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Historical Weather Data Supported Hybrid Renewable Energy Forecasting using Artificial Neural Network (ANN)

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Abstract

This paper aims to develop a novel hybrid system for wind and solar energy forecasting. The uniqueness or novelty of the proposed system is obvious because there are no available research works related to the hybrid forecasting system of renewable energy. The proposed ‘Hybrid (wind-solar) Energy Forecasting Model’ is dedicated to short-term forecasting (three-hour ahead) based on artificial neural network (ANN) learning algorithm. The network learning or training algorithm will be implemented using ANN Toolbox which is widely used simulation software incorporated in MATLAB. Eleven different climatological parameters of the last six years of a typical subtropical climate based area Rockhampton in Central Queensland; Australia has been taken for analysis investigation purpose and will be considered as the inputs of ANN model for hybrid (wind-solar) energy forecasting. The ANN will be trained in such a way that with minor modifications in the programming codes, it can perform the hybrid forecasting within the range from hourly (short term forecasting) to daily (medium term forecasting). This feature is one of the major innovations and indicating the great robustness of the proposed hybrid renewable energy forecasting system. As the hybrid forecasting system is quite a novel approach, the accuracy of the system will be revealed by comparing the results with the corresponding values of stand-alone forecasting model referred to as the persistent model. Finally, the fully developed system package may be commercialized and/or utilized in further research projects for researchers to analyze, validate and visualize their models on related domains.

Keywords: Renewable energy; hybrid forecasting; neural network; feedforward network; historical weather data.

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1. Introduction

The growth of the world's human population has created several problems. One of them is global warming caused by the abundance of CO_2 in the atmosphere. Many of these gases are produced from electrical plants burning fossil fuel all over the world. To reduce these emanations out into the atmosphere alternative sources of energy must be used. In the last two decades solar energy and wind energy have become an alternative to traditional energy sources. These alternative energy sources are non-polluting, free in their availability and renewable. Wind, solar and other renewable energy sources are an important part of today's electricity generation and the part of energy they supply to the power grid will definitely be increasing over the next decades. Traditional as well as current energy production technologies have relied primarily on fossil fuels worldwide, but this must change since fossil fuels are in limited quantities. Not only are fossil fuel resources depleting, the traditional energy delivery system is also brought into question; that is the centralized fashion for energy delivery. The use of renewable technologies such as wind turbines and/or solar PV allows for the opportunity to develop distributed generation to decentralize the mode for energy transportation. Alternative and renewable green-energy sources including photovoltaic (PV), wind, hydrogen fuel cells, Proton Exchange Membranes (PEMs) are emerging as viable economic and sustainable alternatives to conventional fossil fuel generating stations, especially for remote isolated and arid communities. These emerging alternative sources are termed as green-energy sources.

However, a drawback, common to solar and wind options, is their unpredictable nature and dependence on weather changes. Wind and solar energy resources, unlike dispatchable central station generation, produce power dependable on external irregular source and that is the incident wind speed which does not always blow and solar radiation which does not always emission when electricity is needed. This results in the variability, unpredictability, and uncertainty of wind and solar resources. Therefore, the forecasting of wind and solar energy is one of the major challenges for system planners and engineers. However, with the increased complexity in comparison with single energy systems, optimum forecasting of hybrid system becomes most challenging and complicated. Fortunately, the problems caused by variable nature of these resources can be overcome by integrating these two resources as a hybrid system. This hybrid system must be completely reliable and this reliability absolutely depends on the precise deliverance of the energy forecasting of the hybrid renewable energy sources. Such hybrid forecasting has significant impact on the optimum power flow, transmission congestion, power quality issues, system stability, load dispatch, and economic analysis.

Predictions have been used by the human kind since the dawn of time. Today, they are essential in several areas of economy and industry, where they serve as a basis for making decisions and developing strategies. However, forecasts are of value only if they are specially tailored to the intended application. Forecasting systems must be developed in concert between users and analysts [1], in order to define the context and the objectives of their application.

