

Artificial Intelligence Techniques in Solar Energy Applications

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1. Introduction

Many human mental activities such as writing computer programs, doing mathematics, engaging in commonsense reasoning, understanding language, and even driving an automobile are said to demand "intelligence". Over the past few decades, several computer systems have been built that can perform tasks such as these. Specifically, there are computer systems that can diagnose diseases, plan the synthesis of complex organic chemical compounds, solve differential equations in symbolic form, analyze electronic circuits, understand limited amounts of human speech and natural language text, or write small computer programs to meet formal specifications. We might say that such systems possess some degree of artificial intelligence. Most of the work on building these kinds of systems has taken place in the field called Artificial Intelligence (AI) (Nilsson, 1980). Most AI programs are quite complex objects and mastering their complexity is a major research goal. A comprehensive study of the problems that exist in AI programs requires a precise formalization so that detailed analyses can be carried out so as satisfactory solutions can be obtained (Bourbakis, 1992).

The main objectives of AI research are (Akerkar, 2005):

- Understand human cognition
- Cost-effective automation replaces humans in intelligent tasks.
- Cost-effective intelligent amplification builds systems to help humans think better, and faster.
- Superhuman intelligence builds programs to exceed human intelligence.
- General problem-solving solves a broad range of problems.
- Coherent discourse communicates with people using natural language.
- Autonomy has intelligent systems acting on own initiative.
- Training of the system should be able to gather own data.
- Store information and know how to retrieve it.

The aim of this chapter is to introduce briefly the various AI techniques and to present various applications in solar energy applications. Solar energy applications include the

estimation of solar radiation, solar heating, photovoltaic (PV) systems, sun tracking systems, solar air-conditioning systems and many others. Therefore, the possibilities of applying AI in solar energy applications will be shown.

2. AI techniques

AI techniques have the potential for making better, quicker and more practical predictions than any of the traditional methods. AI consists of several branches such as artificial neural network (ANN), fuzzy logic (FL), Adaptive Network based Fuzzy Inference System (ANFIS) and Data Mining (DM).

2.1 Artificial Neural Networks (ANN)

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Fig 1. Here, the network is adjusted, based on the comparison between the output and the target, until the network output matches the target. Typically many such input/target output pairs are needed to train a network (MATLAB Neural Network Toolbox 4.0.4).

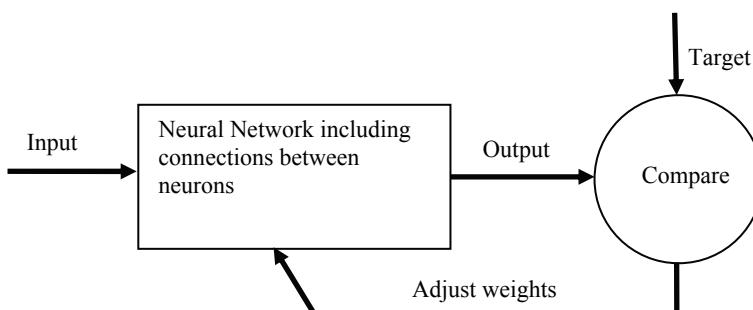


Fig. 1. Basic Principles of Artificial Neural Networks

ANNs have been applied successfully in a number of application areas. Some of the most important ones are (Kalogirou, 2000; 2001):

1. *Function approximation.* Mapping of a multiple input to a single output is established. Unlike most statistical techniques, this can be done with adaptive model-free estimation of parameters.
2. *Pattern association and pattern recognition.* This is a problem of pattern classification. ANNs can be effectively used to solve difficult problems in this field, for instance in sound, image, or video recognition. This task can even be made without an *a priori* definition of the pattern. In such cases the network learns to identify totally new patterns.
3. *Associative memories.* This is the problem of recalling a pattern when given only a subset clue. In such applications the network structures used are usually complicated, composed of many interacting dynamical neurons.

4. *Generation of new meaningful patterns.* This general field of application is relatively new. Some claims are made that suitable neuronal structures can exhibit rudimentary elements of creativity.

