Short Term Wind Speed Forecasting with Evolved Neural Networks

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ABSTRACT

Concerns about climate change, energy security and the volatility of the price of fossil fuels has led to an increased demand for renewable energy. With wind turbines being one of the most mature renewable energy technologies available, the global use of wind power has been growing at over 20% annually, with further adoption to be expected. As a result of the inherent variability of the wind in combination with the increased uptake, demand for accurate wind forecasting, over a wide range of time scales has also increased.

We report early work as part of the EU FP7 project 'ORIGIN', which will exploit wind speed forecasting, and implement and evaluate smart-meter based energy management in 300 households in three ecovillages across Europe. The ORIGIN system will capitalise on automated weather-station data (available cheaply) to inform predictions of the wind-turbine generated power that may be available in short term future time windows. Accurate and reliable wind-speed forecasting is essential in this enterprise.

A range of different methods for wind forecasting have been developed, ranging from relatively simple time series analysis to the use of a combination of global weather forecasting, computational fluid dynamics and machine learning methods. Here we focus on the application of neural networks, without (for the time being) the use of numerical weather predictions or expensive physical modelling methods. While work of this nature has been performed before, using past wind speeds to make predictions into the future, here we explore the use of additional recent meteorological data to improve on short-term forecasting. Specifically, we employ evolved networks and explore many configurations to assess the merits of using additional features such as cloud cover, temperature and pressure, to predict future wind speed.

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1. INTRODUCTION

Significant continuing penetration of renewable energy electricity generation is predicted over the next 20 years, with projections in Europe suggesting that the share of gross generation due to renewable sources will rise to 20% in 2020 and 23% in 2030. Some studies predict even higher growth scenarios. This is largely driven by rapid growth in wind energy, especially in the next decade; but with continuing impressive growth rates beyond the next decade. In total, wind energy in 2030 is expected to provide over 15 times as much electricity as in 2000.

Though wind, solar and other renewable energy sources have many advantages, it is well known that their exploitation is a significant challenge, owing to the common mismatch between availability and demand. Simply put: solar energy is (almost by definition) rarely available when we need to warm our homes. Meanwhile, exploitably windy weather is rarely coincident with energy demand (e.g. several hours of wind overnight provides, with current implemented technology and systems, almost entirely wasted energy). The rampant expected increase in renewable generation has therefore sparked in recent years a surge in research that aims to address this problem of aligning demand and supply. One such project is 'ORIGIN (Orchestration of Renewable Integrated Generation in Neighbourhoods)', funded within the EU FP7 programme, from late 2012 to late 2015. ORIGIN will implement smart energy management within three ecovillage communities (i.e. communities that have their own renewable generation sources) in Europe, via smart metering and associated technology. The heart of the ORIGIN system will be regular demand re-alignment or other energy management suggestions (and/or direct controls) to householders and facilities managers. These suggestions and controls will be optimised (via a carefully designed evolutionary algorithm) to balance ideal outcomes within individual households with those of the community as a whole. Meanwhile, the optimisation process will be grounded in predictions of both renewables supply and household/community demand over a range of future time windows. From hereon we concentrate on the first stage of our research on one of the tasks that will support the ORIGIN energy management system, This concerns the prediction of wind energy availability in short term windows.

In this article we therefore report on early stage work towards providing robust predictions for available wind-generated power in short term windows. This relates specifically, of course, to implementations of the ORIGIN system (or similar systems) within communities that have wind turbine facilities. Such implementation (in any community) will recommend the installation of an automated weather station at a suitable place within the community (if one is not already available); such weather stations are available at reasonable cost (e.g. around USD 5,000), and provide hourly readings for several weather variables, including (which we look at here): cloud cover, humidity, pressure, temperature, visibility, wind direction, and wind speed. One of the three eco-villages involved in the ORIGIN project is the Findhorn community in the North of Scotland. A weather station is currently being installed at Findhorn, however we are fortunate to have three years' of historical weather station data available from a site nearby (RAF Kinloss), which we use in the experiments reported here.

