temperature and humidity as training data (Welch *et al.* 2009). Their results showed that although some Neural Networks outperform others, this improved accuracy comes at the expense of longer training time. Similarly, the use of training data spanning only one week may not allow an analysis against long-term (seasonal) effects. Reikard also used Neural Networks for short-term wind speed forecasting with both wind speed and temperature used for training (Reikard 2008). The use of additional meteorological data (i. e. temperature) in the training was found to reduce the forecast error for wind speed but the methodology applied also showed that Neural Network prediction accuracy decreases as the temporal prediction range grows (for longer periods ahead). The current paper will show that seasonal effects should be factored in with long-term predictions but the prediction accuracy is strongly affected by the length of (historical) data used for training the Neural Network (varied between 5 hours and 168 hours). Alternatively, long-term wind power forecasting has been conducted by Cali at al. (Cali *et al.* 2008) using a multi-model approach with wind speed, wind direction, ambient pressure, temperature and humidity as training data. However, the predictions were implemented for relatively large time-steps which render the wind power predictions at a much longer temporal resolution than typically expected variations in load (demand) that wind energy systems need to meet. As such, investigating seasonal parameters which have the propensity to affect short-term forecasts when applied over prolonged periods, spanning many seasons, is important.

In addition to research undertaken into the effect of meteorological parameters on the accuracy of Neural Network predicted wind speed, the effects of temporal resolution for time steps and the size of data used to train a Neural Network has also been done and the results showed that only one year training data can provide satisfactory prediction accuracy of monthly wind energy(Tu *et al.* 2010) . However, prediction of long-term (monthly) wind energy was only investigated. Additionally, other studies have applied Neural Networks to wind power predictions of up to 30 hours ahead (Bhaskar and Singh 2012), but the effect of including other meteorological parameters such as solar irradiance, to help refine wind power predictions, was not done. More importantly, the impact of changing the Lengths of Training Pattern (LTP) on the prediction accuracy was also not investigated. A combination of Neural Network and Genetic Algorithm (GA) has also been used for short-term wind power predictions (Kolhe 2011) where it has been found that combining GA with Neural Networks improves the prediction accuracy. However, results also showed that prediction accuracy is affected during periods of strong variation in wind speed. This suggests that more investigation into the effect of seasonal variations on the accuracy of Neural Network predictors may also be warranted whereby parameters, such as temporal resolution of training data, are investigated if they have an effect on the accuracy of wind speed prediction. In this regard, the current research also investigates this issue with different time steps of wind speed data (0.5 hour to 3 hours).

With the above in mind, there have been no studies which the present authors are aware of that investigate the effect of seasonal variations onto the prediction accuracy of wind speed using Neural Networks. Moreover, the current research also investigates the significance of simultaneously including location-specific solar irradiance data (W/m^2) on the accuracy of wind power predictions. This work is done across seasons and also investigates the effect of the LTP and temporal resolution on the accuracy of short-term wind energy predictions. Measured wind speed data for a Western Australian location are used to implement the predictions and the power characteristics of two wind turbines (2kW, 30kW). The paper is divided as follows: Section 2 describes the methodology including the wind data, wind turbines, solar irradiance data and Neural Networks used; Section 3 presents the results followed by the discussion in Section 4 and finally the conclusions in Section 5.

2. METHODOLOGY

Wind speed is stochastic in nature, but once predicted, the available wind energy can be estimated to reasonable accuracy using a suitable wind turbine model. In this paper, short-term wind energy forecasting is performed using two types of Neural Networks, namely: Feed Forward (FF) and Radial Basis Function (RBF) Neural Networks. These two techniques are categorised as supervised networks because the training algorithm is initially developed using known pairs of input-output patterns (i.e, a historical time series of calendar date versus wind speed, wind speed and direction, or wind speed and solar irradiance). The forecasting process is tested over a prolonged period (one year) so as to identify the effect of seasons on prediction accuracy. Although the forecasting is done over one year period, the prediction step where mainly an hour-ahead, i.e., 8760 predictions are done to forecast the wind speed over one year.

2.1 Wind data and wind turbine models

The available time series consists of half hourly resolved wind speed and direction data measured by the Bureau of Meteorology (BOM) at a height of 10 meters at the Ocean Reef meteorological station (Western Australia, latitude: -31.75^o, longitude: 115.8^o) (BOM

2012a). These data cover a period from January 2001 to December 2009. Data spanning either a single year (2001) or six years (2001-2006, around 70% of the available data) are used to first formulate and train the Neural Networks while data for the years 2007-2009 is subsequently used for testing accuracy. In this study, the temporal resolution of the (source) training data is half hour based. However, to help study the effects of using other resolutions such as hourly, two hours and three hours are also investigated by binning the half hourly data and deriving average wind speeds over the binned periods. Lower resolutions such as weekly or monthly are not considered because these time steps will unnecessarily smooth much of the intermittency characteristics of wind speed as well as impact the ability of the Neural Networks to resolve seasonal effects. To convert the kinetic energy of wind speed to wind power, the power characteristic curves of commercially available wind turbines are used. In this research, the characteristics of 2kW and 30kW off-grid wind turbines are considered and Figure 1 gives the power-vs-wind speed curves for both turbines with basic operating data being available (Anhui Hummer Dynamo Co. Ltd 2012).

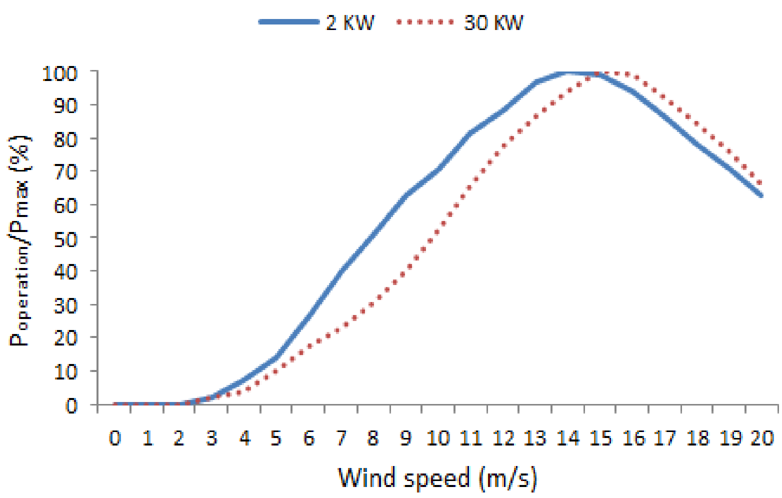

Figure 1: Power curve of off-grid wind turbines (Anhui Hummer Dynamo Co. Ltd 2012). Power generated has been normalised by the respective (peak) power capacity.