ANNs have been applied successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and many others. Some of the most important ones are in pattern, sound and speech recognition, in the analysis of electromyographs and other medical signatures, in the identification of military targets and in the identification of explosives in passenger suitcases. They have also been used in weather and market trends forecasting, in the prediction of mineral exploration sites, in electrical and thermal load prediction, and in adaptive and robotic control. Neural networks are used for process control because they can build predictive models of the process from multidimensional data routinely collected from sensors (Kalogirou, 2000; 2001).

The network usually consists of an input layer, some hidden layers and an output layer. In its simple form, each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. Knowledge is usually stored as a set of connection weights (presumably corresponding to synapse efficacy in biological neural systems). Training is the process of modifying the connection weights in some orderly fashion using a suitable learning method. The network uses a learning mode, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. The weights after training contain meaningful information whereas before training they are random and have no meaning (Kalogirou, 2000; 2001). Figure 2 illustrates how information is processed through a single node. The node receives weighted activation from other nodes through its incoming connections. First, these are added up (summation). The result is then passed through an activation function; the outcome is the activation of the node. For each of the outgoing connections, this activation value is multiplied by the specific weight and transferred to the next node.

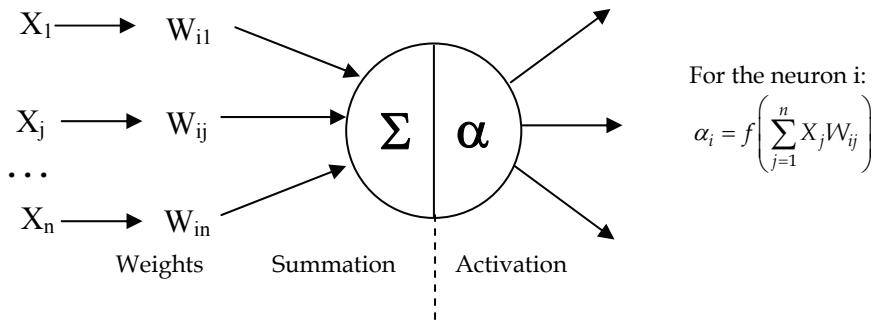


Fig. 2. Information processing in a neural network unit

More details on neural networks can be found in Kalogirou (2000; 2001).

2.2 Fuzzy Logic (FL)

Fuzzy logic has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multivalued logic. However in a wider sense, fuzzy logic (FL) is

almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with unsharp boundaries in which membership is a matter of degree. In this perspective, fuzzy logic in its narrow sense is a branch of fuzzy theory. Even in its more narrow definition, fuzzy logic differs both in concept and substance from traditional multivalued logical systems (MATLAB Fuzzy logic toolbox user's guide).

The following is a list of general observations about fuzzy logic:

- *Fuzzy logic is conceptually easy to understand.* The mathematical concepts behind fuzzy reasoning are very simple. Fuzzy logic is a more intuitive approach without the far-reaching complexity.
- *Fuzzy logic is flexible.* With any given system, it is easy to add on more functionality without starting again from scratch.
- *Fuzzy logic is tolerant of imprecise data.* Everything is imprecise if you look closely enough, but more than that, most things are imprecise even on careful inspection. Fuzzy reasoning builds this understanding into the process rather than tacking it on to the end.
- *Fuzzy logic can model nonlinear functions of arbitrary complexity.* You can create a fuzzy system to match any set of input-output data. This process is made particularly easy by adaptive techniques like Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which are available in Fuzzy Logic Toolbox software.
- *Fuzzy logic can be built on top of the experience of experts.* In direct contrast to neural networks, which use training data and generate opaque, impenetrable models, fuzzy logic lets you rely on the experience of people who already understand the system.
- *Fuzzy logic can be blended with conventional control techniques.* Fuzzy systems don't necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.
- *Fuzzy logic is based on natural language.* The basis of fuzzy logic is human communication. This observation underpins many of the other statements about fuzzy logic. Because fuzzy logic is built on the structures of qualitative description used in everyday language, fuzzy logic is easy to use (MATLAB Fuzzy logic toolbox user's guide).

