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Forecasting of Photovoltaic Power Yield Using Dynamic Neural Networks

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***Abstract*— The importance of predicting the output power of Photovoltaic (PV) plants is crucial in modern power system applications. Predicting the power yield of a PV generation system helps the process of dispatching the power into a grid with improved efficiency in generation planning and operation. This work proposes the use of intelligent tools to forecast the real power output of PV units. These tools primarily comprise dynamic neural networks which are capable of time-series predictions with good reliability. This paper begins with a brief review of various methods of forecasting solar power reported in literature. Results of preliminary work on a 5kW PV panel at King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, is presented. Focused Time Delay and Distributed Time Delay Neural Networks were used as a forecasting tool for this study and their performance was compared with each other.**

Keywords-Irradiance; Time-series forecasting; Dynamic Neural Networks

I. INTRODUCTION

There has been a concern on how to dispatch renewable sources to electric grids. This includes controlling the PV system in the best way that guarantees safety, security, and economical operation of energy dispatch. Thus it is inevitable to explore ways of forecasting the power yield of these sources to support optimal generation planning studies. PV plants usually consist of PV arrays connected to inverters that change the DC output to AC and perform Maximum Power Point Tracking (MPPT) function. The AC power is then sent to power transformers that will step up the voltage and connect the PV system to either the distribution or transmission power network. The overall PV generation plant configuration is shown in Fig. 1.

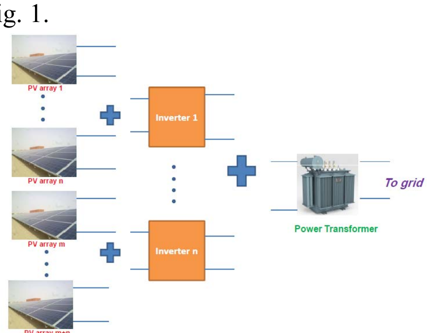


Figure 1. Overview of PV generation plant

The output power produced by PV arrays usually varies with sunshine or irradiance. The irradiance is zero at night and starts to increase gradually during the day and reaches its maximum level in the afternoon and then decreases back to zero again. The out power exhibits similar non-linear behavior. Clouds and heavy dust might cause a sudden fall in the yield of PV plants. Fig. 2 shows typical output of PV plants taken on hourly basis. This data was for a 10MW PV plant, Fig. 3, in MASDAR city, Abu Dhabi, U.A.E, connected to power distribution network at 11kV level.

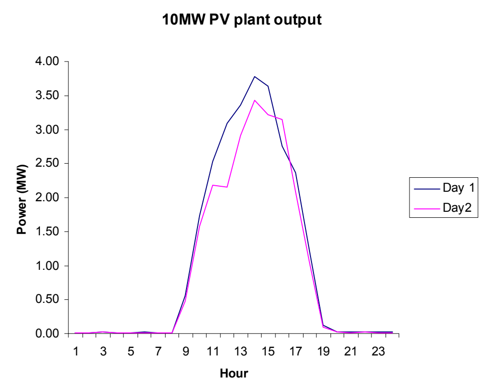


Figure 2. Power generated from 10MW PV plant on two consecutive days (1-2/1/2010, Source: Abu Dhabi Distribution Company (ADDC))


Figure 3. Masdar 10MW PV plant, Abu Dhabi, U.A.E.

The output of PV plant shows non-linear behavior which varies from day to day. Data from smaller scale solar systems with smaller recording time intervals of 10 minutes exhibits output of more vivid nonlinearity. This is shown in Fig. 4. The output shown is that of a 5kW PV array, Fig. 5, installed at King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia, connected to small local loads. This fact encouraged researchers to propose nonlinear predictors for forecasting the yield of PV systems. Furthermore, the requirement is for an online predictor that can be applied with ease and simplicity. A powerful candidate of this trait is dynamic neural networks. In the following section, a literature survey of reported PV forecasting methodologies is presented and analyzed.

II. Solar Power Forecasting: Overview

The prediction of the power produced by PV plants was the theme of a considerable number of research work reported in literature [1-9]. One proposed approach is to use mathematical equations of PV panels [1]. These mathematical models were based on equations of Sun's position and simplified models of PV cells. Numerical Weather Predictions (NWP) were used as additional inputs to the developed models. However, forecasting power for large PV plants or widely spread PV arrays with many PV modules of different manufacturers, different tilting angles and various converter efficiencies makes the mathematical approach tedious and can lead to errors in physical models of these PV systems [2].