Broadly speaking, predicting available wind power relies on predicting wind speed, and we focus here entirely on predicting wind speed. We look at predictions from 1 hour to 24 hours ahead. As noted in the review in section 2, Numerical Weather Prediction (NWP) models are known to be more accurate than ANN or statistical approaches from 3–6 hours ahead onwards, but it is of general interest to investigate how ANNs (based only on lcoal data) perform, since NWP may be either unavailable, too expensive, or relatively inaccurate for specific sites. Also, a future technique that may work well in some sites, where NWP can be used, is to develop a model that combines predictions from NWP with ANNs that exploit local data. The particular contribution we make to the general enterprise of predicting wind speed is to assess the use of further relevant inputs (available from an automated weather station) beyond wind speed alone. Previous related work has almost exclusively focused on using past wind-speed data. Our data are available from: `http://is.gd/ORIGINwind`.

The remainder of this article is set out as follows. In section 2 we provide a brief review of the recent literature in wind-speed prediction. Section 3 then describes a number of baseline approaches that enable a more balanced view of the performance of more sophisticated approaches. 'Persistence', for example,is an approach that simply guesses that the wind speed at time $t+1$ (or $t+N$ when predicting N units in advance) will be the same as it was at time t. This is a fairly accurate approach in short term windows, and section 3 evaluates this approach along with a number of similar approaches that also consider season, time of day and moving averages. Section 4 then describes and evaluates our initial experiments using evolved artificial neural networks, and compares them with the best baseline approaches. We conclude in section 5.

2. WIND-SPEED PREDICTION

While the field of short-term wind power prediction has been described as being young [5], a number of review papers already exist [13, 5, 14, 6] with over 380 references in the most recent. With the rise of wind power generation in many countries, short term prediction has rapidly risen from being a fringe topic to become a key tool, not only for the wind power generation companies themselves but also for the transmission system operators (TSOs) that must manage the energy balance on the grid as a whole. With the associated growth in research, we cannot hope to provide more than a broad summary of the general research directions here.

Broadly speaking, approaches to short term wind power prediction fall into two categories: physical and statistical. Physical approaches start with a numerical weather prediction (NWP), including not only wind direction and speed but also pressure, temperature, humidity and other data, provided by a meteorological institution. However, such predictions do not directly provide wind speed at the turbine location, but provide forecasts at points on a relatively coarse grid. Forecasts for a carefully selected set of grid points are converted into wind speed at the hub height of the turbine through the use of models of the physical processes, taking into account the roughness of the terrain and the presence of obstacles.

In contrast, statistical and machine learning methods can be applied without the expense (computational and otherwise) of obtaining good quality NWP predictions and running sophisticated physical models. A range of methods have been used, including autoregressive moving average models (ARMA) [11, 16, 9], Kalman filters [2] and neural networks [4, 15]. Finally, machine learning techniques may be profitably combined with the physical approaches, providing a final correction to the outputs of the physical models [18, 17].

In terms of performance, purely statistical or machine learning approaches can perform well over shorter time scales, but prediction methods using NWP forecasts tend to outperform time series approaches for lookahead times of more than three to six hours [6]. This makes sense, given that NWP forecasts may be provided only every 3 hours, meaning that the current wind speed will be much more informative for forecasting, for example, 15 minutes ahead, than an old forecast. Hence the limited usefulness of the forecast may not warrant the cost of obtaining it and running the physical models to estimate wind speed at the turbine. As the lookahead increases, the current wind speed becomes less relevant while the meteorological knowledge encapsulated in the forecast becomes invaluable. Hence in this paper we concentrate on short-term prediction.

Neural networks have been applied to the task of wind speed prediction both as the primary prediction method and as a more minor component in a larger system. As an example of the latter, Salcedo-Sanz et al. [18, 17] take the results of global forecasting models and downscale using fifth generation mesoscale models (MM5). The results are then used as inputs into a neural network. They consider both the use of single models with a single neural network [18] and the use of multiple global forecasting models, multiple parame-

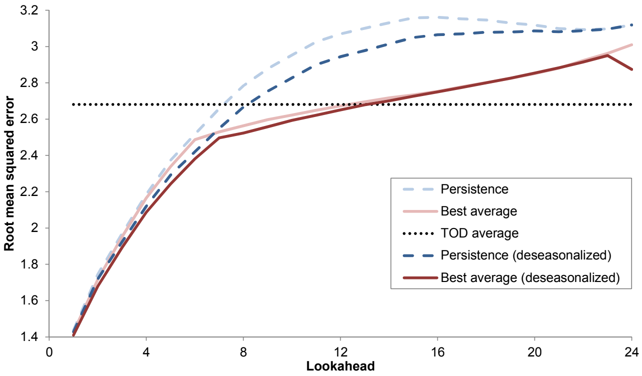

Figure 1: Forecasting accuracy for simple techniques, to be used as a baseline.

terizations of the mesoscale models, all of which are fed into a bank of neural networks [17].