Generally, a fuzzy logic model is a functional relation between two multidimensional spaces. The relation between the input and output fuzzy spaces is known as fuzzy associative memories (FAM). Inside FAM, the linguistic variables and the attributes are specified and the associative rules between different fuzzy sets are elaborated in order to set up the following construction:

IF (premises) THEN (conclusions)

Every premise or conclusion consists of expressions as

(variable) IS (attribute)

connected through the fuzzy operator AND.

To implement a fuzzy system the following steps needs to be followed:

- *Fuzzification* is a coding process in which each numerical input of a linguistic variable is transformed in the membership function values of attributes.
- *Inference* is a process which is done in two steps: (i) The computation of a rule by intersecting individual premises, applying the fuzzy operator AND, (ii) Often, more rules drive to a same conclusion. To obtain the confidence level of this conclusion (i.e.,

the membership function value of a certain attribute of output linguistic variable) the individual confidence levels are joined by applying the fuzzy operator OR.

- *Defuzzification* is a decoding operation of the information contained in the output fuzzy sets resulted from the inference process, in order to provide the most suitable output crisp value. There are a number of methods which can be used for defuzzification presented by Paulescu et al. (2008).

2.3 Adaptive Network based Fuzzy Inference System (ANFIS)

The ANFIS model is a hybrid framework that is obtained by combining the concepts of fuzzy logic and neural networking into a unified platform. The model has a fuzzy inference system in the form of an adaptive network for system identification and a predictive tool that maps a given input space to its corresponding output space based on a representative training data set. The ANFIS inference system relies on both fuzzified human knowledge (human knowledge modelled in the form of fuzzy "if-then" rules) and a set of input-output data pairs (patterns) to accomplish the process of input-output mapping. The ANFIS modelling strategy is widely used in applications or systems that involve uncertainty or imprecision in the definitions of the variables constituting the system's behaviour. In other words, it has the ability to qualitatively model and represent human knowledge without the need for precise or quantitative definitions. Moreover, it is capable of modelling and identifying nonlinear systems as well as predicting chaotic time-dependant behaviour (Soyguder and Allı, 2009). There are mainly two approaches for fuzzy inference systems namely Mamdani and Sugeno. The difference is originated from the consequent part where fuzzy membership functions are used in Mamdani and linear or constant functions are used in Sugeno. One must have data at hand in order to apply Sugeno approach, whereas there is no such requirement for Mamdani approach (Ozger and Yıldırım, 2009). The architecture of ANFIS is shown in Fig. 3.

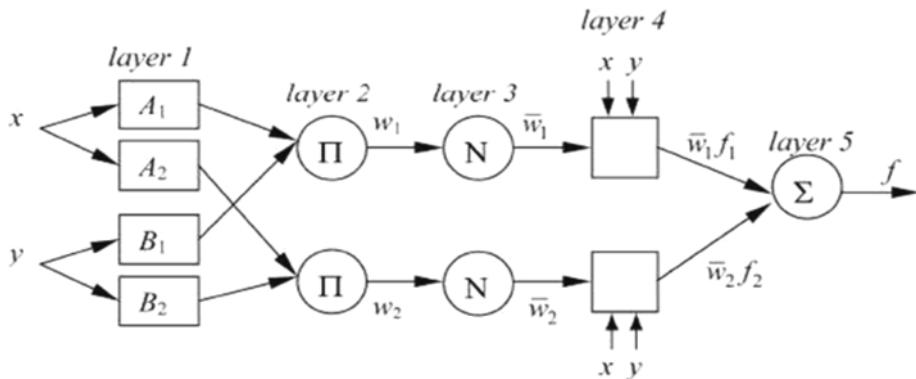


Fig. 3. ANFIS architecture

The functionality of nodes in ANFIS can be summarized as follows (Efendigil et al., 2009):

- *Layer 1:* Nodes are adaptive; membership functions (MFs) of input variables are used as node functions, and parameters in this layer are referred to as antecedent or premise parameters.
- *Layer 2:* Nodes are fixed with outputs representing the firing strengths of the rules.

- *Layer 3*: Nodes are fixed with outputs representing normalized firing strengths.
- *Layer 4*: Nodes are adaptive with node function given by Layer 1 for a first-order model, and with parameters referred to as defuzzifier of consequent parameters.
- *Layer 5*: The single node is fixed with output equal to the sum of all the rules' outputs.

