Mini Review on the Application of Neural Networks in Solar Energy Conversion

Alibakhsh Kasaeian, Mohammad Sameti

Abstract—People and animals are much better and faster at recognizing while computers are an integral part of day to day activities in engineering design. Artificial neural networks are applied to problems where the relationships may be quite dynamic or non-linear. ANNs provide an analytical alternative to conventional techniques which are often limited by strict assumptions of normality, linearity or variable independence. Neural networks can be applied to the solar system models to make sensible decisions in different areas. Paper presented here reviewed the most important applications of the neural networks in the solar energy systems.

Keywords—Artificial neural network (ANN), Solar systems

I. INTRODUCTION

Artificial neural networks (ANNs) are, as their name indicates, computational networks which attempt to simulate the networks of nerve cell (neurons) of the biological (human or animal) central nervous system. This simulation is a gross cell-by-cell (neuron-by-neuron, element-by-element) simulation. It borrows from the neurophysiological knowledge of biological neurons and of networks of such biological neurons. It thus differs from conventional (digital or analog) computing machines that serve to replace, enhance or speed-up human brain computation without regard to organization of the computing elements and of their networking.

II. APPLICATION OF ANNS IN SOLAR SYSTEMS

A. Solar Collectors

Artificial Neural Networks (ANNs) methodology is applied to data obtained from a solar PV panel with given capacity. The main objective is to determine the optimal time horizon having the highest representative for generated electricity prediction of small scale solar power system applications [1].

The thermal performance of a solar air collector depends on different design components as collector slope, absorber plate emissivity, emissivity of glass cover, air temperature, air velocity and number of glass cover. In a study for fixed solar irradiation (I) and Reynolds number varying from 2,000 to 6,000 and different number of glass covers (N), the optimal values of air velocity (V), collector slope (b), absorber plate emissivity (ep), and emissivity of glass cover (eg) and air temperature (ta) were obtained. So, the maximum thermal performance of the solar air collector was obtained. The ANN method was used for optimization process [2].

A new formula based on artificial neural network (ANN) technique was developed to determine the efficiency of flat plate solar collectors [3].

Another work was done to prove whether neural networks can be used for the prediction of collector performance parameters. The results proved that this can be performed with satisfactory accuracy. The advantages of this method are the speed and the avoidance of the need to perform long series of tests [4].

B. Solar Radiation

Some works [5-11] has been done to generate, using neural networks (NNs), reliable and useful time-series sets of hourly data of global and diffuse solar irradiance for each month, and keeps records of climatic data in some form or another. They particularly look at the Multi-Layer Perceptron (MLP) network which has been the most used of ANNs architectures both in the renewable energy domain and in the time series forecasting. They have used a MLP and an ad-hoc time series pre-processing to develop a methodology for the daily prediction of global solar radiation on a horizontal surface [12].

Beam solar radiation at surface level is an important parameter in designing systems by employing solar energy, such as high temperature heat engines, high-intensity solar photovoltaic cell, building designing, horticulture and so on. ANN have been used for range of objectives, such as constraint satisfaction, content addressable memories, control, data compression, diagnostics, forecasting, general mapping, multi sensor data fusion, optimization, pattern recognition [13].

C. Solar Refrigeration

A direct and inverse artificial neural network (ANN and ANNi) approach were developed to predict the required coefficient of performance (COP) of a solar intermittent
refigeration system for ice production under various experimental conditions. The used inputs parameters were: the solution concentration, the cooling water temperature, the generation temperature, the ambient temperature, the generation pressure and the solar radiation [14,15].

A feed forward (FFBP) with one hidden layer, a Levenberge-Marquardt learning (LM) algorithm, hyperbolic tangent sigmoid transfer function and linear transfer function for the hidden and output layer respectively, were used [15].

