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Solar radiation forecast based on fuzzy logic and neural networks

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ABSTRACT

This paper presents a solar radiation forecast technique based on fuzzy and neural networks, which aims to achieve a good accuracy at different weather conditions. The accuracy of forecasted solar radiation will affect the power output forecast of grid-connected photovoltaic systems which is important for power system operation and planning. The future sky conditions and temperature information is obtained from National Environment Agency (NEA) and the sky and temperature information will be classified as different fuzzy sets based on fuzzy rules. By using fuzzy logic and neural network together, the forecast results can follow the real values very well under different sky and temperature conditions. The effectiveness of the approach is validated by a case study where four different scenarios are tested. The Mean Absolute Percentage Error (MAPE) is much smaller compared with that of the other solar radiation method.

1. Introduction

Solar energy is well known as clean energy because there are no carbon emissions during its generation. With the development of photovoltaic (PV) technology, large scale grid-connected PV power plants have been built around the world in recent years [1]. The integration of a large number of embedded PV generators will have far reaching consequences not only on the national transmission and generation system but also on the distribution networks. PV will be a very important generation source for the microgrid (MG) [2]. However, due to the variability of solar irradiation and ambient temperature, the power output of PV plants is nondeterministic and stochastic.

The recent trend toward a low-carbon society has accelerated the rapid introduction of PV systems for power generation. In response to this, electric utilities need to predict the output power of PV systems [3]. The total power production of a PV plant in a specified future time period can not be determined precisely due to the variations of weather conditions, control strategies, and shadow conditions, etc. For this reason, any grid-connected PV plant has to be considered as an uncontrollable and non-dispatchable power generator in the utility network, whose power output fluctuation will impact the power system stability [4]. In order to cooperate with power distribution planning and operation, distribution automation and demand side management, the generation forecast of the grid-connected photovoltaic system plays an important role in scheduling generation to meet the load demand. The generation forecast, particularly the short term forecast, is a challenging task for the PV power system as its power output varies largely with the external conditions like sunshine, temperature, etc.

The weather conditions such as temperature and irradiance are important factors in the performance of any photovoltaic module. An accurate measurement of the effective irradiance level and different PV output voltage or current will affect the accuracy of the forecasted solar power [5]. If the maximum power tracking algorithm is used, the PV output power will be highly related to the solar irradiance. Solar irradiance in moderate climates is mostly characterized by short time fluctuations. It is necessary to forecast the solar irradiance for solar power output.

Several models have been developed in order to generate the solar irradiance data based on stochastic models such as autoregressive (AR), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and Markov chain [6–9]. However, these models which are based on the probability estimation do not always give good accuracy. In fact, it is rather difficult to forecast accurately the behavior of solar irradiance by these stochastic models, because they need the bases of the precise definition of problem domains as well as the identification of mathematical functions. This is just the reason why most stochastic models were found with relatively big errors and sometimes difficult to be adopted widely.

In order to overcome this problem, Artificial Intelligence (AI) techniques [10] have been applied with success for modeling and

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forecasting of solar radiation data [11]. With special abilities in simulating and mapping complicated systems automatically, neural networks are used to learn the behavior of solar irradiance and they are subsequently used to simulate and predict this behavior. The advantage of Artificial Neural Network (ANN) simulation over standard mathematical models is that it does not require the knowledge of internal system parameters; involves less computational effort; and offers a compact solution for multiple-variable problems. However, the sky conditions are defined by fuzzy clustering: an input datum may belong to different conditions simultaneously, pertaining to each condition at different temperature behavior. Neural networks can not tell the difference between them. A fuzzy model of solar irradiance on inclined surfaces has been developed by Gomez and Casanovas [12]. The fuzzy model includes concepts from earlier models, though unlike these models, it considers non-disjunctive sky conditions. The only disadvantage is that the accuracy of forecast results based on fuzzy logic is not as good as that of neural networks in one weather condition.

This paper proposes a new solar radiation forecast technique based on neural networks and fuzzy logic. The main idea of this technique is to achieve good accuracy at different sky conditions. The sky conditions and temperature information will be classified as different fuzzy sets based on the fuzzy rules. The past and future sky conditions and temperature data information can be obtained from National Environment Agency (NEA). The historical solar radiation, sky conditions and temperature data will be used to train the basic neural networks. The fuzzy model can tell the difference between the different sky conditions and it will forecast the solar radiation together with trained neural networks.