The hub height of a wind turbine affects the generated wind power (Genç *et al.* 2012). To accurately estimate the power extracted by the wind turbine, the effect of wind shear, which represents the variation of wind speed with elevation, is typically considered. In most studies, the wind speed shear is described by the shear exponent coefficient (α) shown in equation (1). Because the modelled wind turbines operate at a height of 18m, but the meteorological wind data is originally measured at 10m, each data point for wind speed is revised to the operating height of the wind turbine (Belfkira *et al.* 2009):

$$v = v_0 \left(H/H_0 \right)^{\alpha} \tag{1}$$

In this regard, v and v_0 are the wind speed at H and H_0, respectively, whilst α is the wind shear exponent coefficient. The value of this coefficient has been taken equal to 1/7 commensurate with the value for open land because the location for which the wind power modelling is being undertaken is an unobstructed costal land spot (Belfkira *et al.* 2009). It is worth noting that whilst the value of the shear exponent coefficient for a particular area is not constant along the whole rotor swept area of the wind turbine, ignoring the effect of the wind shear coefficient is proven to result in overestimating the wind power extracted from a wind profile for large turbines. This is particularly evident for the cases where the hub height is much greater than the height of the meteorological anemometer used to measure wind speed (Bechrakis and Sparis 2000, Wagner *et al.* 2011). Previous studies have also shown variations of wind shear coefficient is insignificantly changed across seasons (summer and autumn compared to winter and spring) (Ray *et al.* 2006). Therefore, in this study a single wind shear coefficient is considered across all seasons.

2.2 Solar irradiance data

In order to train the Neural Networks on both wind speed and solar irradiance at the relevant geographical location, solar irradiance data has been derived using the ASHRAE clear-sky model (Bakirci 2009). The parameters of the ASHRAE model are retrieved from the literature (Wong and Chow 2001). Before the ASHRAE derived (hourly) solar irradiance data was used in the Neural Networks, its accuracy was checked against daily total measured solar irradiance data (BOM 2012b). This process can be undertaken when no well resolved (e. g. hourly) exists. Figure 2 shows these comparisons whereby the data derived using the ASHRAE model (for each day) has been formed by summing the hourly resolved predictions over 24 hours. The figure shows the irradiance predictions based on the clear sky model are able to accurately follow the peak solar irradiance values. It should be noted here that any other reasonably accurate model (or even measured data) could have also been used to demonstrate the validity and effects of coupling wind speed predictions with representative solar irradiance data.

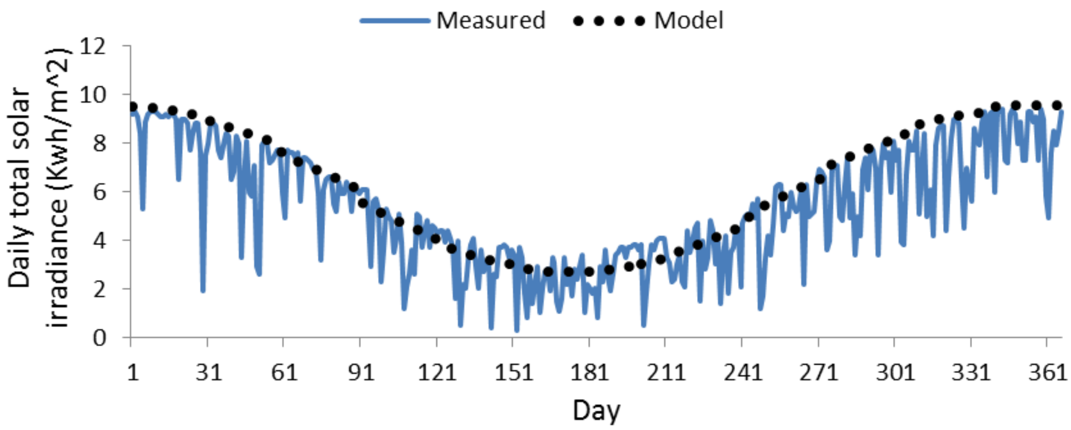

Figure 2: A comparison of daily (cumulative) total solar irradiance derived using the ASHRAE model compared to measured (meteorological) daily totals data. (latitude: -31.75^0, longitude: 115.8^0, 2004).

2.3 Neural Networks

Neural Networks consist of interconnected computational units which imitate the structure of biological neurons. These neurons are independent processing units and the connections between these units (weights) are used to store the acquired data. In this paper, FF-NN and RBF-NN are used to forecast wind speed (only) using different combinations of meteorological training data. The general structure of these networks, shown in Figure 3, comprises of an input layer, a hidden layer, and a linear output layer. The function of the input layer is to distribute input data in order to initiate the computations. Typically, the span of the time series used to train a Neural Network, for example a single year which can be hourly resolved to yield 8760 data points, is further subdivided into batches. The number of data points in each batch dictates the number of neurons in the input layer. For example, an LTP of 10hours when half hourly resolved wind speed data is used will result in 20 neurons in the input layer, for both FF-NN and RBF-NN. The output of any neuron in the hidden layer of a FF-NN is a result of activating a sigmoid function using the weighted sum of the input signals. The sigmoid activation function has the following form (Fengming *et al.* 2011):

$$f(z) = 1/(1 + \exp(-az)) \tag{2}$$

In this regard, a is the slope parameter of the sigmoid function and z is the weighted sum of neuron inputs which is given as:

$$z_k = \sum_{j=1}^{M} w_{kj} y_j \tag{3}$$

In the above equation, y_j is the input signal, w_{kj} is the connection weight and M is the number of values in the input pattern. The connection weights are dictated by the learning algorithm which the Neural Network uses when being training on historical data. In this study, three different algorithms were trialled (the gradient decent algorithm, Levenberg-Marquardt algorithm and adaptive gradient decent algorithm). Based on preliminary testing, it was observed the adaptive gradient decent algorithm yielded the best accuracies and, as such, was deployed in the FF-NN throughout the results which appear in this paper. The output of the sigmoid function is only positive numbers between 0 and 1. Each neuron in the Neural Network compares the output of its activation function against a predefined threshold to decide whether to produce an output or not. In this research, the number of hidden neurons in the FF-NN was taken to be 10 in agreement with the literature (Bechrakis and Sparis 2000, Öztopal 2006). The design of a Feed Forward Neutral network also usually involves the selection of many control parameters. As there is no commonly agreed upon consensus (in the published literature) in relation to the specific rules for nominating these parameters, an iterative process was undertaken to resolve the best set of these which satisfy a pre-set convergence criteria (the performance goal). Table 1 lists the value of these control parameters.

The difference between FF-NN and RBF-NN lies mainly in activation function as well as the role and number of neurons in the hidden layer. The activation function of FF-NN is a sigmoid function whereas for the RBF-NN its activation function for the hidden neurons is a Gaussian function and expressed as (Xiaomei *et al.* 2011):

$$f\left(y_p - c_i\right) = \exp\left(-\left(1/2\delta_j^2\right)\left\|y_p - c_i\right\|^2\right) \tag{4}$$

In this regard, c and δ are the centre and the mean square deviation of the Gaussian function and y_p is the p^{th} input pattern whereby the Gaussian function is bell-shaped with a maximum of 1. Neurons are activated (produce an output) based on how close the net input is from a chosen value of averaged inputs. While FF-NN acts as a global approximation network, since the network's output is decided by all neurons of the hidden layer, RBF-NN acts as local approximation network. This means the hidden layer in RBF-NN redistributes the input data and each output is determined by specified hidden units (Xie *et al.* 2011).