D. Solar Air Conditioning

As shown in figure 6 a solar-assisted air-conditioning system provided with two storage tanks is under study. In this case, the unique Artificial Neural Network (ANN) model with the lowest number of input variables has been proposed with the main purpose to predict the coefficient of performance and the cooling capacity of the absorption chiller. The configuration 5-9-2 (5 inputs, 9 hidden and 2 output neurons) was found to be the optimal topology [16].

In order to assess the accuracy of the neural models, we analyze the results in terms of the Root Mean Square Error (RMSE) and Mean Bias Error (MBE) expressed as a percentage of the measured mean. The RMSE gives the dispersion of the experimental data and is defined as:

\[
RMSE = \sqrt{\frac{1}{N} \sum (x_{\text{estimated}} - x_{\text{measured}})^2}
\]

(1)

\[
MBE = \frac{1}{N} \sum (x_{\text{estimated}} - x_{\text{measured}})
\]

(2)

where \(x_{\text{estimated}}\) is the predicted value, \(x_{\text{measured}}\) is the measured value, and \(N\) is the number of data patterns [17].

E. Solar Water and Air Heater

An implementation of the genetic algorithm in a design support tool for (large) solar hot water systems is described in reference [18]. The tool calculates the yield and the costs of solar hot water systems based on technical and financial data of the system components. The genetic algorithm allows for optimization of separate variables such as the collector type, the number of collectors, the heat storage mass and the collector heat exchanger area. Optimizations can be focused on, for example, payback time and CO emission reduction. Constraints such as maximum initial costs and installation space can be taken into account [18].

Two of the most important parameters of a solar water heating system that need to be determined accurately are the estimation of the system useful energy gain and the water temperature rise at the end of a solar energy collection period [19].

Simulation of an integrated collector storage system with ANNs is another application. This is the only way to simulate such a system as no readymade routine is available in TRNSYS to model this type of systems [20].

The cross section of the integrated collector storage system (ISC) is shown in Figure 7. Artificial neural network (ANN) model is also introduced for modeling the layer temperatures in a storage tank of a solar thermal system. The model is based on the measured data of a domestic hot water system. In order to keep a high level stratification an internal heat exchanger has been developed and installed into the storage tank of a DWH (Domestic water heating) system.

An ANN model was developed to describe the thermal stratification in a solar storage tank [21]. Another large scale application is designing solar thermal water heating system for supplying an aquaculture system with the required hot water demand was presented. A methodology of sizing the solar thermal water heating system using genetic algorithm was proposed [22].

Solar Air Heaters (SAHs) have low thermal efficiency because of low convective heat transfer coefficient between the air and absorber plate which leads higher temperature to the absorber plate causes maximum thermal losses to ambient. Artificial roughness or various arrangements in the flow duct (collector box) have been used to create turbulence near the collector wall or to break the boundary layer [23]. By considering the different system and operating parameters to obtain maximum thermal performance. Thermal performance is obtained for different Reynolds number, emissivity of the plate, tilt angle and number of glass plates by using genetic algorithm [24].

As discussed in reference [25], for the set shown in Figure 8 the experimental data and predicted values for variation of useful energy transferred to the water with defined setup specifications in a specific area are illustrated in Figure 9.

Reference [32] showed that the method based on an artificial neural network provides better results than the alternative classical methods in calculation of the energy provided by a PV generator, mainly due to the fact that this method takes also into account some second order effects, such as low irradiance, angular and spectral effects.

Predicting the output from a grid-connected photovoltaic (GCPV) system is another mechanical-electrical application of ANNs in renewable energy. In reference [33] the Artificial Immune System (AIS) was selected as the optimizer for the training process of the Multi-Layer Feed forward Neural Network (MLFNN).

ANNs can be used to generate the model of the solar system to find the optimum operating condition that will produce maximum system efficiencies. Historical input–output system data that was collected experimentally is used to train an ANN that predicts the collector, PV module, pump and total efficiencies [34].
F. Solar Thermal Electricity Plant

Performance prediction in solar plants is usually done with ANNs [35-38]. Evolutionary (genetic) optimization algorithm is used to design a parabolic trough thermal solar plant project in Málaga (south of Spain) [35]. The design variables are the collector surface, the size of the thermal storage and the power of the auxiliary system.