In Section 2, the mathematical modeling of PV, neural network and fuzzy logic are also introduced. The equivalent circuit of PV and its output power formulation are introduced in Section 2.1. The feed-forward neural network (FNN) algorithm and fuzzy logic are shown in Section 2.2 and 2.3 respectively. The proposed solar radiation forecast technique based on fuzzy logic and neural networks is implemented in Section 3. Simulation results for four scenarios and their analysis are discussed in Section 4.1. The results of comparison with the other methods are shown in Section 4.2. The final conclusion is presented in Section 5.

2. Mathematical modeling

2.1. Equivalent circuit and power output of PV

PV is an attractive source of renewable energy for distributed urban power generation due to their relatively small size and noiseless operation. Their applications are expected to significantly increase all over the world. Solar photovoltaic power is a generic term used for electrical power that is generated from sunlight. A solar photovoltaic system converts sunlight into electricity. The fundamental building block of solar photovoltaic power is the solar cell or photovoltaic cell [13,14]. A solar cell is a self-contained electricity-producing device constructed of semi-conducting materials. Light strikes on the semi-conducting material in the solar cell, creating direct current (DC) [15].

Fig. 1 shows the voltage and current characteristic curves of a photovoltaic (PV) cell. It is very easy to find the maximum power point with the help of a power curve in Fig. 1. When the PV works at the maximum power point, the energy transfer efficiency from sunlight to electrical power is at its maximum [14].

The equivalent circuit of a PV module used is shown in Fig. 2. In the calculation of the power output of a PV module, we assume that a maximum power point tracker will be used. Manufacturers of PV modules supply information on the voltage and current of the maximum power point at a reference temperature and a reference irradiance. The output current I can be expressed as a function of the output voltage V from the equivalent circuit of the PV module.

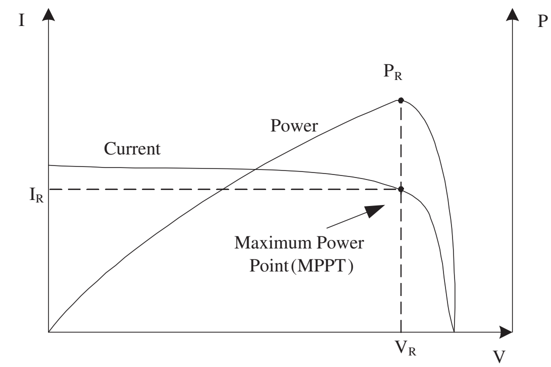

Fig. 1. *V–I* characteristic curve and maximum power point of PV.

Normally, the power output curve at every hour is used for power system optimization. In this paper, the forecasting data of the PV power output based on the maximum power point tracker is used for implementation of PV modules.

In the PV system, the maximum power output is presented by (1) [1,16].

$$p_s = \eta SI(1 - 0.005(t_o - 25)) \tag{1}$$

where, η is the conversion efficiency (%) of the solar cell array; S is the array area (m^2); I is the solar radiation (kW/m^2); and t_o is the outside air temperature (°C).

2.2. Feed-forward neural networks

Feed-forward Neural Network (FNN) is the most popular and most widely used model in many practical applications [17]. In this paper, it is used to forecast the solar radiation based on the past one month solar radiation and weather data. It is formed by a large number of highly interconnected processing elements through a learning process [18]. FNN is able to learn the complex relationships between the inputs and the specific targeted output after training.

A basic neural network consists of three layers. They are input layer, hidden layer and output layer. In a multi-layer FNN, neurons are organized in a distinct layered topology as shown in Fig. 3. A FNN only allows data flow in a forward direction, i.e., the data flows from the input layer neurons, through the hidden layer neurons, and finally reaching the output layer neurons.

The widely used learning method in FNN is the backpropagation algorithm. Backpropagation is a form of supervised learning in which the network is provided with examples of inputs and a target output. The training starts with random weights and the objective is to adjust them to make sure that the error is minimal. The values of the hidden layer neurons can be expressed in (2).

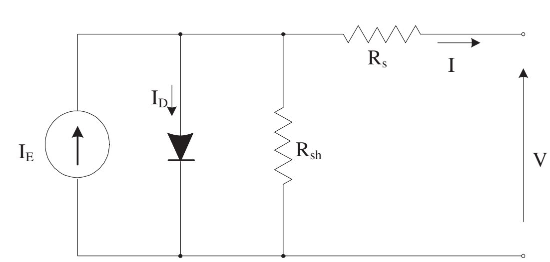

Fig. 2. Equivalent circuit of a PV module.