Further details on the training algorithm of RBF-NN are also available in the literature (Xiaomei *et al.* 2011, Xie *et al.* 2011).

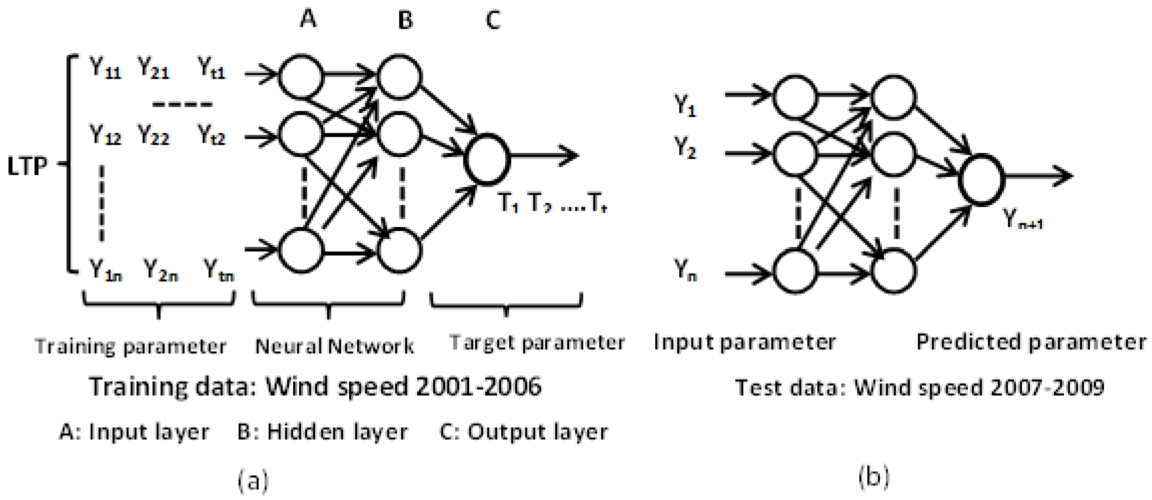

Figure 3: General structure of FF-NN and RBF-NN: (a) training phase (2001-2006); (b) test phase (2007-2009).

The other difference between a FF-NN and RBF-NN is the former uses a fixed number of neurons in the hidden layer whereas the latter uses a variable number of neurons in the hidden layer (self-defined by the Neural Network). Training coefficients of Radial Basis Function Neural Network are also listed in Table 1. The consequences of the above are that RBF-NN trains itself over different ranges of the training data (e. g. different ranges of wind speed) where FF-NN is trained on the total range.

Table 1: Training coefficients of the Neural Networks used.

Network type	**Training coefficient**	**Value**
FF-NN	Momentum constant	0.6
	Learning rate	0.8
	Performance goal	1e-4
	Number of hidden neurons	10
RBF-NN	Spread of radial basis function	20
	Performance goal	1e-5

2.4 Accuracy

The accuracy of hourly wind speed and wind power predictions is expressed as the Absolute Percentage Error (APE) which is calculated as follows:

$$APE = \left| \left(y(t) - \hat{y}(t) \right) \Big/ y(t) \right| \times 100\% \quad (5)$$

The Mean Absolute Percentage Error (MAPE) is used to assess the overall accuracy of the used Neural Networks and it is calculated as follows:

$$MAPE = (1/N) \sum_{i=1}^{N} APE \quad (6)$$

In the above equations, $y(t)$ is the measured wind speed over a time interval (t), $\hat{y}(t)$ is the predicted wind speed (over the same time interval) and N is the number of data points in each year. The time interval (t) represents the resolution of the training and test data (0.5, 1, 2 or 3hours). In the plots and tables which follow, the overall prediction accuracy is expressed by calculating the median value of $APE's$ and the median value of $MAPE's$ for the test data (2007, 2008, and 2009).

3. RESULTS

In this research, the effect of four training parameters on the prediction accuracy of FF-NN and RBF-NN when applied to wind energy prediction is investigated, namely the span of training data, the resolution of training data, the Length of Training Pattern (LTP) and the type of training data.

3.1 Span of training data

To demonstrate the effect of the span of training data on the prediction accuracy of FF-NN and RBF-NN, Both Neural Networks are trained using hourly resolved data which spans either a single year (2001) or six years (2001-2006) with the LTP fixed at 10 hours. The prediction error corresponding to each set is shown in Figure 4. Whilst the length of training history does not appear to affect the errors qualitatively, the results do reveal that using six years data set to train the FF-NN provides a marginal improvement in the prediction accuracy, compared to one year training data sets. Quantitatively, no appreciable improvement occurs with RBF-NN, which the results also show already has an accuracy of about one order of magnitude better than FF-NN. This also indicates that RBF-NN maybe more accurate than FF-NN for the same span (size) of data set.

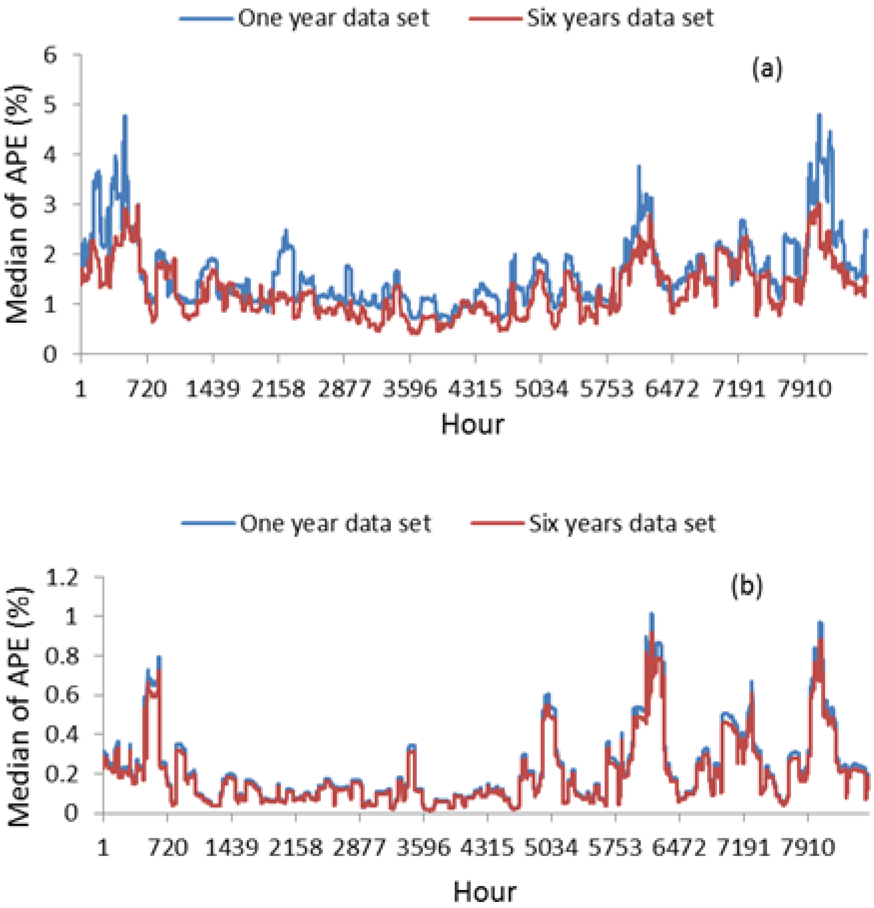

Figure 4: The effect of the span of training data on the prediction accuracy. Wind speed training data (only) are used: (a) FF-NN; (b) RBF-NN.