The aim of short-term forecasting of hybrid wind-solar power output is to contribute to a secure and economic power system operation. Such forecasting provides end-users with estimations of the future hybrid wind-solar generation, usually for the next 24-72 hours, thus tackling the intermittent nature of wind and solar that is feared by the traditional energy sectors. A crucial point is that hybrid power forecasting methods should be designed for operational use, for real-time application. Commonly, this real time aspect is referred to as online, in opposition to offline when working on historic data for research purposes. Increasing the value of hybrid power generation through the improvement of forecasting systems' performance is one of the priorities in wind energy research needs for the coming years [2].

2. Background

Forecasting is the process of making statements about events whose actual outcomes (typically) have not yet been observed. Prediction is a similar, but more general term. With the advent of widespread, high-speed computing, forecasting capabilities have been extended to fields such as meteorology where calculation capacity was a major constraint. As a result, it is now possible to forecast complex processes such as wind and solar power production with reasonably good accuracy.

2.1. Wind Energy Forecasting

Three main classes of techniques have been identified for short-term wind forecasting. These are statistical methods, ANN methods and numeric weather prediction (NWP) methods. The numeric weather prediction methods have been found to dominate the literature, almost exclusively, for forecasts over 10 hours ahead [3, 4]. However, the published statistical and artificial neural network (ANN) methods based on observations appear to be more accurate over shorter periods (minutes to a few hours). They are also much simpler than the NWP methods.

2.2. Solar Energy Forecasting

Generation of solar radiation, in particular, wind speed and temperature data, has been the objective of several studies. Among these studies, Gordon and Reddy developed a solar radiation generator on an hourly, [5], and on a daily basis [6]. Baklouktsis et al. [7] made stochastic simulations of hourly and daily-average wind speeds. Knight et al. [8] presented techniques for the generation of hourly solar radiation and ambient temperature data (GEN), as well as suggestions for humidity and wind speed. The GEN algorithm developed in [8] requires the input of the monthly-average solar radiation value and generates the hourly solar radiation values based on the cumulative frequency distributions of the daily clearness index. ‘Typical meteorological year’ (TMY) is one of the most common synthetic weather data sequences used in solar system simulations. TMY of hourly weather data usually consists of 12 months of hourly data. Each month is selected from long-term weather data as being the best representative of that particular month or is generated from several years of weather data which would yield the same statistics (such as the average solar radiation and clearness index) as those of several years’ data. The three main criteria used to define ‘typical’ are the distributions, the sequences of daily variables, and the cross-correlations. Klein and Beckman present in [9] a method for estimating the loss-of-load probability of stand-alone photovoltaic systems using such solar radiation data. TMY of hourly weather data have been developed and commonly used in simulations for many locations as discussed in references [8-10]. The biases introduced by synthetic solar radiation data have also been investigated by some research teams, for example, Knight et al. [8], Bourges and Kadi [11], Gansler et al. [12] and Morgan [13]. Knight et al. [8] compared the statistics obtained from synthetically generated weather data, long-term (22 years), and TMYs at three locations in the USA. The statistics they present indicate that the accuracy of the generated data in reproducing the statistics is nearly equal to that of the TMY data. The most serious shortcoming is stated as the cross-correlations that are not directly reproduced by the modelling techniques presented in [8]. Knight et al. [8] assume that simulations which run with generated data for a single 1-year period would yield quite similar results to those obtained from simulations driven by many years of measured data. Bourges and Kadi [11] analysed four different synthetic weather data sets and compared the results to those using long-term data (LTD).

Morgan [13] is one of the rare researchers who analysed the system performance of a hybrid photovoltaic–wind system using synthetic weather data. Morgan [13] used synthetically generated hourly varying solar radiation and monthly-average values for the wind speed and the ambient temperature as input weather data for his simulation program.

2.3. Technical Review on Wind and Solar Energy Forecasting

In the technical literature, several methods to predict wind and solar power have been reported, namely physical and statistical methods. In this section, literature review of existing wind and solar power prediction or forecasting methods is presented. In general, models can be classified as either involving Numerical Weather Predictions (NWP) as input or not. With regard to methods that incorporate NWP data, two mainstream approaches exist: the physical and the statistical approach. The physical methods use NWP and physical considerations to reach the best possible estimate of the wind speed at the location of the wind farm. A power curve is then used to convert the wind forecast into the power forecast. Statistical models try to find the relationship between a number of explanatory variables including NWP forecasts, and measurements of past power production or meteorological variables. The statistical methods can be seen as regression models that try to estimate the parameters of a function linking future wind power to available explanatory data.

