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Adaptive Prediction of the Performance of a Photovoltaic Solar Integrated System

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Abstract

The performance of an experimental photovoltaic (PV) solar system is predicted using adaptive artificial neural networks (ANNs). The performance of the system is represented by its important efficiencies. An ANN model that predicts these efficiencies from relevant measurements exits in the literature. Adaptive online techniques are applied to the existing ANN model for the PV solar integrated system. The on-line ANN uses the error between the ANN predicted efficiency and the efficiency measurement from the appropriately selected sensors and efficiency laws to update the network's parameters recursively. The adaptation scheme is based on the Kaczmarz's algorithm and improves the ANN prediction accuracy when the PV solar system parts degrade, the date within the year changes and in the presence of modeling errors. Thus, the ANN prediction capability improves especially over the long time horizon. The adaptive model for the PV solar system can be used to estimate precisely the system parameters which will produce maximum efficiencies and consequently will enable the best design for the PV solar system.

Keywords: *PV Solar System, Adaptive Algorithm, Neural Networks*

1. Introduction

It is extremely important to run solar systems at their maximum efficiencies to reduce their cost especially in the case of electric power generation from solar energy. The PV systems responsible for electric power generation from solar energy are still very expensive which motivates researchers to come up with innovative techniques to increase the efficiency of such systems and thus reduce their cost. This will make them more attractive. One of the major challenges in solar systems is to predict their efficiencies accurately due to the environmental changes and the fact that efficiency depends on many parameters. A good approach in this case is to use artificial neural networks to predict efficiencies from appropriate inputs.

Artificial neural networks (ANN's) have received a lot of attention in recent years due to their attractive capabilities in forecasting, modeling of complex nonlinear systems and control. Applications of neural networks are numerous and include many various fields among which are engineering and business. ANN's have been used for forecasting solar system efficiencies [1], camless engine torque [2], load [3,4], gasoline consumption [5], energy [6], space weather [7], outdoor sound transmission [8], stream flow [9], wind waves [10] and financial indicators [11,12]. Examples of industrial processes for which modeling and control using neural networks have been investigated include internal combustion engines [2,13], two-stage combustor burning ethylene in air [14] and steel making process [15]. The ANN model is trained with historical time series input-output process data or observations and is then used to predict the output in the future. Due to gradual degradation of the underlying process, the short-term predictions will be more accurate than the long-term ones. Thus, there is a need to adapt the neural net in order to better accommodate the changing environment and improve the net's prediction accuracy especially when the forecasting horizon is long.

In this paper we consider an experimental PV solar integrated system which consists of a solar trainer which contains a photovoltaic panel, a DC centrifugal pump, flat plate collectors, storage tank, a flowmeter for measuring the water mass flow rate, pipes, pyranometer for measuring the solar intensity, thermocouples for measuring various system temperatures and wind speed meter. This PV solar integrated system was modeled with ANN's in [16]. Historical input-output system data collected experimentally was used to train an ANN that predicts the collector, PV module, pump and total efficiencies. The model predicts the efficiencies well and was utilized in [1] to find the operating conditions of the system that will produce the maximum system efficiencies. This information is very hard to obtain by just looking at the available historical input-output data. The neural net model of

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the PV solar integrated system sets the background for achieving the best system performance.

Adaptive online techniques are applied to the existing ANN model for the PV solar integrated system developed in [16]. The on-line ANN uses the error between the ANN predicted efficiency and the efficiency measurement from the appropriately selected sensors and efficiency laws to update the network's parameters recursively. The adaptation scheme is based on the Kaczmarz's algorithm which updates the linear parameters of the neural net, namely, the output weight vector and bias and consequently improves the ANN prediction accuracy when the PV solar system parts degrade, the date within the year changes and in the presence of modeling errors. Thus, the ANN prediction capability improves especially over the long time horizon. The adaptive model for the PV solar system can be used to estimate precisely the system parameters which will produce maximum efficiencies and consequently will enable the best design for the PV solar system.

2. PV Solar Integrated System Description

The solar system is shown in Fig. 1 and it consists of the following components as numbered in the figure: 1) solar trainer STR-811/EV which contains a photovoltaic panel, 2) a DC centrifugal pump, 3) flat plate collectors, 4) storage tank, 5) a flowmeter for measuring the water mass flow rate, 6) pipes, 7) pyranometer for measuring the solar intensity, 8) thermocouples for measuring various system temperatures and 9) wind speed meter. The photovoltaic panel converts the solar energy to electrical power that drives the DC pump. The pump drives the water in the pipes to the flat plate collectors passing through the flowmeter. The collectors heat the water by the solar energy and the heated water flows into the storage tank which is connected to the DC pump.