Examples of the use of neural networks as the primary prediction method include the work of Cadena and Rivera [4] which simply used current and previous wind speeds collected at the location every hour to predict wind speed one hour ahead, with the network being used iteratively if forecasts further ahead were required. Best results were obtained using only the current and the previous hour's measurements as input to a three node network, suggesting a rather simple model. More and Deo [15] used a similar approach which again used only previous wind speed observations at the site. However, predictions were made for mean wind speeds a day, a week or a month ahead through the use of feed-forward and recurrent neural networks. Results were compared favourably with the time series method ARIMA. Kariniotakis et al. [12] used inputs of current and past wind speed and wind power to predict the average wind turbine power for a wind park up to 2 hours in advance, in ten minute intervals, using recurrent, high order neural networks.

Barbounis and Theocharis [1] and Kalogirou et al. [10] both exploit wind speed readings at remote stations in addition to (or instead of) the readings at the local station, to predict future local wind speeds. Only the current readings are used as inputs by Barbounis and Theocharis, though past wind speeds are taken into account due to the recurrent structure of the neural networks used. Wind speeds are predicted up to 3 hours ahead, in 15 minute increments. Kalogirou et al. use neural networks to predict monthly mean wind speed at a location where data are not available, from the same data at nearby weather stations. Here the emphasis is on extrapolating wind speed data spatially, rather than forward in time.

3. BASELINE TECHNIQUES

In order to evaluate our neural network based approach, we compare with a number of simple baseline algorithms. The persistence model simply uses the current wind speed as the predicted wind speed at all points in the future. A simple generalization is to take the average of the last n recordings as the prediction.

Figure 4 shows the performance of persistence for forecasts from 1 to 24 hours ahead, on 2012 wind data from Kinloss, Scotland. In addition, the results of the moving average approach is also displayed, where, for each value of lookahead, the best sample size on the 2010–2011 data is tested on the 2012 data.

Significant diurnal variation in the wind speed suggests determining the mean wind speed for each hour of the day, over the 2010–2011 period, and using this to deseasonalize the 2012 data prior to applying persistence or moving averages. Figure 4 also shows the result of simply using the calculated mean speeds as the prediction, and the results of combining deseasonalization with the other approaches. The graph for persistence indicates the root mean squared error achieved when the current wind speed is used to predict any future wind speed, applied to the 2012 data. The TOD average line shows results obtained when the average wind speed for the time of day (taken over the 2010-2011 data) is used to make forecasts for 2012, ignoring the recent observations of wind speed. The method used to obtain the 'best average' line was to use the simple average of the last n observations (the sample) as the forecast — a simple generalization of persistence. This was tested on the 2010-2011 data to obtain the best sample size, n, which was then used to obtain forecasts on the 2012 data.

The deseasonalized results were obtained by first deseasonalizing the data by first dividing each wind speed by the appropriate 2010-2011 time of day average. Then the persistence and best average methods were used as before, but on the deseasonalized data. Finally, each (deseasonalized) forecast was multiplied by the time of day average to obtain the final forecast.

As one would expect, the predictive value of current and recent wind speeds is greatest over short time scales — when predicting over 13 hours ahead, the simple daily average performs better. However, the best results from these simple methods provides a baseline with which to perform comparisons.

4. EVOLVED NEURAL NETWORKS

Training Artificial Neural Networks (ANNs) with evolutionary algorithms (EAs) is well known to provide various advantages over backpropagation and other standard ANN training algorithms [3, 19, 20, 7]. Among these advantages are often-reported improved generalization performance (when appropriate model selection and validation approaches are used in the EA training environment), as well as the unbridled flexibility available in the choices of topology, activation functions, and performance metric(s). We expect to explore the latter flexibilities later in the project (for example to evolve networks with specific attention to minimising error at high wind speeds, since this relates most saliently to energy availability). Presently, we report on the use of a straightforward EA to evolve standard three-layer ANNs with fixed topologies (a different fixed topology for each experimental setup, as clarified below). At present, we pay no particular attention to using a state of the art optimization algorithm to train the ANNs (e.g. such as CMAES [8]), since, when it comes to using EAs for learning, the use of a particularly high-performance optimizer is arguably at odds with the need to learn reliable and robust models. However there remains a need to search the space with suitable efficiency to arrive in the region of good models, and so this is an area we wuill return to in the near future.