For a physical model, the input variables will be the physical or meteorology information, such as description of orography, roughness, obstacles, pressure, and temperature. The statistical method aims at finding the relationship of the on-line measured power data. For a statistical model, the historical data of the wind farm may be used. Physical method has advantages in long-term prediction while statistical method does well in short-term prediction [14]. In the recent years, some new methods are catching researcher’s attention, namely methods based on artificial intelligence like artificial neural network (ANN) [15], fuzzy logic and neuro-fuzzy [16,17], evolutionary algorithms [18], and some hybrid methods [19,20].

2.4. Hybrid (Wind-Solar) Forecasting

From the literature review it is very apparent that a great deal of works has already been done and is going on by researchers for individual wind and solar energy forecasting. With the complementary characteristics between solar and wind energy resources for certain locations, hybrid solar-wind power generation systems offer a highly reliable source of power. But this reliability absolutely depends on the precise deliverance of the energy forecasting of the hybrid renewable energy sources. This inventiveness can be claimed because so far there is no clue of progresses or works are found related to the hybrid forecasting system of renewable energy. It is in fact very exhilarating that the concept of ‘Hybrid Renewable Energy System’ (HRES) is extensively accepted in veracity but still now there is no evidence or sign of research work done to develop a forecasting model which can bring into being hybridized or combined power forecasting from a wind-solar hybrid system.

3 Computational Intelligence Based Hybrid Forecasting Model Development

Artificial Neural Network (ANN) and the concept of causal method (causal method is a type of quantitative method or estimating approach based on the assumption that future value of a variable is a mathematical function of the values of other variable(s)) will play the key role to develop this project.

Hybrid power forecasting is far from being a trivial problem. Roughly, three stages will be engaged throughput the system development process; firstly, the ‘meteorological’; which consists in forecasting wind speed and solar radiation at the level of the considered site for the next hours or days, and secondly the ‘energy conversion’ stage that involves the transformation of the wind speed and solar radiation to power. Finally, merging the forecasted power form wind and solar and providing the combined output as a hybrid energy forecasting will be performed.

3.1. Artificial Neural Networks (ANNs)

ANNs are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task [21]. Fundamental processing element of a neural network is a neuron. Multilayer perceptrons are the best known and most widely used kind of ANN. The units are organized in a way that defines the network architecture. In feedforward networks, units are arranged in layers: an input layer, one or more hidden layers and an output layer. The model of a neuron is shown in Fig. 1. A neuron j may be mathematically described with the following pair of equations [21]:

$$u_j = \sum_{i=0}^{p} w_{ji} y_i \qquad (1)$$

$$y_j = \varphi(u_j - \theta_j) \qquad (2)$$

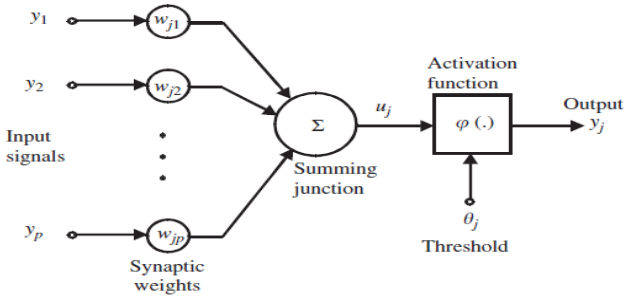

Fig. 1. Nonlinear model of a neuron [21].

The artificial neuron receives a set of inputs or signals y with weight w, calculates a weighted average of them (u) using the summation function and then uses some activation function (linear, sigmoid or hyperbolic tangent) j to produce an output y. The use of threshold y has the effect of applying an affine transformation to the output u of the linear combiner in the model of Figure 1 [21-22].

The sigmoid logistic nonlinear function is described with the following equation:

$$\varphi(x) = \frac{1}{1+e^{-x}} \qquad (3)$$

3.2. Meteorological Data (Wind, Solar) Collection of the Subtropical Climate

Rockhampton which is a sub tropical town in Australia was selected for using the proposed Artificial Neural Network (ANN) model. The selected station is ‘Rockhampton Aero’, having latitude of -23.38 and longitude of 150.48. The data is available in time intervals of one hour. Eventually one hour interval was taken for case study. ANN is being used as the technique to model the system. Required data for using in the proposed ANN model were provided from Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia. These hourly raw data were gathered for a period of six years from 2005 to 2010 (up to 4th August). The single output parameter of the model is hybrid (wind-solar) energy forecasting. For small scale experiment, related data of 4 months were gathered. These set of data were divided into two groups: the training subset and the testing subset. For the training subset related data of 3 months were considered and used for learning the model and for the testing subset related data of 1 month was used to test the capability of the model.