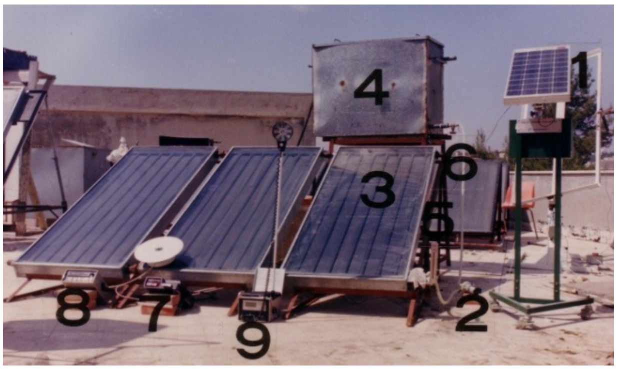

Fig. 1. Photograph showing the PV solar system

Data relevant to the system performance was collected for different days and every 15 minutes during the day. The following data was recorded: water inlet temperature to the collectors, water outlet temperature of the collectors, ambient temperature, temperature of the photovoltaic cells, solar intensity, wind speed, water mass flow rate, photovoltaic panel current and voltage. Using this data four different system efficiencies were calculated, namely, the flat plate collectors efficiency, the photovoltaic panel (module) efficiency, the DC pump efficiency and the overall system efficiency.

The collector efficiency is the ratio of heat gained by water to the incident solar radiation on the collectors and is written as

$$\eta_c = \frac{MC_p(T_o - T_i)}{I_s A_c} \tag{1}$$

where, M is the water mass flow rate, Cp is water heat specific value, To is the outlet water temperature, Ti is the inlet water temperature, Is is the solar intensity and Ac is the solar collector area.

The PV panel efficiency is the ratio of power produced by the panel to the incident solar radiation on the panel, that is

$$\eta_m = \frac{IV}{I_s A_c} \tag{2}$$

where, I is the module current and V is the module voltage.

The efficiency of the pump is calculated as

$$\eta_p = \frac{\rho g Q H}{IV} \tag{3}$$

where, ρ is the water mass density, g is the gravity acceleration, Q is the water volume flow rate and H is the pump head.

The total efficiency is defined as the product of the pump efficiency and the module efficiency and is written as

$$\eta_t = \eta_p \eta_m \tag{4}$$

3. Neural Net Model

We will model the PV solar system with artificial neural networks (ANN's). Knowledge about the system dynamics and mapping characteristics is implicitly stored within the network that is trained using historical time series input-output process data. The ANN model is a nonlinear functional approximation of the real system. Neural networks were originally inspired as being models of human nervous system. They have been shown to exhibit many abilities, such as learning, generalization, and abstraction [17]. Useful information and theory about ANN's can be found in [18]. These networks are used as models for processes that have input-output data available. The historical observations allow the neural network to be trained such that the error between the real output and the estimated (neural net) output is minimized. The model is then used for different purposes among which are estimation and control.

The neural net structure is shown in Fig. 2. The inputs feed forward through a hidden layer to the output. The hidden layer contains processing units called nodes or neurons. Each neuron is described by a nonlinear sigmoid function. The inputs are linked to the hidden layer which is in turn linked to the output. Each interconnection is associated with a multiplicative parameter called weight. The input weights are associated with the links between the inputs and the hidden layer, whereas the output weights are associated with the links between the hidden layer and the output.