4.1 Algorithm/Experiment Details

In all experiments reported here, the EA is a steady state model with a population size of 20. Each chromosome in the population encodes an ANN as an array of double precision numbers, each representing a specific link weight or node bias. All weights are initialised to uniform random value between -1 and 1 (also, input data are normalised,as described below). Following evaluation of each member of the initial population, the following sequence of events then comprises a 'generation': (i) a single parent is selected via binary tournament selection; (ii) a child is produced from this parent by choosing an ANN weight uniformly at random, and adding a Gaussian perturbation with mean zero and std 0.1; (iii) the child is evaluated; (iv) if the child's fitness is no worse than that of the current worst in the population, it replaces that current worst; otherwise it is discarded. In all experiments, the EA terminates after 10,000 generations.

The fitness of an ANN is its mean-squared-error (MSE) over the training set. Model selection - i.e. the choice of ANN from the training process that is felt most likely to generalise well to unseen data, is done by simply choosing the network that performed best on the testing set (which had no other influence on the training process). Finally, all results reported here are for the performance of this selected model on the unseen set. In all experiments reported here, the training set comprised 2010 data, the testing set comprised 2011 data, and the unseen set comprised 2012 data.

In the early part of this investigation we are primarily interested in the potential accuracy of wind speed prediction when additional data beyond historical wind speed (available from modern automated weather stations) are taken into account. Specifically we consider cloud cover fraction, humidity, barometric pressure, wind direction, temperature, and visibility. For each of these (and for wind speed itself), hourly data were available for the great majority of the hours in each of 2010, 2011, 2012, from a weather station close to the Findhorn ecovillage site.

In addition, concerning both wind speed-only, and additional data scenarios, we note that previous work has not explored the adoption of *change* in wind speed as an input to the ANN. For example, consider the task of predicting wind speed at time T+2 (`ws[T+2]`), given as input the wind speeds at times T and T+1 (`ws[T]` and `ws[T+1]`). Intuition suggests that a worthwhile alternative to this approach would be to encode the inputs instead as `ws[T+1] - ws[T]` and `ws[T+1]`; i.e. the wind speed at T+1, and the change in wind speed from T to T+1. This transformation of the input would seem to present the ANN with a less onerous task (i.e. a more navigable landscape) in discovering features that may contribute to robust predictions. Hereafter, we refer to this approach to presenting the data to the ANN as the 'delta' approach.

To explore these questions we report on a series of two further experiments beyond the baseline experiments reported earlier. The further experiments can be characterised as follows:

1. ANNs using historical wind speed data only, with inputs over both short term and long term historical windows;

2. ANNs using all available data types, but with inputs over short-term historical windows.

3. ANNs using two types of historical data – wind speed and one other – for each of the additional types of data considered.

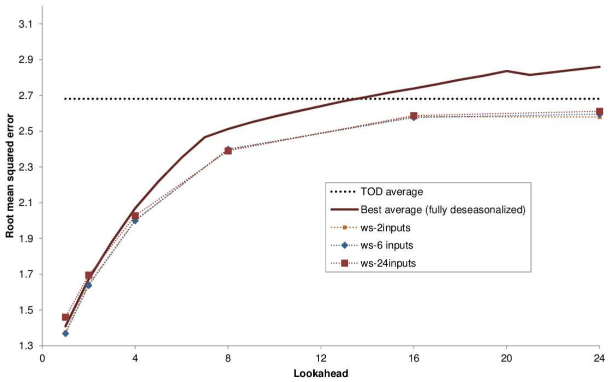

Figure 2: Forecasting accuracy of evolved ANNs using only wind speed input data.