3.2 Resolution of training data

The effect of temporal resolution of the historical training data is also investigated whereby hourly, two hours and three hours' time series are formed by averaging the original (measured) half hourly meteorological data. Figure 5 shows a comparison between the prediction accuracy related to using different temporal resolutions over a single season. A single season is used in this analysis (Figure 5) because, as will become evident from this study, strong seasonal effects can manifest themselves. The results show that prediction error for Neural Networks appears best for hourly resolution compared to the others. One distinctive feature from these results is that using half hourly resolution appears to provide the least accuracy compared to 1-3 hours resolution. This may be due to the fact that half hourly wind speed data more realistically represents the variability of wind speed which results in a greater degree of uncertainty when the Neural Networks attempt to resolve the wind speed over the next time period. More comment and data analysis in relation to this is given within the Discussion section. With the above in mind, the ensuing results were all derived for Neural Networks trained using (hourly resolved) six years training data set.

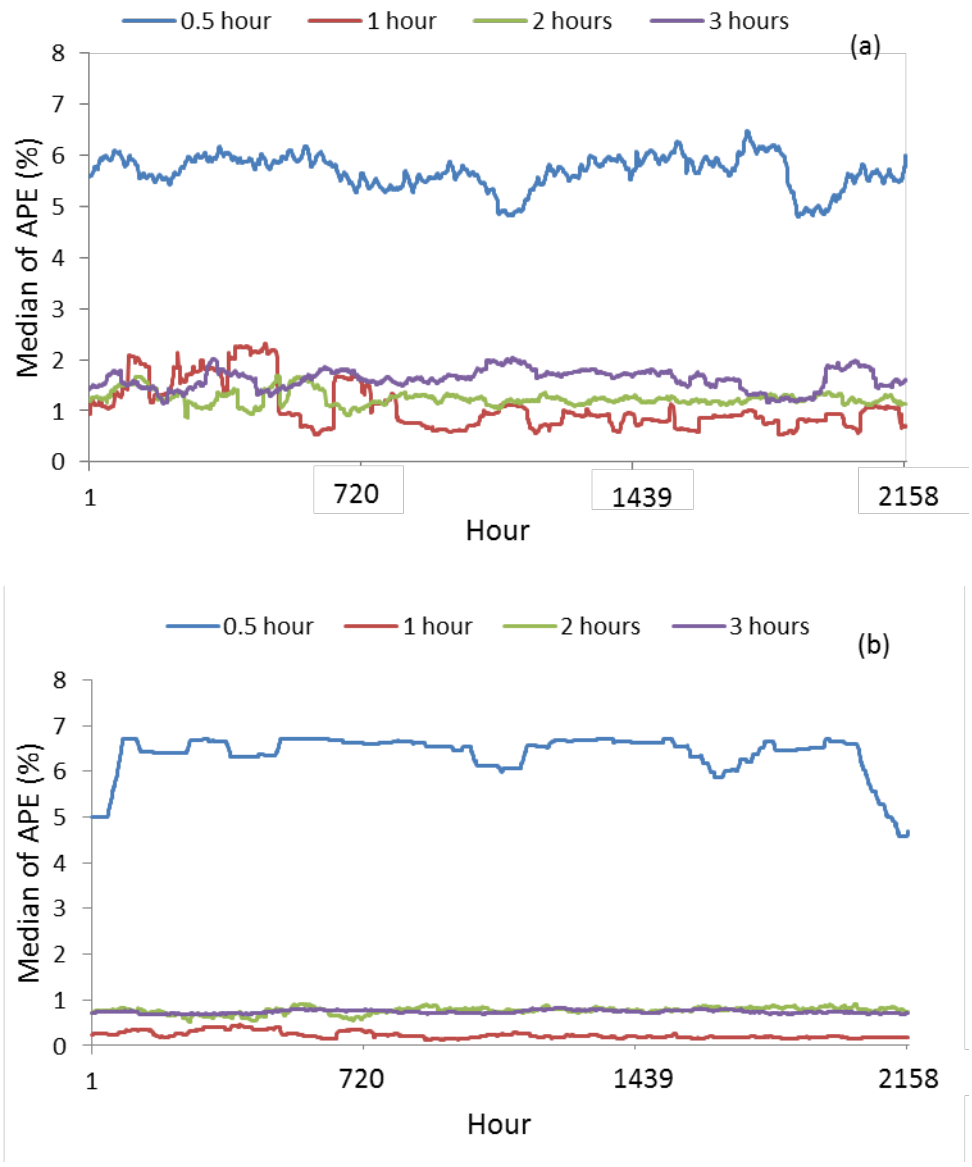

Figure 5: The effect of different training data resolutions of the prediction accuracy of Neural Networks: Wind speed training data (only) are used: (a) FF-NN; (b) RBF-NN.

3.3 Type of training data and LTP

To further study the effect of the LTP on the prediction accuracy of the employed Neural Networks, both FF-NN and RBF-NN are trained with four different Lengths of Training Patterns (5, 10, 60 and 168 hours). This is an important consideration because even if the networks are trained using hourly resolved historical data, the LTP dictates how far back in the time-series should the network consider when predicting each next (hourly) time step. A shorter LTP may be hypothesised to yield better predictions if applied to a stochastic parameter such as wind speed. An additional hypothesis to test is, in addition to LTP, what impact on the accuracy of predicted wind speed is associated with using different combinations of (historical) meteorological data. To resolve this question, the training data is also made up of three different combinations of meteorological data: wind speed (only), wind speed and direction, or wind speed and solar irradiance. Figure 6 presents the overall trends for the prediction error in both FF-NN and RBF-NN when predicting hourly resolved wind speed averaged over three years ahead (2007-2009). In the results shown, the Neural Network is trained using wind speed data (alone) and the different seasons are also denoted according to the Australian Bureau of Meteorology (BOM) (BOM 2012a). In this regard, the national summer season is made up of the three (hottest) months of December, January and February. These results show that for both FF-NN and RBF-NN, the accuracy is not consistent throughout the year but experiences a relative trough (low range) during autumn and winter. Outside this period, errors increase and reach their highest values during summer and spring. These results clearly indicate that prediction accuracy for wind speed varies across the year. Moreover, when wind speed data (only) is used to train the Neural Network, the accuracy of both networks tested in this study remains prone to seasonal influences, even though in this instance RBF-NN is clearly more accurate than FF-NN. These results also demonstrate that more research is needed into the veracity of different prediction methodologies which are undertaken over only relatively short periods (e.g., over a week or few months only) as these may fail to resolve longer seasonal trends. This also exemplifies the need for the accuracy of wind speed prediction methods to be tested over prolonged periods (e. g. one year or more) so as to capture such seasonal influences. Unfortunately, it would appear that research into predicting wind speed (and power) over prolonged periods (to account for seasonal influences) is not always apparent in the published literature.