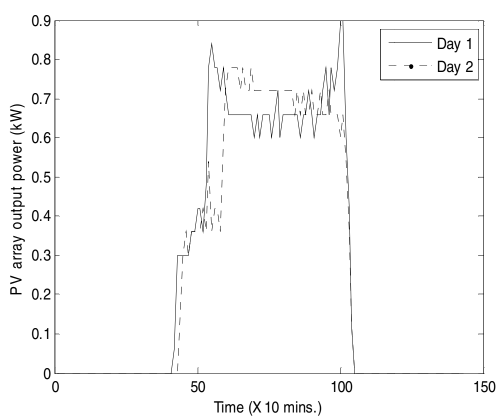


Figure 4. Typical power output of KFUPM 5kW PV array, 3-4 Feb. 2011

Figure 5. 5kW PV array at KFUPM beach, Dhahra, Saudi Arabia

Linear time-series models were reported in [3] where normalized solar power was predicted using adaptive type models. Statistical normalization of solar power is first done using clear sky model. The clear sky model is obtained using statistical smoothing techniques which is basically weighted quantile regression analysis. Auto Regressive (AR) and AR with exogenous input (ARX) models are tested; numerical weather predictions (NWPs) are fed to the latter. It was concluded that historical solar data are most important inputs for short forecasts (2 hours ahead) while NWPs are most important for longer forecasts. Others researchers used regression analysis and weather information to predict the power output of a 220kW system [4]. A PV simulator was used that takes as input solar radiation on inclined surfaces and I-V characteristics of PV cell derived from standard PV parameters to calculate the final predicted power output. These linear time-series forecasting methods will not suit PV systems as the output is rapidly changing in a non-linear manner.

Forecasting irradiance and then converting to power is a strategy used by many research works in literature. Autoregressive Integrated Moving Average models (ARIMA) and ARMA ones were used in [5] and [6]. In these models, current values are modeled as linear combination of previous values and inputs. The linearity of combination might be questionable when PV outputs exhibits non-linear behavior due to dust, cloud or other reasons. Furthermore, the conversion, of irradiance to power, is usually done by equations that use system efficiency, outside air temperature, array area along with forecasted insolation. Efficiency of PV systems was assumed to be constant. However, this is not the case in reality and thus this will introduce error in calculation over time.

Static Artificial Neural Networks (ANNs) were shown to outperform regression models in the estimation of the maximum power output of PV modules [7]. Multi-layer perceptron (MLP) Feed Forward Neural Network (FFNN) was used. Inputs to the ANN were temperature, wind velocity, and insolation. Time was taken into account by considering it as an additional input. Two days data from different seasons were used for training. Diversion in patterns was recommended for better predictions. Similar work was done in [8] where MLP NN was trained to predict the power output and energy of a PV module. Ambient temperature, irradiance, array voltage, and current were monitored in this approach. It can be said that such an approach is largely suitable for small PV applications. Monitoring currents and voltages of modules will need numerous advanced sensors and will introduce additional errors to the system. Furthermore, static NNs usually take considerable amount of historical data and good number of different inputs for proper training and is inflexible in handling the time factor.

The approach of our work is to use dynamic neural networks to forecast power yield of PV systems. These networks can incorporate temporal data better than static neural networks. Few papers have explored this method of forecasting PV power. Nonlinear Autoregressive Neural Network with External input (NARX) was used to predict power output of a kW PV system [2]. However, in reality radiation models of inclined surfaces were a prerequisite input to their NARX model which is not always available. Recurrent NN was also investigated for isolation forecasting and then converted to power values using linear equations that have efficiency and area of PV arrays as constants [9]. This conversion method has problems mentioned in preceding paragraphs. The objective of our work is to use minimal historical power data and few inputs to build a dynamic NN forecaster for a PV system regardless of size and type of the arrays. Direct forecasting of power outputs of PV arrays was explored using two Dynamic NNs; Focused Time Delay NN (FTDNN) and Distributed Time Delay NN (DTDNN).

III. DYNAMIC NEURAL NETWORKS: FTDNN AND DTDNN

The first type of dynamic NN explored in this work is the FTDNN [10]. These networks have time-delays only in the input layer to accommodate time-series inputs. Fig. 6 shows a simple schematic of FTDNN configuration with one input only. In case where several inputs are fed to the network, each will be delayed in a manner similar to that of Fig. 6. The network shows m delayed inputs fed to the input layer. $Z^{-1}$is a unit delay operator that yields $u(n-1)$ when it operates on a given input $u(n)$. The connections between m inputs and p_1 neurons in the input layer are given weights that are lumped to a matrix W_1 called the input weight matrix. Similar matrices exist between hidden layers and between final layer and output layer. Furthermore, the output of each neuron is offset by a value called bias that is lumped into a vector b_n for a given n^{th} layer.

