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Short–mid-term solar power prediction by using artificial neural networks

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Abstract

Solar irradiation is one of the major renewable energy sources and technologies related with this source have reached to high level applications. Prediction of solar irradiation shows some uncertainties depending on atmospheric parameters such as temperature, cloud amount, dust and relative humidity. These conditions add new uncertainties to the prediction of this astronomical parameter. In this case, prediction of generated electricity by photovoltaic or other solar technologies could be better than directly solar irradiation.

In this paper, firstly, Artificial Neural Networks (ANNs) methodology is applied to data obtained from a 750 W power capacity of solar PV panel. The main objective of this paper is to determine time horizon having the highest representative for generated electricity prediction of small scale solar power system applications. It is seen that 5 min time horizon gives the best solar power prediction for short term and 35 min could be used for medium terms in April. In addition, these time horizons have increased to 3 and 40 min for very short time and medium time prediction respectively during August. During April and August Root Mean Square Errors (RMSEs) between measured and testing values changed between 33–55 W and 37–63 W ranges respectively. Especially, during August for solar irradiation, stationary conditions are observed and these situations let ANN predict easily generated electricity from 30 to 300 min ahead.

Keywords: Artificial neural network; PV; Power prediction; Solar irradiation; Turkey; Weighting

1. Introduction

Under global climate change man should interest in renewable energies especially solar and wind. All renewable energies are different forms of solar energy, except geothermal and tidal. Unfortunately renewable energy sources have some problems related with continuity. In other words, these sources have discontinuity problems.

As known that, solar energy can be used for many applications such as thermal, PV and passive heating. Recently, with the increasing significance on environmental problems, clean energy generations become dominant in every aspect of energy use. Solar energy is very clean but not persistent for long durations. Even so, at times of potential availability other and especially, fossil fuel combustion must be substituted with clean and environmentally friendly solar energy. So far, there have been many scientific studies concerning solar energy by different scientists who have treated the problem of solar energy evaluation by different approaches (Şen, 2004).

Solar irradiation changes with time and area, in addition to topographic conditions elevation variation take primarily

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role. Because of astronomical phenomena, seasons arise and they are important for heating and cooling depending on sun's position and area of location in the northern or southern hemispheres. Although these features provide some advantages in solar engineering applications, but some disadvantages originate from discontinuous appearance of solar irradiation. Additionally, power prediction is a new concept and has gained economical value. If investors know prediction of electricity to be generated in shortterm, midterm and longterm, properly, it would be easy to market and make decision about energy planning for them. Short term solar power prediction and details of progress is explained by Şen (2004). Additionally solar irradiation properties of the study area are given by Şen and Şahin (1997, 2000, 2001) related with solar irradiation and artificial neural networks and load prediction (Dillon et al., 1991; Chartoniuk and Chen, 2000).

Generally in mentioned papers solar irradiation estimation was based on sunshine duration. In addition to these, papers related with load prediction have been taken by a lot of authors (Drezga and Rahman, 1999; Chow and Leung, 1996; Senjyu et al., 2002). But, in these papers load generally refers to grid connected and mostly stable systems. Hippert et al. (2001) also focused on a review paper related with short term load forecasting. As mentioned before, generally grid connected and loads of stable systems have been considered like Mandal et al. (2006). But, solar irradiation, especially at midlatitudes, is not a stable parameter and so generation of electricity for this area will not be stable and include high uncertainties for prediction.

Prediction of generated electricity by solar photovoltaic cells under climatic conditions of Istanbul, Turkey has not been considered yet. In this paper, short and medium term power prediction is carried out in details. One of the other main aims of this paper is to evaluate short–medium term power forecast and minimize prediction errors by using Artificial Neural Networks (ANNs).

In the literature, there have been several studies about photovoltaic applications using ANNs (Mellit and Kalogirou, 2008; Mellit et al., 2005; Mellit and Pavan, 2010; Almonacid et al., 2011). The study of Mellit and Kalogirou (2008) includes a review of the artificial intelligence techniques relating to the PV applications. Also, Mellit et al. (2005) proposed an ANN for prediction of daily solar radiation to apply for sizing a PV system, obtaining correlation coefficient of 98% and the mean relative less than 1.5%. Additionally, 24-h forecast of solar irradiance by using artificial neural network was performed by Mellit and Pavan (2010) for performance prediction of a grid-connected PV plants at Trieste, Italy, having correlation coefficient in the range 98–99%. Almonacid et al. (2011) have studied relating to the calculation of the energy provided by a PV generator using artificial neural networks. In this research (Almonacid et al., 2011) results show that the method based on an artificial network provides better results than the alternative classical methods. For instance, the errors in ANN are between 6% and 8%, while the errors in classical methods (only take into account the effect of irradiance and temperature) are between 6% and 30%.

2. Artificial neural network

Artificial Neural Networks (ANNs) are widely used in a variety of practical tasks from process monitoring, fault diagnosis and adaptive human interference to natural events and artificial intelligence such as atmospheric processes and computers. ANNs are very important in control system applications because of their universal mapping characteristics and learning ability. ANN process can be considered as a black-box modeling with a set of input factors and output variables which are results of input factors treatment through a systematic neural network.

The first appearance of ANN concept in the literature is due to Mc Culloch and Pitts (1943) who suggested the cell model. In such a model, ANNs are exemplified as a set of logical statements. Later, in 1949 researches concentrated their attention on the learning ability of human and its modeling which can be accounted as the pioneering work on the ANNs (Hebb, 1949). However, actual leaps in the ANN development appeared towards 1980 through various researches (Hopfield, 1982; Kohonen, 1982; Anderson, 1983; Rumelhart et al., 1986).

Initially, ANN can be divided into two parts as architecture and neurodynamics (functional properties). The former defines the structure of the network as the number of artificial neurons and their interconnectivity whereas the latter includes their properties as to how the neural network learns, recalls associates and continuously compares new information with existing knowledge and how it classifies new information and the development of new classifications, if necessary. Neural network architecture includes many interconnected neurons or processing elements, with familiar characteristics such as inputs, synaptic strengths, activation, output and bias (Fig. 1).

An artificial neuron has n inputs as x_i ($i = 1, 2, 3, \ldots, n$) which show the source of input signal. This source should be environment or a neighboring neuron. Each input is weighted before reaching the main body of processing

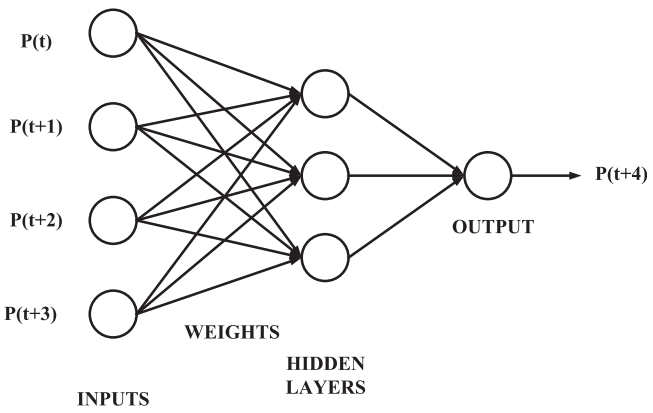

Fig. 1. General ANN architecture.