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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

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.

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 [1].

2. Background

In the 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 [2]. In the recent years, some new methods are catching researcher's attention, namely methods based on artificial intelligence like artificial neural network (ANN) [3], fuzzy logic and neuro-fuzzy [4,5], evolutionary algorithms [6], and some hybrid methods [7,8].

2.1. 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

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. 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. Required data for using in the proposed ANN model were provided from Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia.

3.2. Significant Input Parameter Selection for Hybrid Forecasting System

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.

3.3. Development of Hybrid Renewable Forecasting System

Fig. 1 illustrates the proposed 'Hybrid (wind-solar) Energy Forecasting Model'. The model is dedicated to short-term forecasting (three-hour ahead) based on neural network, 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 Fig. 1, 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 and causal model [9] 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.

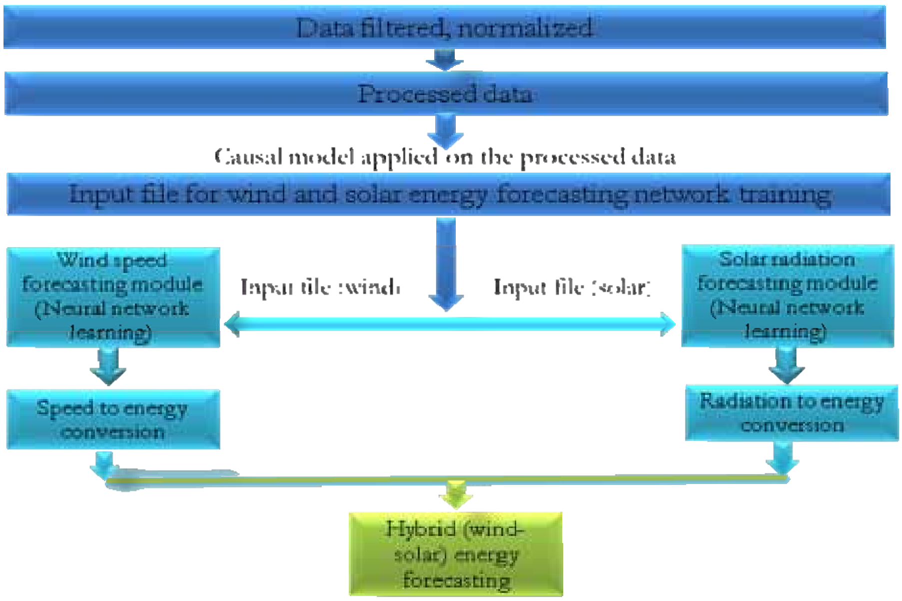

Fig. 1. Proposed hybrid (wind-solar) energy forecasting model.

4. Testing and Model Validation

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 widely accepted mathematical equations. 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. 2 (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.

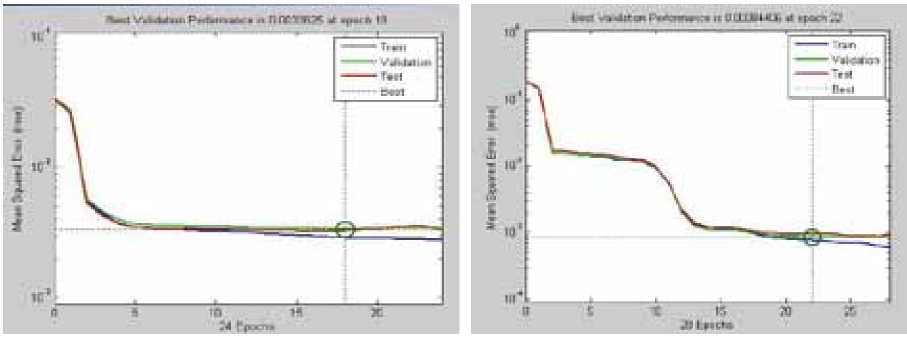

Fig. 2. (a) Plot of the training, validation and test errors for wind speed prediction; (b) Plot of the training, validation and test errors for solar radiation prediction.

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. 3 (a) and (b) represent the results respectively. Fig. 4 (a) and (b) represent the comparison between the actual outputs and the predicted outputs of the test data (wind and solar) set respectively.

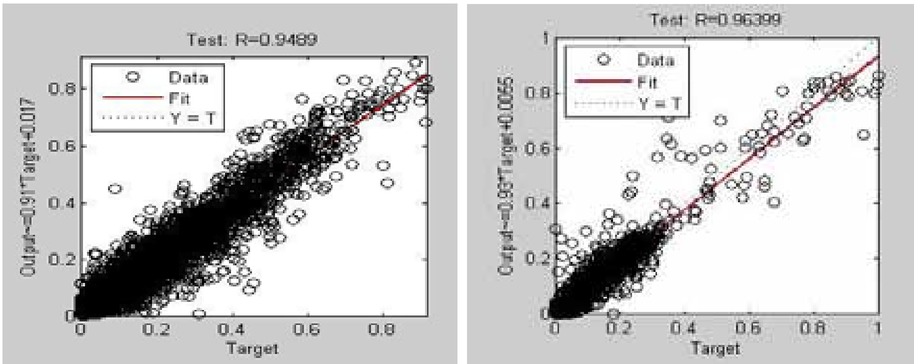

Fig. 3. (a) Regression analysis of test data (wind) set; (b) Regression analysis of test data (solar) set.

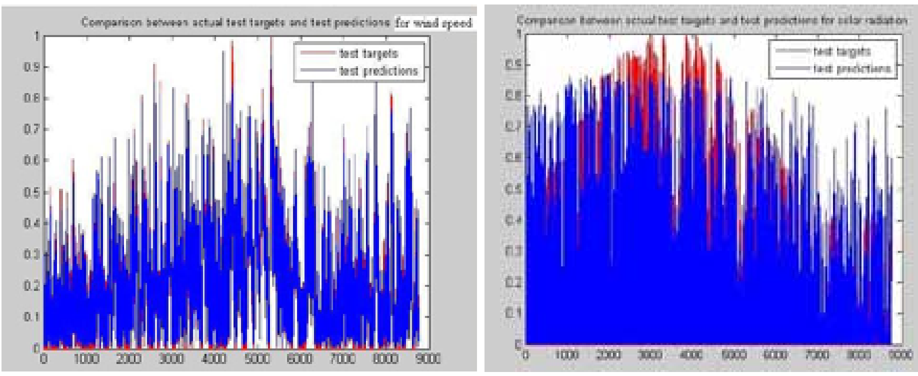

Fig. 4. (a) Comparison between the actual outputs and the predicted outputs of the test data (wind) set; (b) Comparison between the actual outputs and the predicted outputs of the test data (solar) set.

6. 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. 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).

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