The structure of Fig. 6 can be simplified as shown in Fig. 7(a) where weights matrices W and biases b vectors are lumped and shown in the figure. Time-delays are represented by a "TDL" box that stands for Tapped Delay Line. $f_n(.)$ represents the activation function of the n^{th} layer. The activation function chosen for input and hidden layers was the tansigmoid function which is equivalent to the hyperbolic tangent function given by:

$$tanh\,(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{1}$$

For a given continuous input x. The output activation function $f_o(.)$is usually a purelin function which is a linear summation of the outputs of the output layer neurons. An example of application of FTDNN in engineering can be found in [11]. The other dynamic network is the DTDNN that has delays distributed over all layers. Fig. 7(b) shows a DTDNN with delays both in input layer and second layer. This network is well-known for its application in phoneme recognition [12].

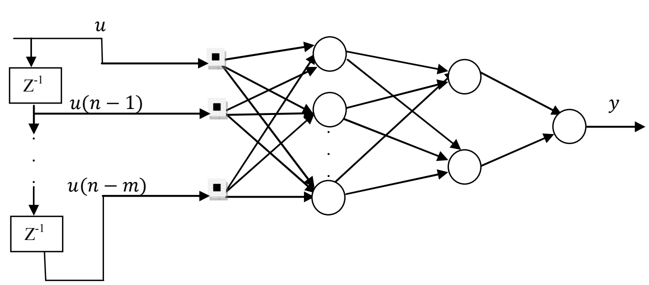
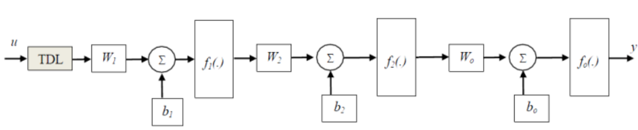
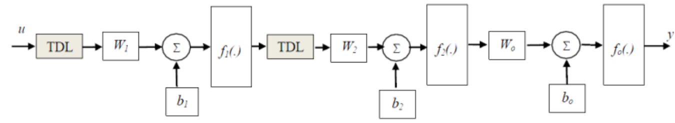


Figure 6. Focused Time Delay NN



(a)



(b)

Figure 7. Simplified configuration: (a) FTDNN (b) DTDNN

IV. SIMULATION RESULTS AND DISCUSSION

A. *One Step ahead prediction*

FTDNN was trained and tested on real data from the PV array in Fig. 4. The data was measured at a ten minutes interval i.e. 144 size of data points is collected in 24 hours. The only type of input used in this work is the power yield of the PV system. The input delay vector used in our test is D = [0: 8] i.e.,

$$y(n+1) = f(u(n), u(n-1), .., u(n-8)) \tag{2}$$

Ten neurons were used for the hidden layer and the famous Levenberg-Marquardt algorithm [13] was used to train the network and update the weights. The network was trained using real power output data of the array for 4 days (03-06/02/2011). Validation of the performance of the network was done by testing the feeding of PV data output for 07-08/02/2011. The prediction horizon of the network was chosen to be one i.e. the network is a step ahead predictor, This implies a ten minute ahead predictor as the resolution of data points is ten minutes. Result of testing the network is shown in Fig. 8. Root Mean Square Error (RMSE) is calculated as follows:

$$RMSE = \sqrt[2]{\frac{\sum_{i=1}^{i=n}({P_a}^i - {P_p}^i)^2}{n}} \tag{3}$$

Where P^i_a is the i^{th} actual output power, P^i_p is the i^{th} predicted power by network, and n is number of data points. The results, both the plot and RMSE, show a satisfactory performance for FTDNN as a PV power predictor.

TDNN is similar to FTDNN but with the difference that tapped delays are distributed in the network in more than one layer; i.e. not only in the input layer as the case of FTDNN. Delays up to 4 were used in the input layer and 3 in the hidden layer. Again, the network is a step ahead forecaster. Five neurons were used for the hidden layer and conjugate gradient backpropagation with Fletcher-Reeves updates [14] was used to train the network. It is worth mentioning that it took considerable effort to find a suitable training algorithm for DTDNN networks that is stable on both one step and multi-step forecasting. Moreover, the training phase was noticeably slower for this network than the FTDNN. The same data used for FTDNN training and testing was also used in DTDNN. Fig. 9 shows the prediction plots along with RMSE calculation. DTDNN showed almost similar performance to that of FTDNN with slight surpass of FTDNN.