When historical windows of two or more steps are involved, we always use the 'delta' approach, following preliminary tests confirming that the 'delta' approach was never (with statistical significance) worse than the standard approach in this context. When there are only two historical inputs, the first input was the difference in wind speed between times $t-1$ and t, and the second was wind speed at time t. In general when the historical input window is N hours, the Nth input was always wind speed at time t, while the ith input ($0 < i < N$) indicated the difference in wind speed between times $i+1$ and i. . In all cases, we report on separate experiments that predict H hours in advance, where H ranges through 1, 2, 4, 8, 16 and 24.

4.2 ANNs: wind speed only

Two subsets of experiments were done to evaluate the performance of evolved ANN windspeed prediction using only historical wind speed data-points as inputs. Experiments were done with historical input windows of size 2, 6 and 24 hours respectively

Results are summarised in figure 2. The plots show the mean result of ten runs on the unseen year 2012 data, and are contrasted with the best of the baseline methods (from Figure 1), also showing the TOD line as reference. The three experiments are difficult to separate in the plot, so Table 1 provides the mean and standard deviation of the error (absolute wind speed in metres per second) for the configurations tested in this set of experiments. The best mean result for each lookahead time is highlighted in bold.

Evolved ANNs with a 6-hour historical wind speed input window clearly seem to have the advantage over the 2-hour and 12-hour windows. Intuitively it seems reasonable to expect that the extra information provided in a 6-hour window is beneficial, while the 12-window presumably provides more extra noise than extra signal in this context. However the three further-ahead lookahead results are less clear cut than the short term predictions, as is apparent from the larger standard deviations. All cases perform significantly ahead of the best baseline method.

method	1 hr	2 hrs	4 hrs
2 inputs	1.3746	1.6435	2.0017
std	0.0096	0.0069	0.0062
6 inputs	**1.3678**	**1.6373**	**1.9989**
std	0.0044	0.0013	0.0012
12 inputs	1.4596	1.6952	2.0267
std	0.0278	0.0196	0.0176
Baseline	1.4084	1.6718	2.0682
	8 hrs	16 hrs	24 hrs
2 inputs	2.3966	2.5813	**2.5788**
std	0.0042	0.0022	0.0024
6 inputs	2.3989	**2.5761**	2.5948
std	0.0021	0.0054	0.0021
12 inputs	**2.3897**	2.5868	2.6106
std	0.0104	0.0107	0.0081
Baseline	2.5115	2.7382	2.8591

Table 1: Accuracy for 1, 2, 4, 8, 16 and 24 hour forecasts with evolved ANNs using only wind speed inputs, contrasted with best baseline, showing mean and std of 10 trials.

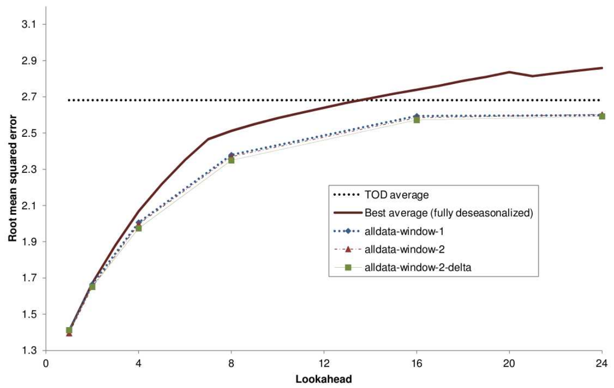

Figure 3: Forecasting accuracy for multiple-data-type ANNs.

4.3 ANNs: seven data types

In the first subset of these experiments, the ANNs had 7 inputs. These were the 7 values at time t of the main data types available in a typical automated weather station, namely: cloud cover, humidity, pressure, temperature, visibility, wind direction and wind speed.

In the second subset of these experiments, the ANNs had 14 inputs, covering the values at time t and $t-1$ of the seven data types. In the third subset of these experiments, the $t-1$ value for each data type was replaced by its 'delta' value – i.e. the value at time t minus the value at time $t-1$.

Results are summarised in figure 3. The graphs show the mean result of ten runs on the unseen year 2012 data.

Table 1 indicates the mean and standard deviation of the error (absolute wind speed in metres per second) for the configurations tested in this set of experiments. The best mean result for each lookahead time is highlighted in bold.