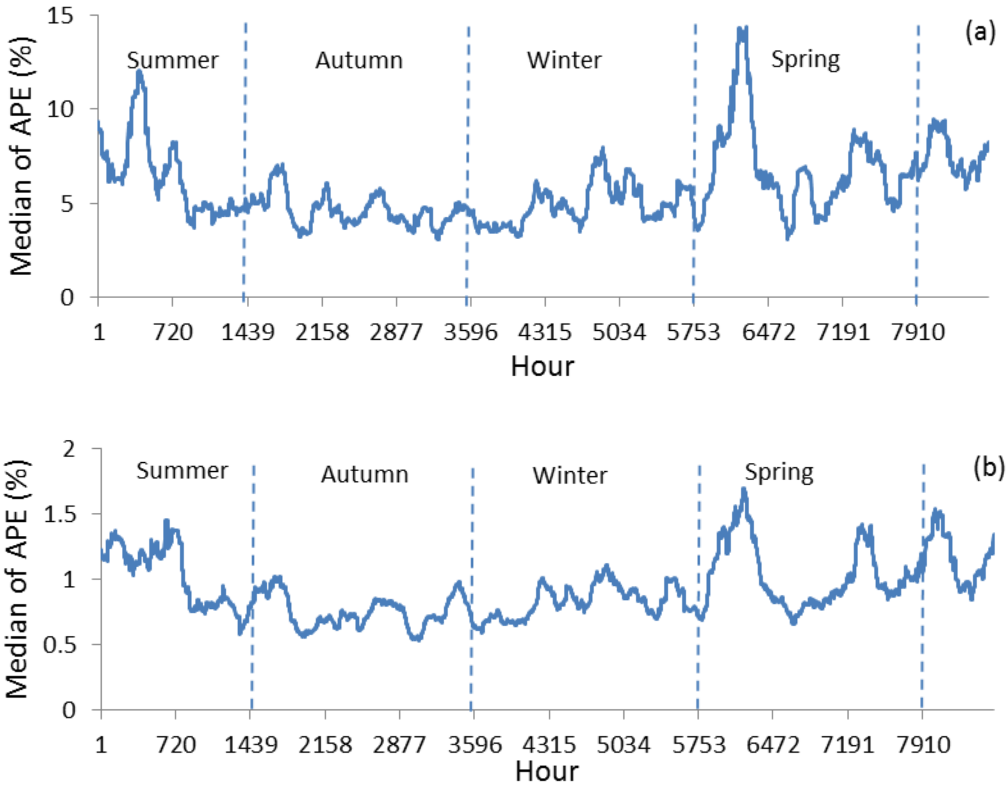

Figure 6: Prediction errors using 168 hour input data of wind speed (only) for the years 2007-2009: (a) FF-NN; (b) RBF-NN. The first day in the figure corresponds to 1st January.

Figure 7 shows the effect of changing LTP on the prediction accuracy of FF-NN and RBF-NN. Results indicate the performance of both Neural Networks is improved by decreasing the LTP but the gain achieved in accuracy is not linear and appears to diminish as LTP is reduced from 168 hours to 10 and 5 hours. No considerable improvement is achieved by going lower than LTP=10. The results also show that RBF-NN remains more accurate than FF-NN. The more important observation is that although using a shorter LTP appears to improve the prediction error for both networks, it also appears to be less effective as a strategy to smooth out the seasonal influence for FF-NN. In comparison, the performance of RBF-NN not only becomes much better when reducing LTP but seasonal influences on the error of prediction are also damped.

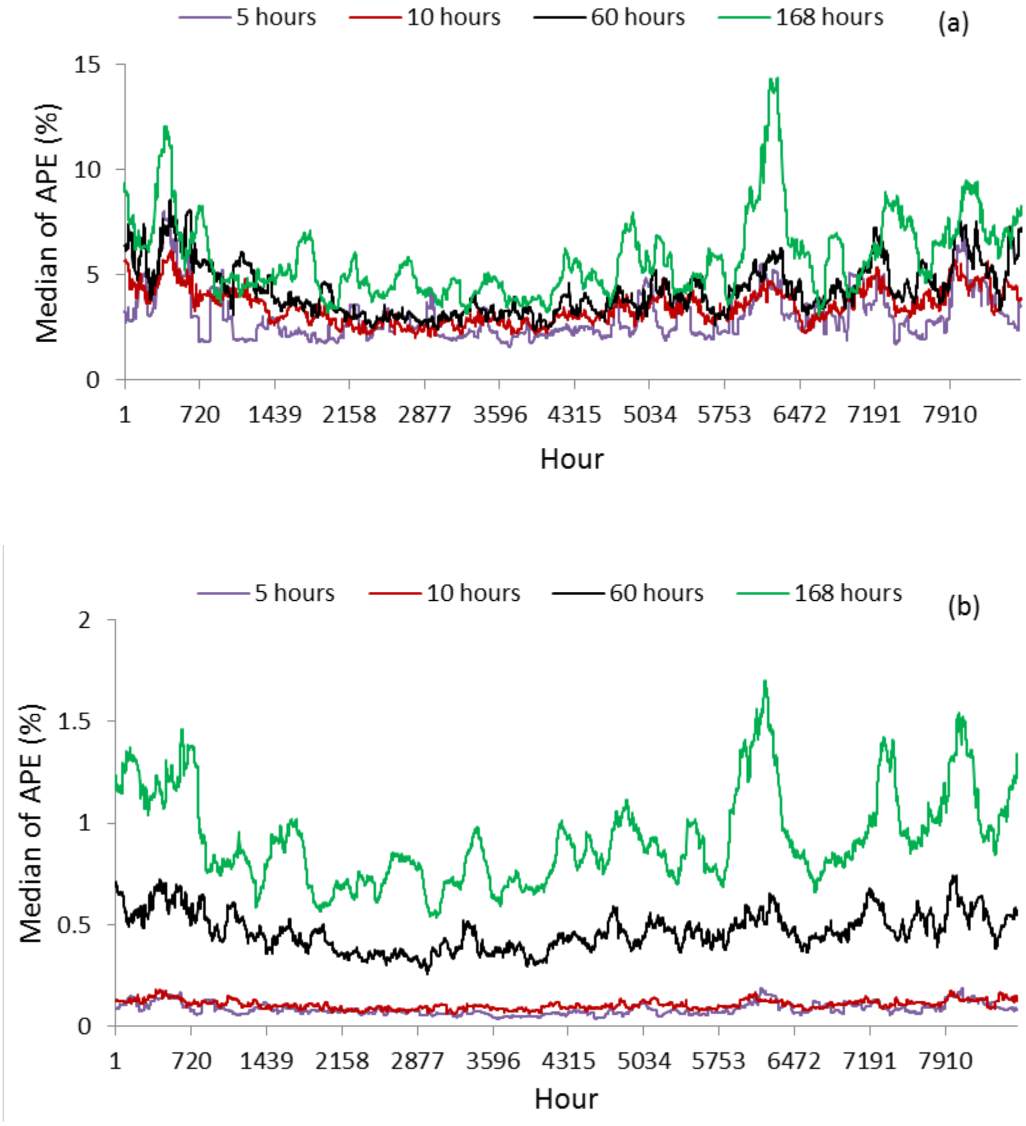

Figure 7: The effect of LTP on the prediction accuracy over the years 2007-2009: (a) FF-NN; (b) RBF-NN. Hourly resolved data is used in training the Neural Network.