3.3. Significant Feature Selection for Hybrid Forecasting System

When considering short term wind and solar power forecasting there are a number of choices in relation to which parameters to forecast and what level of aggregation to consider. The first choice relates to whether to forecast wind/solar parameters and infer or calculate wind/solar power from those predictions or alternatively to forecast wind/solar power directly using a suitable model.

The selection of the input parameters for the ANN is of crucial importance for the performance of the forecast. Wind velocity and wind direction are, of course, the most important parameters for the wind power forecast. However, with the neural network approach it is easily possible to incorporate additional parameters. In this project, eleven different climatological parameters namely air temperature, wind speed, wind direction, solar radiation, relative humidity, rainfall, VWSP wind speed, VWDIR wind direction; maximum peak wind gust, evaporation and average absolute barometer will be considered as the inputs of ANN model for hybrid (wind-solar) energy forecasting. This number of climatological parameters is the highest in comparison to other stand-alone forecasting approaches founded in the literature review.

Sulaiman et al. [23] presented three ANNs with different types of inputs for predicting the output of a grid-connected PV system. The authors found that the temperature and the solar radiation are the most relevant factors in affecting the PV system performances. In this project of hybrid forecasting these two (temperature and solar radiation) most important factors are also considered. Several solar radiation parameters has been estimated or forecasted in the literature such as: global solar radiation, irradiance, irradiation and clearness index. Some authors reported that their results can be extended to predict solar energy conversion for a photovoltaic system. Kawaguchi et al. [24] proposed an ANN for the prediction of the electric power generation of a PV solar cell, the network inputs are composed of experimental electrical and metrological parameters measured during five days only, while the output is the prediction for three hours of peak generation.

3.4. Development of Hybrid Renewable Forecasting System

Fig. 2 illustrates the proposed ‘Hybrid (wind-solar) Energy Forecasting Model’. The model is dedicated to short-term forecasting (three-hour ahead) based on neural network [16-20], [25, 26] learning algorithm. The network learning or training algorithm will be implemented using ANN Toolbox which is widely used simulation software incorporated in MATLAB. At the initial stage of the system development as shown in Figure 3-2, the historical weather data provided by CSIRO will be filtered. Then those data will be normalized as the rescaling (normalization) of the input training data is important to improve the training convergence of an ANN [27-29] and causal model [30] will be applied on the normalized data set to prepare the input and testing files to train and test the corresponding wind and solar networks. Two separate modules, one for wind and another for solar will be developed for the purpose of three hourly forecasting of wind speed and solar radiation as well as converting the speed and radiation to wind and solar energy respectively based on the delivered data. Each of these modules will be consisting of several trained neural networks for three hourly wind and solar energy forecasting based on the supplied historical weather data.