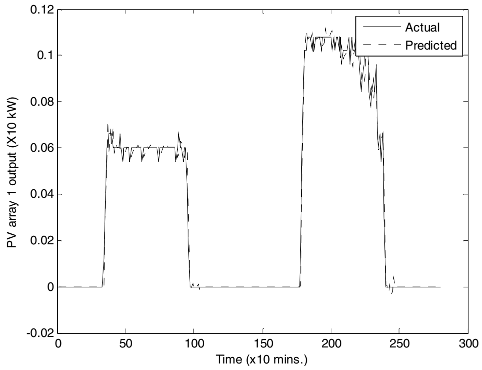


Figure 8. Testing FTDNN for PV array output 7-8/2/2011, RMSE = 0.0039kW

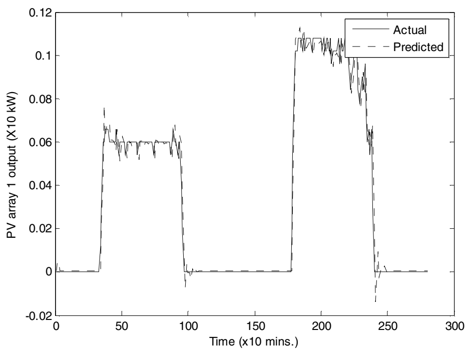


Figure 9. Testing DTDNN for PV array output 7-8/2/2011, RMSE= 0.0054kW

B. Multi-step forecasting

The dynamic NNs were further challenged by testing their capabilities in performing multi-step ahead predictions. The number of steps chosen for this test is 6 steps ahead i.e. 60 minutes or 1 hour forecasting. Figs. 10 and 11 show the results of FTDNN and DTDNN respectively. FTDNN shows a slightly better performance than DTDNN.

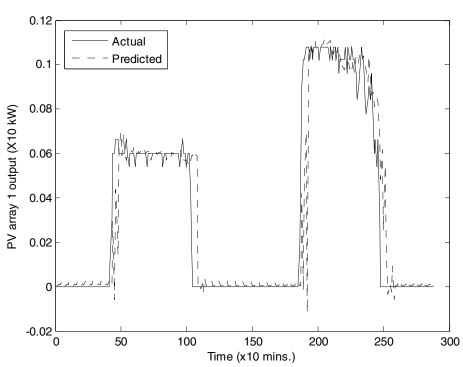


Figure 10. Multistep ahead testing of FTDNN for PV array output 7-8/2/2011, RMSE = 0.0165kW

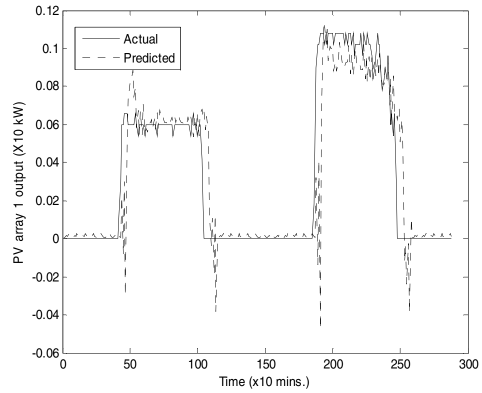


Figure 11. Multistep ahead testing of DTDNN for PV array output 7-8/2/2011, RMSE = 0.0205kW

As expected, the performance of the networks deteriorated but is still acceptable. The fact that the network is taking only historical values of output with small size and still performing well shows the suitability of the proposed methodology for predicting very short term power forecasts. The following can be deduced from the results presented:

1) The network is capable of handling time-series data and changing values on small time scale.

2) The presented Dynamic NNs Neural networks have the ability to accommodate the non-linearity inherent in the solar power data and thus are expected to surpass other linear predictors.

3) Minimum input required to train the network unlike other approaches that require intensive historical data which causes storage problems and might not be possible if history is not available.

4) Point (3) implies that error introduced in input measurements will be condensed.

5) Based on the above, it is possible to use the proposed methodology for online and real-time dispatching of PV plants.

6) The proposed forecasting approach is not site specific; i.e. it can be applied to any PV plant in any location regardless of angle and tilts of panels.

7) The proposed method does not depend on the type of PV cell used i.e. type of PV cell is not an input to its computational process. This is not the case for reported methods that use mathematical models of PV to predict the output power.

8) The following can said regarding the tested Dynamic NNs tested:

a) FTDNN showed a slightly better performance than DTDNN. This is true for both step ahead and multistep forecasting.

b) It takes considerable effort and time to find suitable training algorithm for DTDNN.

c) Distriubted time-delays over dynamic NNs layers does not improve the forecasting capabilities of these networks. In contrast, adding delays to hidden layers complicates the training phase of the network.

d) It can be said that due to the more complex structure of DTDNN, reaching a statisfactory performance for it requires further optimization and epochs. The introduction of additional delays in the network cause additional uncertainity in initial epochs causing greater time and memory consumption [11].

V. Conclusion

The presented paper demonstrated a real life application of dynamic NNs to a renewable energy problem. FTDNN and DTDNN were used to forecast power yield of a PV system connected to a local load. These networks were chosen as an initial step in exploring the capabilities of dynamic NNs in solar power forecasting; other dynamic NN structures will also be tested in future work. The tested networks showed promising results with minimal inputs. FTDNN was found to be a more attractive candidate for forecasting PV output in comparison with DTDNN. This is due to the ease of training the network and improved results that it showed.

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