Figure 8 shows the effect of using different combinations of meteorological data at the input layer when predicting wind speed. Results show that combining wind speed training data with other meteorological parameters (e.g. wind speed and solar irradiance) appears to improve predictions and reduce seasonal effects.

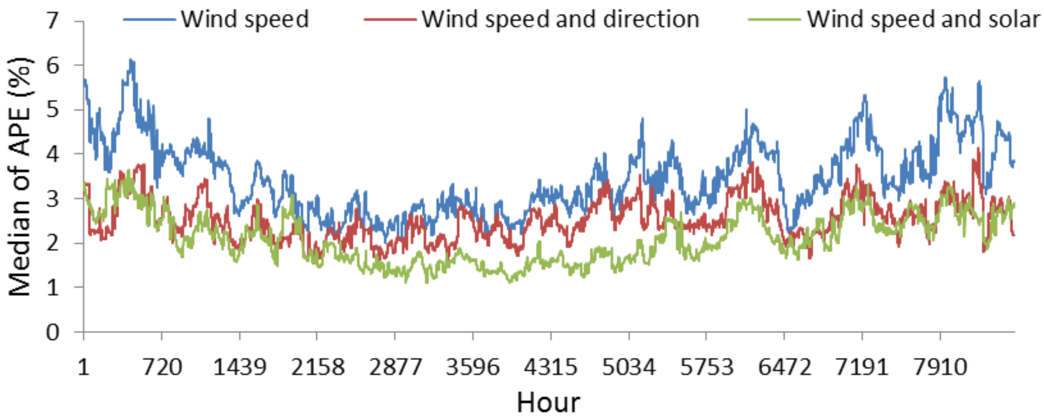

Figure 8: The effect of prediction parameters on the accuracy of wind speed predicted via FF-NN over the years 2007-2009 (LTP=10 hours). Different combinations of (historical) meteorological data are used as inputs when attempting to predict wind speed. Hourly resolved data is used in training the Neural Network.

4. DISCUSSION

Five main observations can be drawn from this study. Firstly, increasing the size of the historical training data set has an insignificant impact on the prediction accuracy of FF-NN and RBF-NN. While the performance of FF-NN minimally improves by using wind speed training data of multiple years, RBF-NN gains no benefit from using more than one year of training data. The reason behind this may be because even a single year (well resolved) wind speed data captures the seasonal effects.

Secondly, FF-NN and RBF-NN both exhibit better performance when trained using hourly wind speed, compared to 0.5, 2 or 3hours. This unexpected behaviour indicates that an intermediate temporal resolution should be targeted, rather than very small or large time resolution. This is believed to indicate that low temporal resolutions (e. g. 2 or 3 hourly) unnecessarily smooth the data and make it harder for the Neural Networks to be adequately trained. Similarly, extremely high resolutions (e. g. 0.5 hours) are inherently susceptible to much variation which also negatively impacts prediction accuracy. To confirm this hypothesis, the standard deviations of the training sets used in this study are calculated and the results depicted in Figure 9. The data shows that half hourly resolved data has a significantly higher variability compared to the other data. This relationship was similarly reflected in predictions (Figure 5). Further statistical analysis is performed on the differently resolved wind speed data using an F-test. Results, not shown here, indicate that half hourly resolved wind speed data and the other temporal resolutions (1, 2 and 3 hours) do come from normal distributions but with different variances indicating significant spread between the different data. This result highlights the significance of appropriately selecting (temporal) resolution.

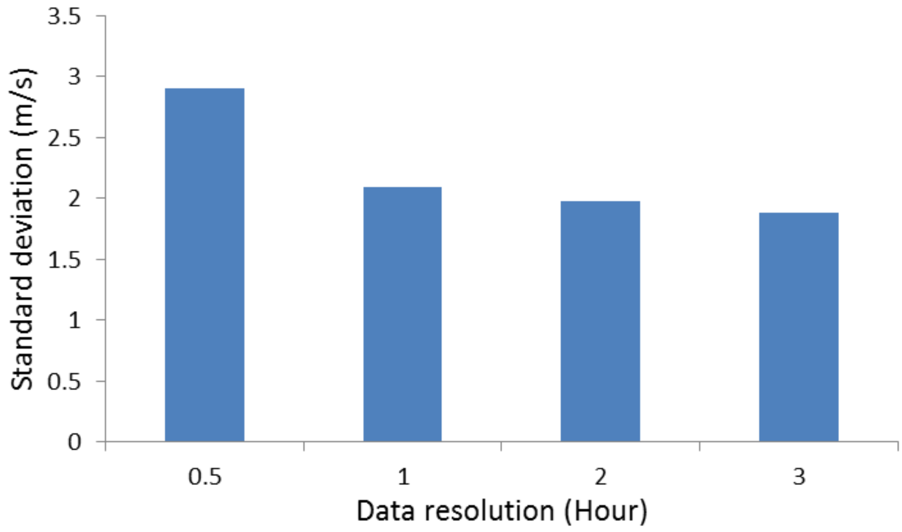

Figure 9: Standard deviations of the wind speed training data with different resolutions.

Thirdly, the seasonal variation of wind speed affects the prediction accuracy of a Neural Network, but the severity of this effect is dependent on the prediction methodology deployed. In this regard, the superiority of RBF-NN in wind speed prediction could be attributed to its "architecture". RBF-NN has the capacity to allocate specific hidden neurons to different ranges of wind speed which span the entire dynamic range represented through meteorological data (in this study mostly 3 to 9 m/s). This allows RBF-NN to map finite ranges within the data (eg., wind speed) to specific neurons in the hidden layer. However, because these allocations are done in the hidden only (not the input layer), this does not affect the time-series nature in the data.. In contrast, the hidden layer of FF-NN tries to find a global approximation that fits the entire dynamic range of input data which is difficult to achieve because of the high nonlinearity in wind speed. As can be seen from Figure 10, the magnitude of wind speed varies between 3 m/s and 9 m/s during summer season while this range reduces during winter between 3 m/s and 7 m/s. Also notable here is the striking resemblance between the seasonal variations of wind speed (Figure 10) and the errors in the predicted wind speed already presented.