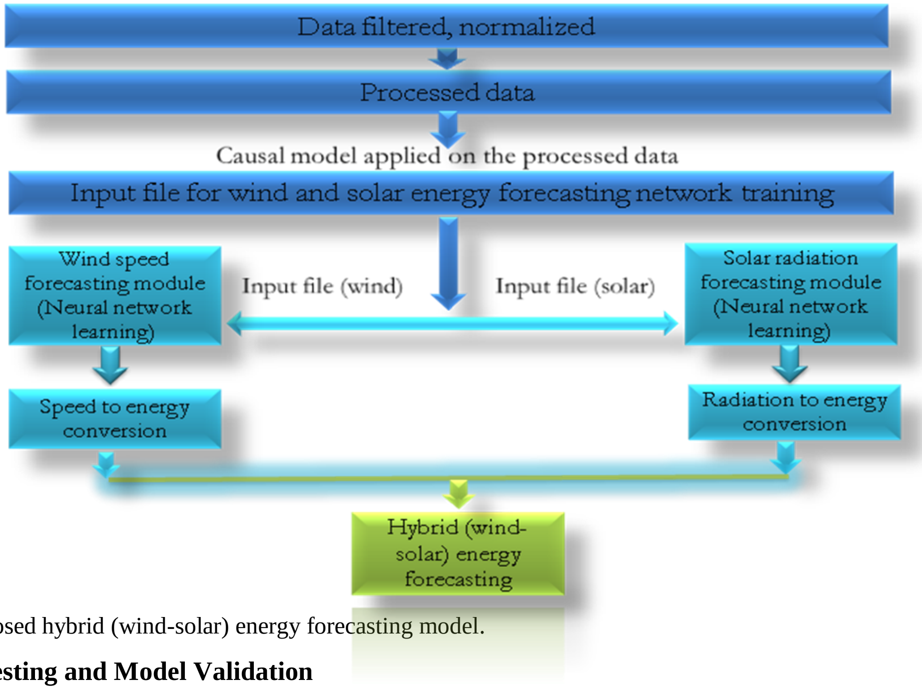

Fig. 2. Proposed hybrid (wind-solar) energy forecasting model.

4. Testing and Model Validation

For testing and model validation, the common practice is to split the data into two subsets:

1. A training set: training set is used to train the network.
2. An independent validation set: validation set is used to validate the results/outputs and many a times third set called cross-validation set is also adopted; which is used for a crosschecking at various stages of training and learning.

The sample was divided into a training set (first 4 months) and a testing set (next 1 month). The outcome of the network was compared with the actual observations with the help of scatter diagrams and time history plots as well as through the error statistics of the correlation coefficient, R, and mean square error, MSE. The testing of the network showed that it predicted the wind speed in a very satisfactory manner with R = 0.9489 for a 3-hour ahead prediction while these values for a 3-hour ahead solar radiation predictions were R = 0.96399 respectively.

The next steps after getting this successful small scale system testing and validation results were relatively straightforward. It was the conversion of the wind speed to wind energy and solar radiation to solar energy with the equations 1 and 2 respectively.

$$p = \frac{1}{2}\rho_{air} C_p \eta_t A_r u^3 \qquad (4)$$

$$Epv = Pout(Ex).(Solar\,Window).(365) \qquad (5)$$

This conversion approach provided the corresponding forecasted energy. These individual wind and solar energy forecasting were merged to reach to the ultimate destination of ‘Hybrid Renewable Energy Forecasting’.

5. Performance Evaluation

Fig. 3 (a) and (b) corresponds to plots of the training errors, validation errors and test errors of wind speed and solar radiation prediction respectively. In these cases, the results are reasonable because of the following considerations:

- The final mean-square errors are small.
- The test set error and the validation set error have similar characteristics.
- No significant over fittings have occurred by iteration18 and 22 (where the best validation performances occur) for wind speed and solar radiation prediction network training respectively.

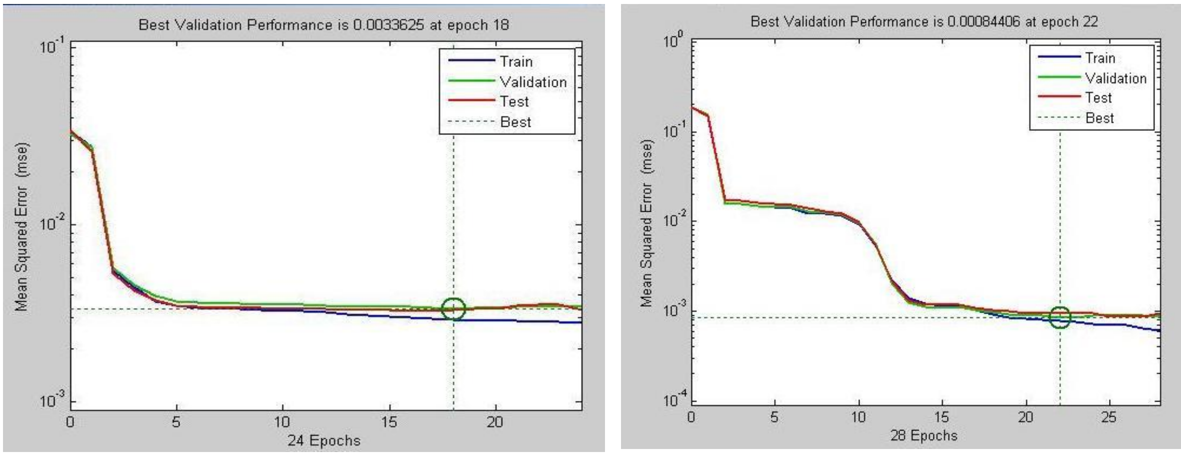

Fig. 3. (a) Plot of the training, validation and test errors for wind speed prediction; (b) Plot of the training, validation and test errors for solar radiation prediction.