2.4 Genetic Algorithms (GA)

Genetic algorithms are inspired by the way living organisms adapt to the harsh realities of life in a hostile world, i.e., by evolution and inheritance. The algorithm imitates the process of evolution of populations by selecting only fit individuals for reproduction. Therefore, a genetic algorithm is an optimum search-technique based on the concepts of natural selection and survival of the fittest. It works with a fixed-size population of possible solutions of a problem, called individuals, which are evolving in time. A genetic algorithm utilizes three principal genetic operators: selection, crossover and mutation (Kalogirou, 2004).

During each step (called a generation) in the reproduction process, the individuals in current generation are evaluated by a fitness-function, which is a measure of how well the individual solves the problem. Then each individual is reproduced in proportion to its fitness: the higher the fitness, the higher its chance to participate in mating (crossover) and to produce an offspring. A small number of newborn offspring undergo the action of the mutation operator. After many generations, only those individuals who have the best genetics (from the point of view of the fitness function) survive. The individuals that emerge from this "survival of the fittest" process are the ones that represent the optimal solution to the problem specified by the fitness function and the constraints (Kalogirou, 2004).

Genetic algorithms (GA) are suitable for finding the optimum solution in problems where a fitness function is present. Genetic algorithms use a "fitness" measure to determine which of the individuals in the population survive and reproduce. Thus, survival of the fittest causes good solutions to progress. A GA works by selective breeding of a population of "individuals", each of which could be a potential solution to the problem. The structure of the standard genetic algorithm is shown in Fig. 4.