These multiple-data-source tests provide mixed results, seeming less effective than baseline for 1 and 2 hours ahead,

method	1 hr	2 hrs	4 hrs
all-1	1.4104	1.666	2.0065
std	0.0131	0.0075	0.0062
all-2	**1.3950**	**1.6507**	1.9972
std	0.0181	0.0139	0.009
all-2d	1.4120	1.6508	**1.9738**
std	0.0263	0.0194	0.0083
Baseline	1.4084	1.6718	2.0682
	8 hrs	16 hrs	24 hrs
all-1	2.3792	2.5937	2.5981
std	0.0054	0.0049	0.0083
all-2	2.3701	2.5848	2.6022
std	0.0086	0.0063	0.0063
all-2d	**2.3492**	**2.5716**	**2.5924**
std	0.0092	0.0099	0.0097
Baseline	2.5115	2.7382	2.8591

Table 2: Accuracy for 1, 2, 4, 8, 16 and 24 hour ahead forecasts with evolved ANNs using all data types, contrasted with best baseline, showing mean and std of 10 trials.

however the delta approach with 14 inputs (2 hours historical data, all data types) yields better mean results for the 4, 8 and 16 hour lookahead windows than the best of the previous wind speed only tests.

4.4 ANNs: selected input combinations

Finally, in each of these experiments there were four inputs. Two of these were always wind speed at time t and the 'delta' wind speed between times t and $t-1$. The other two were similarly a time t value and a delta value (value at t minus value at $t-1$) for a specific other data type. These other data types ranged through cloud cover, humidity, pressure, temperature, visibility and wind direction.

Table 3 indicates the mean and standard deviation of the error (absolute wind speed in metres per second) for the configurations tested in this set of experiments. The best mean result for each lookahead time is highlighted in bold.

The wind speed and temperature evolved ANNs seem more promising than the others at 1, 2 and 4 hours ahead, with the best so far means at these lookahead times. It also does relatively well at 8, 16 and 24 hours, however the wind speed and pressure evolved ANNs seem to outperform it at these further-ahead forecasts.

Since the experiments with temperature and pressure showed more promising outcomes, two further experiments were performed. In the first, we evolved ANNs with 6 inputs, including 3 previous wind speed data points, and 3 previous temperature data points. In the next, also with 6 inputs, we used 2 previous data-points for each of wind speed, temperature and pressure. The best mean result for each lookahead time is highlighted in bold.

The 6-input wind speed and temperature evolved ANNs show the best results of all methods tested in this article at 1 and 2 hour ahead forecasts, while the 6-input wind speed, temperature and pressure evolved ANNs show the best results of all methods at 4, 8 and 16 hours ahead. Both of these methods do relatively well at 24 hours ahead prediction too, however neither outperforms the mean value for 24 hours shown by wind speed only with 2 inputs

We summarise selected results in figure 4, contrasting the

method	1 hr	2 hrs	4 hrs
Temperature	**1.3542**	**1.6100**	**1.9581**
std	0.0055	0.0054	0.0052
Cloud cover	1.3748	1.6412	1.9943
std	0.0068	0.0060	0.0036
Humidity	1.3692	1.6373	1.9889
std	0.0064	0.0038	0.0028
Visibility	1.3756	1.6418	1.9970
std	0.0090	0.0056	0.0043
Pressure	1.3700	1.6329	1.9802
std	0.0065	0.0039	0.0054
Wind direction	1.3715	1.6394	1.9962
std	0.0031	0.0025	0.0039
Baseline	1.4084	1.6718	2.0682
	8 hrs	16 hrs	24 hrs
Temperature	2.3734	2.5769	2.5844
std	0.0064	0.0055	0.0027
Cloud cover	2.3884	2.5775	2.5804
std	0.0018	0.0015	0.0024
Humidity	2.3759	2.5756	2.5808
std	0.0028	0.0023	0.0031
Visibility	2.3967	2.5811	2.5752
std	0.0063	0.0044	0.0018
Pressure	**2.3657**	**2.5704**	**2.5764**
std	0.0049	0.0063	0.0059
Wind direction	2.3891	2.5742	2.5822
std	0.0087	0.0074	0.0019
Baseline	2.5115	2.7382	2.8591

Table 3: Accuracy for 1, 2, 4, 8, 16 and 24 hour ahead forecasts with evolved ANNs using windspeed and one other data type, contrasted with best baseline, showing mean and std of 10 trials.