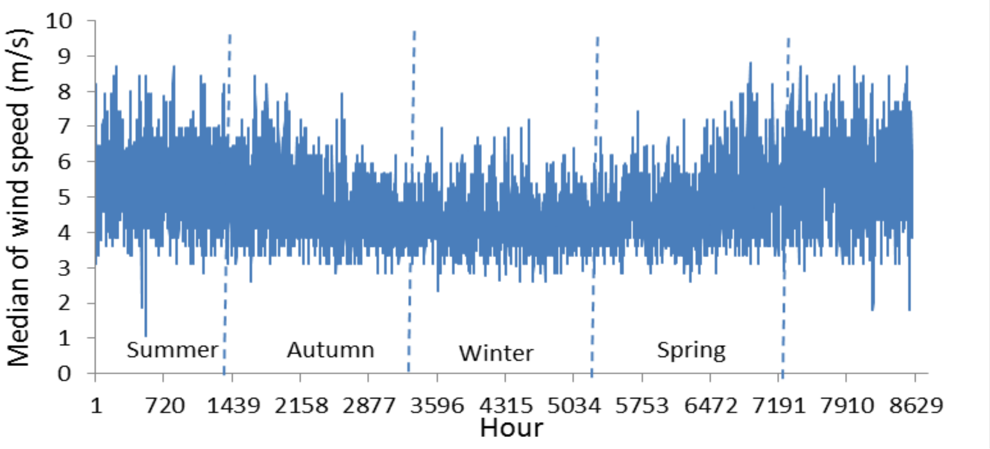

Figure 10: Measured hourly wind speed for the years 2001-2009.

The fourth outcome of this research is that reducing the LTP initially increases the prediction accuracy of the wind resource (Figure 7), for both Neural Network methodologies used, but the degree of improvement in accuracy appears to plateau as LTP is reduced. Table 2 also presents the training time for each methodology used when the LTP is varied between 5 and 168 hours. This data indicates that another merit associated with using a shorter LTP is to improve the time needed to train a Neural Network when predicting the wind resource. This behaviour results because decreasing the LTP reduces the number of neurons in the input layer (Figure 3) which means less time is needed to update the connection weights between the input and hidden layer. The physical significance of this is the network is also better able to predict seasonal variations.

Table 2: Training time for different Neural Networks based on different lengths of training data for wind speed: 5, 10, 60 and 168 hours.

Network	**Time to train Neural Network (seconds)**			
	LTP=5 hours	LTP=10 hours	LTP=60 hours	LTP=168 hours
FF-NN	2,025	2,689	8,003	22,095
RBF-NN	19	21	94	306

The fifth outcome is that incorporating (historical) solar irradiance data along with wind speed, during the training phase, can reduce the prediction error of wind speed in some, but not all, Neural Networks (Figure 8) and that as shown in Table 3 this improvement comes with no negative consequences on the training time of both Neural Networks tested. The physical explanation of this is the Neural Network is better able to discern an (hourly) relationship between the wind speed and the solar irradiance which then allows the Neural Network to better learn the behaviour of wind speed over prolonged periods spanning multiple seasons. To demonstrate the improvements in prediction accuracy which results from including solar irradiance data, the Absolute Percentage Error (Equation 6) is first derived for each (hourly) data point by comparing between the predicted and real value of wind speed. The median of APE's of all the test data (2007-2009) is then derived to show the overall prediction accuracy. Table 3 shows the MAPE for both Neural Networks. These results indicate that for FF-NN, incorporating solar irradiance data when predicting wind speed improves the overall accuracy of the network. Regarding RBF-NN, the overall accuracy is not much affected but this maybe because this network has already reached "high" accuracy and there is no further improvement in accuracy in accuracy when historical training data includes both wind speed and solar irradiance.

Table 3: Training time and MAPE for different Neural Networks based on the selection of various parameters for the input layer (LTP=10 hours) over years 2007-2009.

Network	**Data input (historical)**					
	Wind speed		Wind speed and direction		Wind speed and solar irradiance	
	Time (seconds)	Median of MAPE	Time (seconds)	Median of MAPE	Time (seconds)	Median of MAPE
FF-NN	2689	2.25%	2134	1.5%	2631	1.36%
RBF-NN	21	0.16%	18	0.33%	21	0.24%

The impact of Neural Network training methodology (type of Neural Network and LTP) on the predictions, resolved over different bands across the dynamic range of wind turbine cut-in (2.5 m/s) cut-out speed (11 m/s), is given in Figure 11 for two wind turbines (2kW and 30kW). These results indicate that using smaller LTP (10 hours) significantly reduces the prediction error of the generated power across all wind speeds and that more than a 30% improvement in wind power prediction accuracy can be achieved when 10 hours LTP is used instead of 60 or 168 hours. Figure 11 (a and b) also show that for all LTPs, the power prediction accuracy appears to improve at the higher wind speeds. The reason behind that may be because of the nonlinear shape of the wind turbine power curves (Figure 1).

According to Lange (Lange 2005), the shape of the wind turbine's power curve influences the power prediction error. In the steep part of the wind turbine characteristic curve, a small difference in the wind speed is transferred to relatively larger difference between the corresponding predicted and measured power due to the power law dependency between wind speed and convertible kinetic energy.

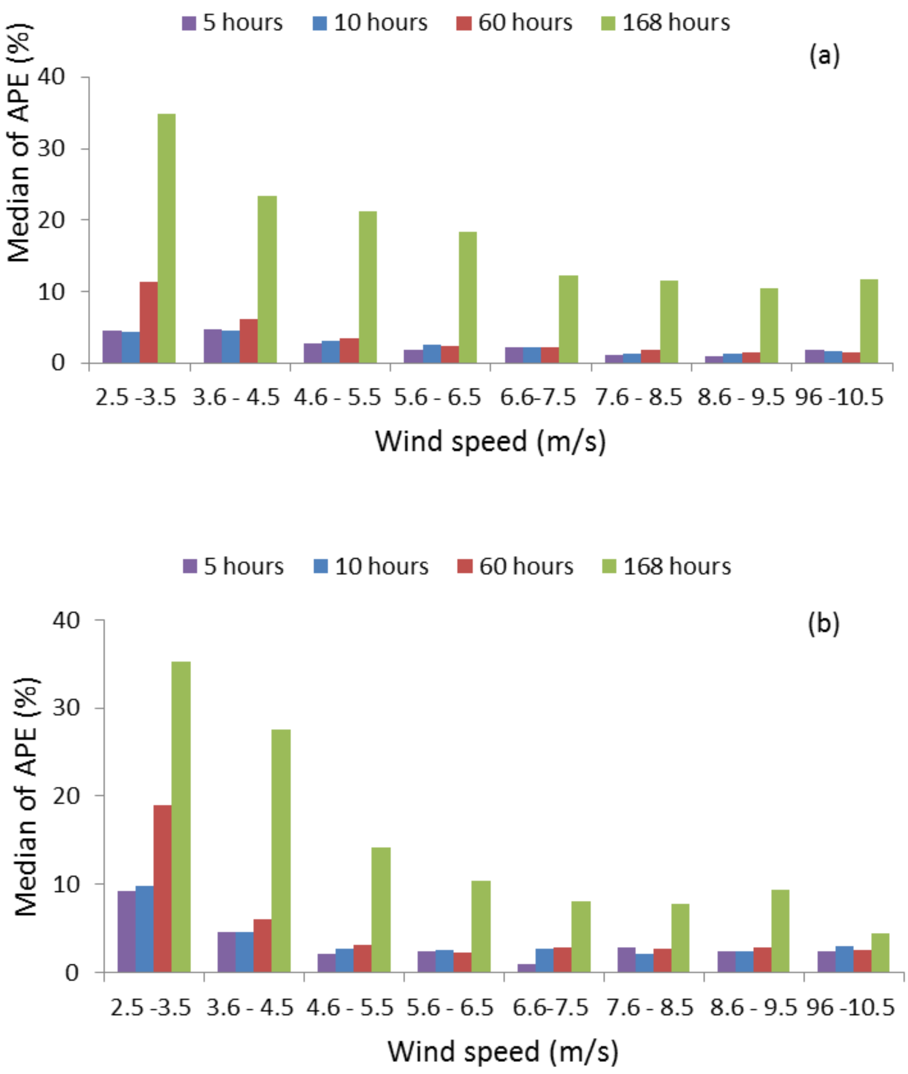

Figure 11: The power prediction error via FF-NN using different LTP over the years 2007-2009: (a) 2kW turbine; (b) 30kW turbine. Hourly resolved data is used in training the Neural Network.