Genetic Algorithm

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Begin (1)
    t = 0 [start with an initial time]
    Initialize Population P(t) [initialize a usually random population of individuals]
    Evaluate fitness of Population P(t) [evaluate fitness of all individuals in population]
    While (Generations < Total Number) do begin (2)
        t = t + 1 [increase the time counter]
        Select Population P(t) out of Population P(t-1) [select sub-population for
                                                       offspring production]
        Apply Crossover on Population P(t)
        Apply Mutation on Population P(t)
        Evaluate fitness of Population P(t) [evaluate new fitness of population]
    end (2)
end (1)

```

Fig. 4. The structure of a standard genetic algorithm (Kalogirou, 2004)

With reference to Fig. 4, in each generation, individuals are selected for reproduction according to their performance with respect to the fitness function. Actually, selection gives a higher chance of survival to better individuals. Subsequently, genetic operations are applied in order to form new and possibly better offspring. The algorithm is terminated either after a certain number of generations or when the optimal solution has been found (Kalogirou, 2004).

2.5 Data Mining (DM)

Data mining is a powerful technique for extracting predictive information from large databases. The automated analysis offered by data mining goes beyond the retrospective analysis of data. Data mining tools can answer questions that are too time-consuming to resolve with methods based on first principles. In data mining, databases are searched for hidden patterns to reveal predictive information in patterns that are too complicated for human experts to identify (Hoffmann & Apostolakis, 2003). Data mining is applied in a wide variety of fields for prediction, e.g. stock-prices, customer behaviour, and production control. In addition, data mining has also been applied to other types of scientific data such as astronomical and medical data (Li & Shue, 2004).

Data understanding starts with an initial data collection and proceeds with activities to get familiar with the data, to identify data quality problems, and to discover first insights into the data. Data preparation covers all activities that construct the final data set to be modelled from the initial raw data. The tasks of this phase may include data cleaning for removing noise and inconsistent data, and data transformation for extracting the embedded features (Li & Shue, 2004). Successful mining of data relies on refining tools and techniques capable of rendering large quantities of data understandable and meaningful (Mattison, 1996). The modelling phase applies various techniques, determines the optimal values of parameters in models, and finds the one most suitable to meet the objectives. The evaluation phase evaluates the model found in the last stage to confirm its validity to fit the problem requirements. No matter which areas data mining is applied to, most of the efforts are directed toward the data preparation phase (Li & Shue, 2004). The process of knowledge discovery in databases can be seen in Fig. 5.

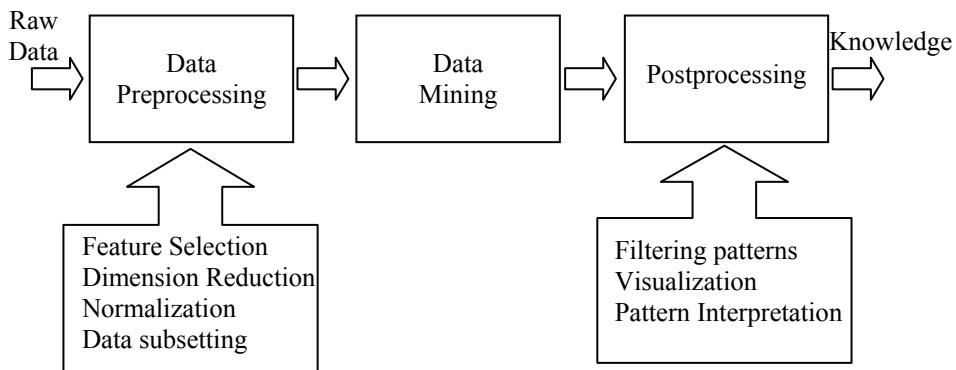


Fig. 5. The process of knowledge discovery in databases

3. Applications of Artificial Intelligence (AI) techniques in the solar energy applications

Artificial intelligence techniques have been used by various researchers in solar energy applications. This section deals with an overview of these applications. Some examples on the use of AI techniques in the solar energy applications are summarized in Table 1.

AI technique	Area	Number of applications
Artificial neural networks	Prediction of solar radiation	11
	Modelling of solar steam-generator	1
	Prediction of the energy consumption of a passive solar building	1
	Characterization of Si-crystalline PV modules	1
	Efficiency of flat-plate solar collectors	1
	Heating controller for solar buildings	1
	Modelling of a solar air heater	1
Fuzzy logic	Photovoltaic solar energy systems	2
	Sun tracking system	1
	Prediction of solar radiation	5
	Control of solar buildings	1
	Controller of solar air-conditioning system	2
Adaptive Network based Fuzzy Inference System	Prediction of solar radiation and temperature	3
Genetic algorithms	Photovoltaic solar energy systems	2
	Determination of Angström equation coefficients	1
	Solar water heating systems	2
	Hybrid solar-wind system	2
	PV-diesel hybrid system	2
	Solar cell	1
	Flat plate solar air heater	1
Data Mining	Solar cell	1