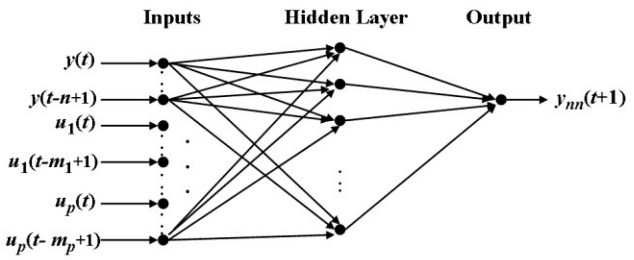

Fig. 2. **Neural net structure**

4. Neural Net Adaptation

The artificial neural net mathematical model that represents the PV solar integrated system operation is written as

$$y_{nn}(t+1) = W_o * \tanh(W_i * U(t) + B_i) + b_o \qquad (5)$$

where, y_{nn} $(t+1)$ is the output of the neural net model that approximates the solar efficiencies, $U(t)$ is a column vector of size N that contains the inputs to the ANN, W_o is a row vector of size h that contains the output weights from the hidden layer to the output with h being the optimum number of hidden nodes, W_i is a matrix of size hxN that contains the input weights from the inputs to the hidden layer, B_i is a column vector of size h that contains the input biases and b_o is the output bias. Note that $\tanh(W_i * U + B_i)$ is the activation function of the hidden layer. It is a column vector of size h.

The ANN model is of the form given in equation (5) can be rewritten as

$$y_{nn}(t+1) = \beta(U(t))\,\alpha \qquad (6)$$

where,

$$\beta(U(t)) = \begin{bmatrix} \tanh(W_i * U(t) + B_i) \\ 1 \end{bmatrix}^{\mathrm{T}} \qquad (7)$$

and

$$\alpha = \begin{bmatrix} W_o^{\mathrm{T}} \\ b_o \end{bmatrix} \qquad (8)$$

It is clear that the estimated (neural network) future value of the output is linear in the parameter α that is a column composed of the output weight vector and bias.

The ANN is used to predict the real system outputs which are the PV solar integrated system efficiencies in the future. Due to possible error sources of the system, the short-term predictions will be more accurate than the long-term ones. The neural net of the PV configuration is adapted using the Kaczmarz's algorithm in order to better accommodate the changing environment and improve the net's prediction accuracy over the long run. This adaptation scheme leads to less computational complexity and quick convergence. The real-time parameter estimation Kaczmarz's algorithm when applied to the ANN model described by equation (6) gives the following recursive adaptation scheme for α

$$\alpha(t+1) = \alpha(t) + \frac{\beta(U(t-1))^{\mathrm{T}}}{\beta(U(t-1))\beta(U(t-1))^{\mathrm{T}}}\, e \qquad (9)$$

$$e = y(t) - y_{nn}(t) \qquad (10)$$

where the error, e, is the difference between the real and estimated outputs at the time instant t, that is

Note that the on-line adaptive algorithm described in equations (9) and (10) assumes that the output efficiency measurement at the current time t is available which is true in the PV solar integrated system since required measurements for efficiencies calculation are available. The adaptation scheme can be demonstrated with the aid of Fig. 3. The estimated output of the ANN model is compared with the measured efficiency. If there is a difference between the two values the parameter estimation Kaczmarz's algorithm updates α (according to equation (9)) to be used in the subsequent predictions. The parameter estimator or adaptive algorithm compensates for system parts degradation and modelling errors, and provides more accurate long-term predictions.

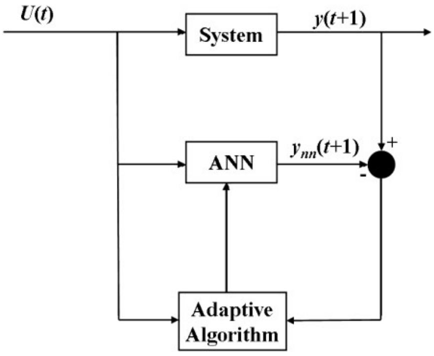

Fig. 2. **Adaptation scheme demonstration**

The importance of the described adaptive ANN model lies behind the fact that the ANN model is used to estimate the inputs to the system that will produce maximum system efficiencies or best performance. The inputs estimation based on the non-adaptive ANN was done in [1] and can be utilized with the adaptive ANN easily since the structure of the net does not change. The parameter values of the net are only adapted to improve prediction accuracy. Thus, the results obtained by the technique developed in [1] will be more accurate with the aid of adaptive neural networks described in this paper.

5. Conclusion

An algorithm for adapting forward artificial neural networks was developed. The presented technique is useful for prediction applications. The adaptation scheme is based on the Kaczmarz's projection algorithm that offers less computational complexity and quick convergence. It uses the real output measurement to correct for errors in the predicted (neural net) output by updating the linear parameters of the network on-line. The developed algorithm can be applied to the neural network model of a PV solar integrated system to estimate precisely the conditions that will produce maximum efficiencies which is a great benefit.

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