method	1 hr	2 hrs	4 hrs
6 inputs: ws + temp	**1.3425**	**1.5906**	1.9435
std	0.0054	0.0015	0.0021
6 inputs: ws + te + pr	1.3462	1.6012	**1.9424**
std	0.0043	0.0040	0.0036
Baseline	1.4084	1.6718	2.0682
	8 hrs	16 hrs	24 hrs
6 inputs: ws + temp	2.3672	**2.5671**	**2.5835**
std	0.0037	0.0032	0.0031
6 inputs: ws + te + pr	**2.3394**	2.5675	2.5896
std	0.0042	0.0077	0.0079
Baseline	2.5115	2.7382	2.8591

Table 4: Accuracy for 1, 2, 4, 8, 16 and 24 hour ahead forecasts with evolved ANNs using windspeed, temperature and pressure, contrasted with best baseline, showing mean and std of 10 trials.

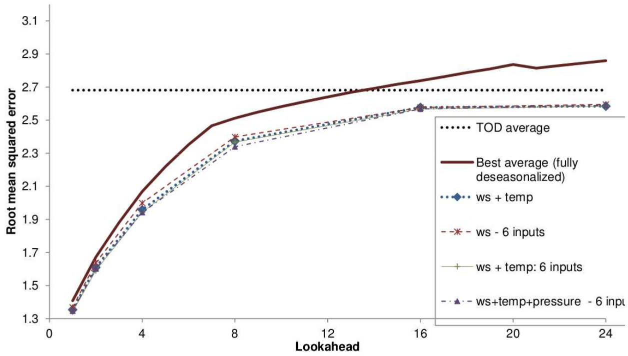

Figure 4: Forecasting accuracy for best 4-input case along with 6-input evolved ANNs including wind-speed, temperature and pressure.

best of the two-data-type 4-input cases with these further experiments, also showing the 6-input wind speed results.

5. SUMMARY, AND A FORECAST OF FUTURE WORK

In connection with a project that aims to optimise the use of renewable energy in ecovillages (via intelligent systems for alignment of supply and demand), we reported here on the early stage of research in support of one element of the project. This element was the prediction of wind speed in future time windows (ranging from 1 to 24 hours ahead) using weather station data. Using three years of data available for a site very close to one of the ecovillages participating in the ORIGIN project, we compared a set of baseline approaches with evolved artificial neural network models. In particular, we focus on the benefits in accuracy that may or may not be available by using additional weather station data (such as temperature, pressure, etc.) as inputs to the ANNs. Using such additional data has not been reported before (or, not reported prominently enough for us to discover) in the context of ANN-based prediction of wind speed.

Here, we tested a limited and eclectic choice of the many possible combinations of inputs and outputs that could be envisaged, focusing on simple combinations and 'extremes'. This was in part to meet the GREENGEC workshop submission deadline with a coherent set of results, but also represents an initial broad survey of the performance profiles available from the other data types, consideration of which will help design ongoing experiments. We find that the use of additional input data seems to have clear advantages over wind speed alone. The best predictions (on average) for 1 and 2 hours ahead were achieved with a combination of wind speed and temperature inputs, while the best medium term predictions (4, 8 and 16 hours) were obtained from combining wind speed, temperature and pressure inputs. Inspection of the standard deviations suggest that the best 'with temperature' evolved ANNs are significantly better than the best 'wind speed only' ANNs for shorter term predictions, however standard deviations creep up as the lookahead time increases and it is harder to assess significance without additional experiments.

Finally, in ongoing work (as well as completing the current study) we will more carefully consider the issues surrounding the relative costs of under and overestimating predicted wind speed. In the ORIGIN context, predicted availabilty of renewable energy in 4 hours (say) could lead to householders delaying expensive bursts of consumption (e.g. electric dryer) until the predicted window. If the prediction was over-estimated, and for a time of day when large sections of the community were hoping to capitalise on it, the cumulative effect over several households would be unfortunate in terms of their forced use of fossil fuel resources. Different degrees of under and over-estimation also have differential consequences owing to the nonlinear relationship between wind speed and wind energy - this is especially important at high wind speeds, where, above a particular threshold of wind speed, most turbines are required to shut down. One of the main reasons for employing EAs in developing forecasting models is to enable the flexibility to differentiate over such scenarios, by means of crafting suitable vectors of objective functions that capture the key performance issues.

6. REFERENCES

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