Table 1. Summary of numbers of applications presented in solar energy applications

3.1 Applications of artificial neural networks

Table 2 shows a summary of applications of artificial neural networks for solar energy applications.

Mellit and Pavan (2010) developed a Multi-Layer Perceptron (MLP) network for forecasting 24 h ahead solar irradiance. The mean daily irradiance and the mean daily air temperature are used as input parameters in the proposed model. The output was represented by the 24 h ahead values of solar irradiance. A comparison between the power produced by a 20 kW_p Grid Connected Photovoltaic Plant and the one forecasted using the developed MLP-predictor shows a good prediction performance for 4 sunny days (96 h). As indicated by the authors, this approach has many advantages with respect to other existing methods and it can easily be adopted for forecasting solar irradiance values of (24-h ahead) by adding more

input parameters such as cloud cover, pressure, wind speed, sunshine duration and geographical coordinates.

Authors	Year	Subject
Mellit and Pavan	2010	Prediction of solar radiation
Benghanem et al.	2009	
Rehman and Mohandes	2008	
Tymvios et al.	2005	
Mubiru and Banda	2008	
Sozen et al.	2004	
Soares et al.	2004	
Zervas et al.	2008	
Elminir et al.	2007	
Senkal and Kuleli	2009	
Moustris, K.	2008	
Kalogirou et al.	1998	Modelling of solar steam-generator
Kalogirou and Bojic	2000	Prediction of the energy consumption of a passive solar building
Almonacid et al.	2009	Characterization of Si-crystalline PV modules
Sözen et al.	2008	Efficiency of flat-plate solar collectors
Argiriou et al.	2000	Heating controller for solar buildings
Esen et al.	2009	Modelling of a solar air heater

Table 2. Summary of solar energy applications of artificial neural networks

Benghanem et al. (2009) have developed artificial neural network (ANN) models for estimating and modelling daily global solar radiation. They have developed six ANN-models by using different combination as inputs: the air temperature, relative humidity, sunshine duration and day of year. For each model, the output is the daily global solar radiation. For each of the developed ANN-models the correlation coefficient is greater than 97%. The results obtained render the ANN methodology as a promising alternative to the traditional approach for estimating global solar radiation.

Rehman and Mohandes (2008) used the air temperature, day of the year and relative humidity values as input in a neural network for the prediction of global solar radiation (GSR) on horizontal surfaces. For one case, only the day of the year and daily maximum temperature were used as inputs and GSR as output. In a second case, the day of the year and daily mean temperature were used as inputs and GSR as output. In the last case, the day of the year, and daily average values of temperature and relative humidity were used to predict the GSR. Results show that using the relative humidity along with daily mean temperature outperforms the other cases with absolute mean percentage error of 4.49%. The absolute mean percentage error for the case when only day of the year and mean temperature were used as inputs was 11.8% while when maximum temperature is used instead of mean temperature is 10.3%.

Tymvios et al. (2005) used artificial neural networks for the estimation of solar radiation on a horizontal surface. In addition, they used the traditional and long-utilized Angström's linear approach which is based on measurements of sunshine duration. The comparison of the performance of both models has revealed the accuracy of the ANN.

Mubiru and Banda (2008) used an ANN to estimate the monthly average daily global solar irradiation on a horizontal surface. The comparison between the ANN and empirical method has been given. The proposed ANN model proved to be superior over the empirical model because it is capable of reliably capturing the non-linearity nature of solar radiation. The empirical method is based on the principle of linearity.

Sozen et al. (2004) estimated the solar potential of Turkey by artificial neural networks using meteorological and geographical data (latitude, longitude, altitude, month, mean sunshine duration and mean temperature). The maximum mean absolute percentage error was found to be less than 6.74% and R^2 values were found to be about 99.89% for the testing stations. For the training stations these values were found to be 4.4% and 99.97% respectively. The trained and tested ANN models show greater accuracy for evaluating the solar resource possibilities in regions where a network of monitoring stations have not been established in Turkey. The predicted solar potential values from the ANN are given in the form of monthly maps.