After this, analysis of the network performance was carried out. A linear regression between the trained network outputs of a test data (wind and solar) set and the corresponding known targets (wind and solar) was performed by regression analysis. Fig. 4 (a) and (b) represent the results respectively. Fig. 5 (a) and (b) represent the comparison between the actual outputs and the predicted outputs of the test data (wind and solar) set respectively.

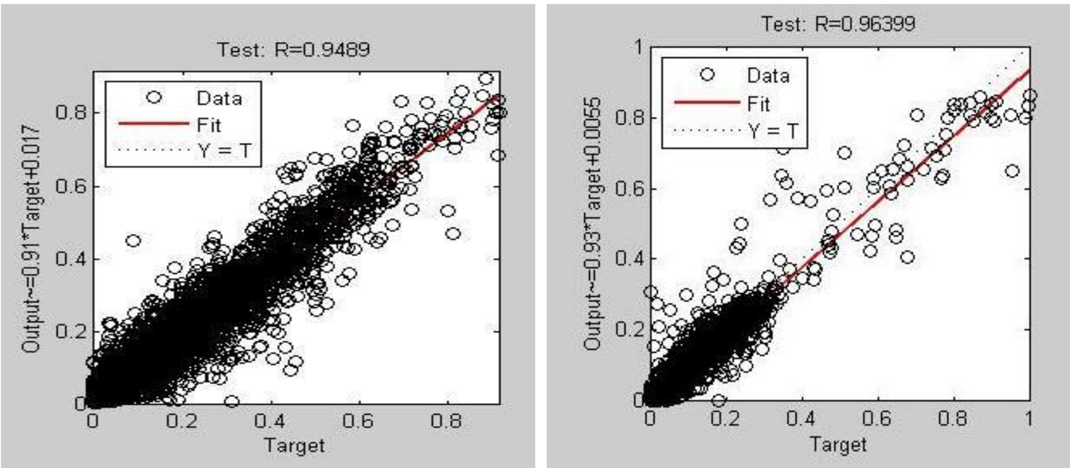

Fig. 4. (a) Regression analysis of test data (wind) set; (b) Regression analysis of test data (solar) set.

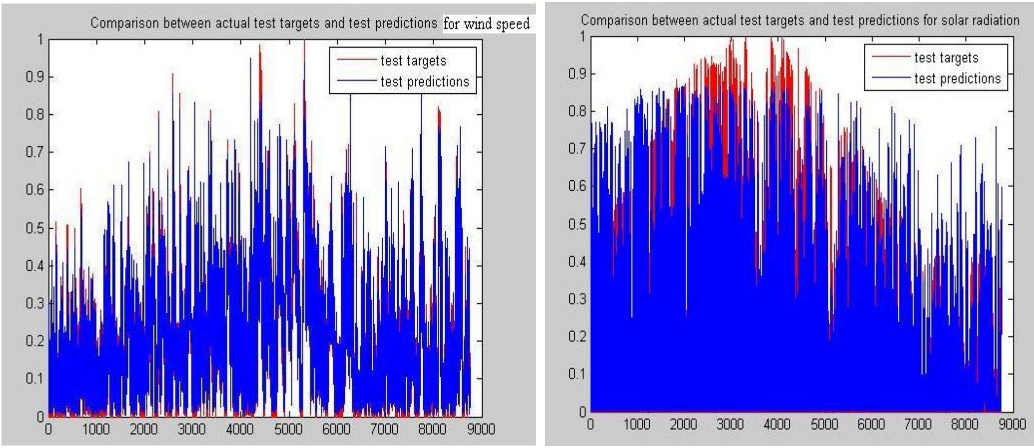

Fig. 5. (a) Comparison between the actual outputs and the predicted outputs of the test data (wind) set; (b) Comparison between the actual outputs and the predicted outputs of the test data (solar) set.