Some restrictions are imposed due to practical reasons. The function to be optimized was profit. As a parameter, the minimum level allowed to activate the block of power (BOP) was introduced a priori of the optimization process.

An experimental solar steam generator, consisting of a parabolic trough collector, a high-pressure steam circuit, and a suitable flash vessel has been constructed and tested in order to establish the thermodynamic performance during heat-up (Figure 11) [36]. ANNs are used to model starting up solar steam generator. In comparison with other existing methods, the proposed model has the following advantages [36]:

1. Gives better mapping than the analytical model and thus the accuracy is higher.
2. The flexibility in modifying the model by varying the input parameters, gives to the designer a more flexible and faster (in obtaining results) design tool.
3. It has been observed also that the proposed model is not very demanding in computational effort, once the network is trained.

G. Photovoltaic

As the main application, ANNs are widely used to size stand-alone photovoltaic systems (Figure 10) [26-31]. The sizing pair $C_A$ and $C_S$ can be given by the following formulae:

$$ C_A = \frac{A_{PV} \cdot \eta_{PV}}{L} \quad \text{and} \quad C_S = \frac{C_U}{L} \quad (3) $$

where $A_{PV}$ is the PV array area, $\eta_{PV}$ is the PV array efficiency, $H$ is the average daily irradiation on the PV array, $L$ is the average daily energy consumption, $C_S$ is the storage capacity and $C_B$ is the useful accumulator capacity [26].
Many of the analytical methods employ the concept of reliability of the system or the complementary term: loss of load probability (LOLP). In reference [28] an improvement for obtaining LOLP curves based on the neural network called Multilayer Perceptron (MLP) is presented.

![Figure 5: Variations of useful energy transferred to the water](image)

![Figure 6: Experimental solar steam generator system](image)

H. Passive Solar Building

The building structure consists of one room with an inclined roof. Two cases were investigated, an all insulated building and a building with one wall made completely of masonry and the other walls made partially of masonry and thermal insulation. The investigation was performed for two seasons: winter, for which the building with the masonry-only wall is facing south, and summer, for which the building with the masonry-only wall is facing north. The building’s thermal behavior was evaluated by using a dynamic thermal building model constructed on the basis of finite volumes and time marching. The comparison results are shown in Figures 13 and 14 [37].

I. Solar Drying

The important climatic variables namely, solar radiation intensity and ambient air temperature are considered as the input parameters for ANN modeling. Experimental data on potato cylinders and slices obtained with mixed mode solar dryer for 9 typical days of different months of the year were used for training and testing the neural network (Figure 15) [38].
J. Solar Energy Electric Vehicle (SEEV)

The combinatorial optimization by genetic algorithm and neural network was used to optimize the energy storage system in SEEV. The optimal result, satisfied with the load requirement, can be obtained and the algorithm can converge stably, if the population size and genetic generation are sufficient [39].

K. Solar Cooker

Reference [40] presents an application of the ANN in prediction of the absorber plate, enclosure air and pot water temperatures of a box type solar cooker with and without reflector for different quantity of water on the solar radiation intensity, ambient temperature, quantity of water and time as hour. In the study, to prove whether neural networks can be used for the prediction of thermal performance parameters of the box type solar cooker. From the results it is proved that the ANN can be used with satisfactory accuracy for the prediction of thermal performance parameters of the box type solar cooker (Figure 16).
OPTIMIZING ARTIFICIAL NEURAL NETWORKS USING GENETIC ALGORITHM AND ARTIFICIAL NEURAL NETWORK, S ROSIEK, FJ BATLLES, & E ALAM, SC KAUSHIK, SN GARG, RENEWABLE ENERGY, 2009, VOLUME 35, ISSUE 12, PAGES 4795-4801.

REFERENCES