Figure 12 similarly shows that incorporating wind direction or solar irradiance adds further improvement to the prediction accuracy of the generated wind power particularly as the rated speed of each wind turbine is approached (9-11 m/s). At low wind speeds, the improvement in prediction accuracy is either negligible or low compared to higher wind speeds. This indicates that the prediction accuracy of Neural Networks can also be affected by the type of input parameters used and the relative improvement also changes with wind speed.

Since solar irradiance can be predicted to some extent for any location via models such as the ASHRAE [29], the use of multi-parameter predictions using Neural Networks have an advantage over those based solely on wind speed. Solar irradiance incorporated into wind speed predictions could also be a reasonable alternative to other meteorological data which must be measured such as humidity, temperature and pressure.

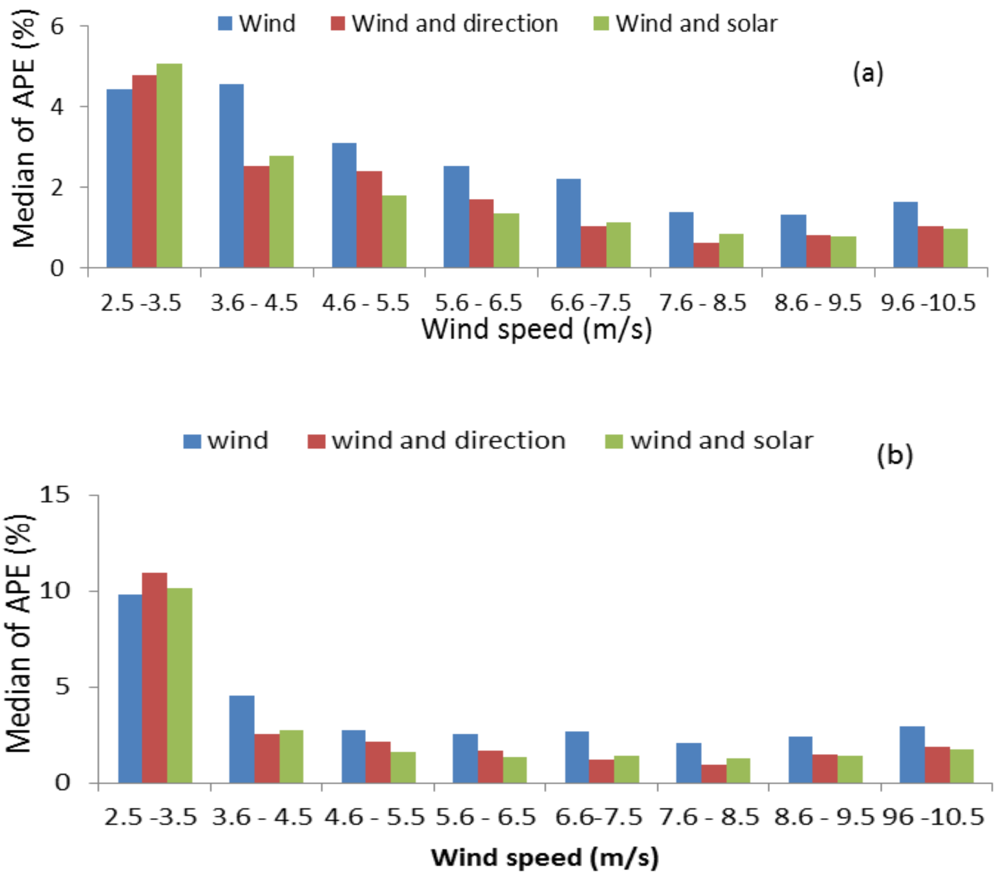

Figure 12: The power prediction error via FF-NN using different training parameters over the years 2007-2009 (LTP=10 hours). Hourly resolved data is used in training the Neural Network.

5. CONCLUSIONS

In this paper, the impact of the Neural Network training methodology employed to forecast short-term wind energy is investigated. The research has analysed the effects on prediction accuracy as a consequence of using different size and resolution of training data as well as the LTP employed. In addition, the effects of these parameters on improving the seasonal prediction error for wind speed and the inclusion of solar irradiance (as a training parameter) on prediction accuracy have also been analysed. Two Neural Networks (FF-NN and RBF-NN) have been trained using one and six years' worth of meteorological wind speed data with half hourly, hourly, two hours and three hours temporal resolution to span the training history (5, 10, 60, and 168 past hours). The research has also looked at the effects of predicting wind speed using only wind speed data as well as wind speed with direction and wind speed with solar irradiance. To assess the impact of Neural Network training methodology on the total power predicted, the power characteristic curves of two commercially available wind turbines have been used.

This paper has found that provided historical meteorological data already spans all seasons (i. e., at least a single year), no significant improvement is achieved by training the networks over more than one year. The results also reveal that seasonal variations can appreciably affect the accuracy of short-term wind speed predictions. The severity of this detrimental influence depends very much on the methodology used. This research has also shown that reducing the length of training data used in Neural Networks improves the accuracy of wind speed prediction and also reduces training time. However, this benefit appears to diminish below a certain value of LTP. The last finding of this study is that incorporating solar irradiance data can improve the prediction accuracy of wind speed with no significant consequences on the training time. This improvement in accuracy appears to be more effective at higher speeds compared to low (cut-in) speeds of the wind turbines. More work is warranted to determine if the outcomes from this research, which are based on the specific Neural Network architectures used (e.g., types, temporal resolution of data, etc), are also applicable to other data sets of wind speed and geographical locations. Unlike other meteorological data, solar irradiance can be easily predicted for geographical locations using well established models such as ASHRAE. This approach of including solar irradiance data when predicting wind speed can help improve estimates of generated wind power at any particular location, especially for remote areas where a record of other meteorological data may not be available. Accurately predicting power generated can help reduce the intermittency associated with wind energy through appropriate sizing and optimisation of energy system component selection. This may also help better size energy storage media such as batteries or hydrogen. Further work needs to be undertaken to explore the effect of using multiple input parameters on the prediction of other renewable resources (such as solar-PV) as well as the impact of using Neural Networks on the ability to meet load requirements in wind energy systems.

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