6. Analysis and Comparison with the Existing Limited Systems

Wind and solar energy forecasting systems are not “plug-and-play” since those are always site-dependent. In order to run with acceptable accuracy when installed to a new site, it is always necessary to devote considerable effort for tuning the models (in an off-line mode) on the characteristics of the local wind profile or on describing the environment of the wind farms. Due to the differences in the existing applications it is difficult to compare prediction or forecasting systems based on available results. An evaluation of prediction systems needs however to take into account their robustness under operational conditions and other factors.

It is found that it is hardly possible to compare the performance of the existing forecasting approaches with this proposed hybrid forecasting approach because these methods depend on different situations, and the data collection is a formidable task. Two main reasons complicate this task. First of all different datasets are used in the studies. These are both different with respect to size and resolution, but also varying weather conditions influences performance results. Secondly different error measures are used. Another very crucial difficulty regarding the comparison issue is that the existing energy forecasting systems are stand-alone or individual (wind or solar) where the proposed system is hybrid energy forecasting which is dimensionally completely different from those of individual forecasting.

However, the crucial robustness problem will be solved by the development of this hybrid forecasting system. The remaining problems to make comparison between methods from different studies possible, a common framework for evaluation of solar power forecasting methods should be developed. This could be inspired by a similar project done in [31] for wind power. Furthermore a project where datasets used in different studies are collected and made available for everybody would enhance the possibilities to compare methods in a much more informative way. Data from more years should be used to find seasonal periodicity and to carry out cross-validation which will implemented in this project.

7. Conclusion

With the complementary characteristics between solar and wind energy resources for certain locations, hybrid solar-wind power generation system is an effective system which has the potential to provide continuous power from renewable energy sources. But this reliability absolutely depends on the precise deliverance of the energy forecasting of the hybrid renewable energy sources. This concept of hybrid forecasting of renewable energy (wind-solar) sources is the unique contribution of this project. This inventiveness can be claimed because although the concept of hybrid forecasting system of renewable energy is simple but so far no clue of progresses or works related to the proposed system are found. In order to utilize potential renewable energy resources like solar and wind energy efficiently and economically, a novel system for hybrid wind and solar energy forecasting for a sustainable future is proposed in this project based on Artificial Neural Network (ANN), which has the ability to attain the global optimum with relative computational simplicity compared to the conventional methods.

References

[1] Chatfield, C. Confession of a pragmatic statistician, *The Statistician*, 51:1-20, 2002.

[2] Thor, S. E. and Weis Taylor, P. Long-term research and development needs for wind energy for the time frame 2000-2020, *Wind Energy*, 5:73-75, 2003.

[3] T. Hart. Numerical prediction model performance summary October to December 2001, *Australian Meteorological Magazine*, vol. 51, pp. 137-141, 2002.

[4] L. Landberg. Implementing wind forecasting at a utility, Proceedings of the Wind Energy Conversion - *17th British Wind Energy Association Conference*, Warwick, U. K., 1995.

[5] Gordon JM, Reddy TA. Time series analysis of hourly global horizontal solar radiation, *Solar Energy* 1988; 41(5):423–9.

[6] Gordon JM, Reddy TA, Time series analysis of daily horizontal solar radiation, *Solar Energy* 1988; 41(3):215–26.

[7] Baklouktsis A, Tsanakas D, Vachtsevanos G. Stochastic simulation of hourly and daily average wind speed sequences, *Wind Engineering.* 1986; 10(1):1–11.

[8] Knight KM, Klein SA, Duffie JA. A methodology for the synthesis of hourly weather data, *Solar Energy* 1991; 46(2):109–20.

[9] Klein SA, Beckman WA. Loss-of-load probabilities for stand-alone photovoltaic systems, *Solar Energy* 1987; 39(6):499–512.

[10] Petrakis M, Kambezidis HD, Lykoidis S, Adamapoulos AD, Kassemenos P, Michaelides IM, KalgiA. N. Celik. Renewable Energy 27 (2002) 107–121 121 Rou SA, Roditis G, Chyrisis I, Hadjigianni A. Generation of a ‘typical meteorological year’ for Nicosia, Cyprus. Renewable Energy 1998; 13(3):381–8

[11] Bourges B, Kadi L. Effects of compressed solar radiation and weather data: sensitivity analysis of solar energy system models. *Proceedings of Eurosun* ’96; Freiburgh; 1996.

[12] Gansler RA, Klein SA, Beckman WA. Assessment of accuracy of generated meteorological data for use in solar energy simulation studies. *Solar Energy* 1994; 53(3):279–87.

[13] Morgan TR, The performance and optimisation of autonomous renewable energy systems. *PhD Thesis*, University of Wales, Cardiff; 1996.

[14] L. Ma, S. Y. Luan, C. W. Jiang, H. L. Liu, and Y. Zhang. A review on the forecasting of wind speed and generated power. *Renew. Sust. Energy Rev*., vol. 13, pp. 915-920, May 2009.

[15] I. J. Ramirez-Rosado, L. A. Fernandez-Jimenez, C. Monteiro, J. Sousa, and R. Bessa. Comparison of two new short-term wind-power forecasting systems. *Renew. Energy*, vol. 34, pp. 1848-1854, Jul. 2009.

[16] G. Sideratos and N. D. Hatziargyriou. An advanced statistical method for wind power forecasting. *IEEE Trans. Power Syst*., vol. 22, pp. 258- 265, Feb. 2007.

[17] C. W. Potter and W. Negnevitsky. Very short-term wind forecasting for Tasmanian power generation. *IEEE Trans. Power Syst*., vol. 21, pp. 965-972, May 2006.

[18] R. Jursa, K. Rohrig. Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models. *Int. J. Forecast*., vol. 24, pp. 694-709, Oct.-Dec. 2008.

[19] T. H. M. El-Fouly, E. F. El-Saadany, and M. M. A. Salama. Improved grey predictor rolling models for wind power prediction. *IET Gener, Transm, Distrib*, vol. 1, pp. 928-937, Nov. 2007.

[20] R. Bessa, V. Miranda, and J. Gama. Improvement in wind power forecasting based on information entropy-related concepts. Presented at the 2008 *IEEE Power & Energy Society General Meeting*, Pittsburgh, Pennsylvania. July, 2008.

[21] S. Haykin. Neural networks: A comprehensive foundation. *New Jersey: Prentice-Hall*, 1999.

[22] Melesse AM, Hanley RS. Artificial neural network application for multi-ecosystem carbon flux simulation. *Ecol Model* 2005; 189:305–14.

[23] S. I. Sulaiman, T. K. Rahman, I. Musirin, and S. Shaari. Performance analysis of two-variate ANN models for predicting the output Power from grid-connected photovoltaic system. *Int. Journal of power, Energy and Artificial Intelligence*, Vol.2, No.1, pp. 73-77, 2009

[24] M. Kawaguchi, S. Ichikawa, M. Okuno and N. Ishii. Prediction of electric power generation of solar cell using the neural network. ISSN 0302-9743, Vol.4253, pp. 387-392, 2006.

[25] Svetlana Borovkova. Estimation and prediction for nonlinear time series. *PhD thesis*, University of Groningen, 1998. http://dissertations.ub.rug.nl/faculties/science/1998.

[26] L.Landberg. Short-term prediction of local wind conditions. *Journal of wind engineering and industrial aerodynamics*, vol. 89, pp 235 -245.

[27] D., Liew, A.C. and Chang, C.S. A neural network short-term load forecaster. *Electric Power Systems Research*, 1994, 28, pp. 227–234.

[28] J. Sola and J. Sevilla. Importance of data normalization for the application of neural networks to complex industrial problems. *IEEE Transactions on Nuclear Science*, 1997, 44(3) 1464–1468.

[29] Guoqiang Zhang, B. Eddy Patuwo and Michael Y. Hu. Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, 1998, Volume 14, Issue 1, Pages 35-62.

[30] U.Focken, M.Lange and H.P. Waldl. Previento: regional wind power prediction system with innovative upscaling algorithm. *EWEC* 2001, Copenhagen.

[31] Madsen H., Kariniotakis G., Nielsen H.Aa., Nielsen T.S. and Pinson P. A Protocol for standardizing the performance evaluation of short-term wind power prediction models. *Wind Engineering* Volume 29, no. 6, (2006).