Soares et al. (2004) used artificial neural networks to estimate hourly values of diffuse solar radiation at a surface in Sao-Paulo City, Brazil, using as input the global solar radiation and other meteorological parameters. It was found that the inclusion of the atmospheric long-wave radiation as input improves the neural-network performance. On the other hand traditional meteorological parameters, like air temperature and atmospheric pressure, are not as important as long-wave radiation which acts as a surrogate for cloud-cover information on the regional scale. An objective evaluation has shown that the diffuse solar radiation is better reproduced by neural network synthetic series than by a correlation model.

Zervas et al. (2008) used artificial neural networks to predict the daily global solar irradiance distribution as a function of weather conditions and each calendar day. The model was tuned using the meteorological data recorded by the "ITIA" Meteorological station of National Technical University of Athens, Zografou Campus, Greece. The model performed successfully on a number of validation tests. The future challenge is to extend the model, so that it can predict the output power of 50kW_p PV arrays. This model will allow to take optimal decisions regarding the operation and maintenance of the PV panels. This work may prove useful for engineers who are interested in solar energy systems applications from both a general and a more detailed point of view.

Elminir et al. (2007) used an artificial neural network model to predict the diffuse fraction on an hourly and daily scale using as input the global solar radiation and other meteorological parameters, like long-wave atmospheric emission, air temperature, relative humidity and atmospheric pressure. A comparison between the performances of the ANN model with that of linear regression models has been given. The neural network is more suitable to predict diffuse fraction than the proposed regression models at least for the Egyptian sites examined.

Senkal and Kuleli (2009) also used artificial neural networks for the estimation of solar radiation in Turkey. Meteorological and geographical data (latitude, longitude, altitude, month, mean diffuse radiation and mean beam radiation) are used in the input layer of the network. Solar radiation is the output. The selected ANN structure is shown in Fig. 6. By using the ANN and a physical method, solar radiation was predicted for 12 cities in Turkey. The monthly mean daily total values were found to be 54 W/m² and 64 W/m² for the training cities, and 91 W/m² and 125 W/m² for the testing cities, respectively. According to the results of these 12 locations, correlation values indicate a relatively good agreement between the observed ANN values and the predicted satellite values.

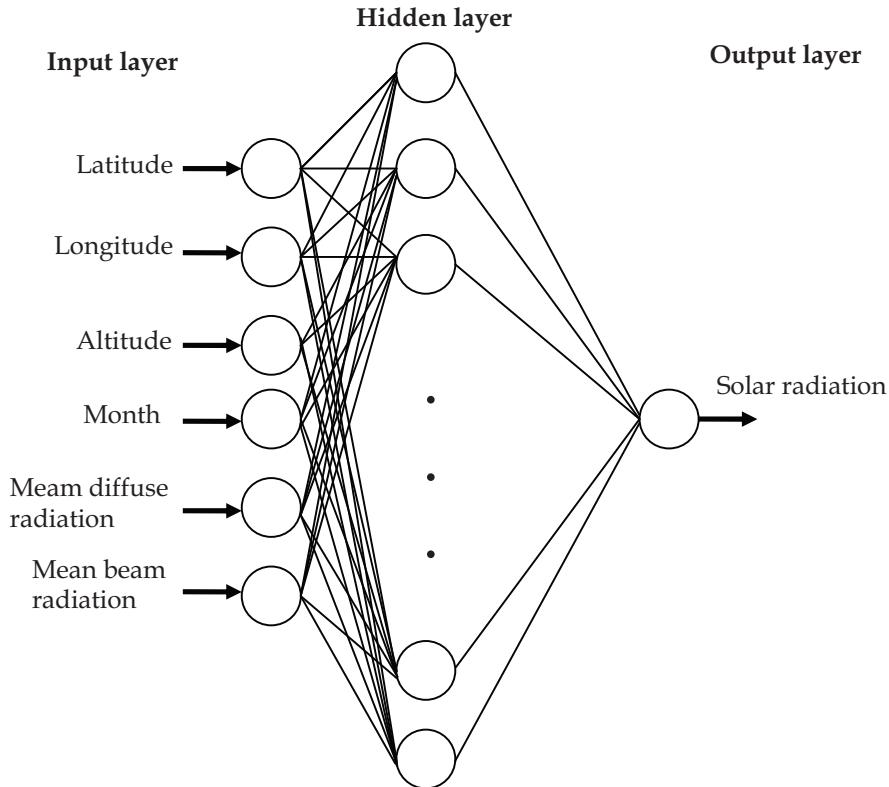


Fig. 6. ANN architecture used for the prediction of solar radiation with six neurons in the input layer by Senkal and Kuleli (2009)

Moustris et al. (2008) used neural networks for the creation of hourly global and diffuse solar irradiance data at representative locations in Greece. A very good agreement with a satisfactory outcome, is obtained between global and diffuse solar irradiance hourly data sets obtained by NNs (when trained with other, easy to find, weather and geographical parameters such as, air temperature, sunshine duration, cloud cover, latitude, etc.), and hourly solar irradiance values taken from pyranometer measurements, for the areas examined. Whenever solar data are missing, or in areas where meteorological stations do not measure and/or keep solar data, full solar irradiance time-series sets could be generated with a rather acceptable accuracy.

Kalogirou et al. (1998) used an artificial neural network to model the transient heat-up response of a solar steam-generation system. The input data are those that are easily measurable, i.e. environmental conditions and certain physical parameters (dimensions and sizes). The outputs are the measured temperatures, obtained over the heat-up period at different positions of the system. The architecture that was ultimately selected is shown in Fig. 7. The predictions of the neural network have been compared with the actual measured data (i.e. the learning set) and to the predictions from a computer program. The modelling of the system presented, was able to predict correctly the profile of the temperatures at various points of the system within 3.9%.

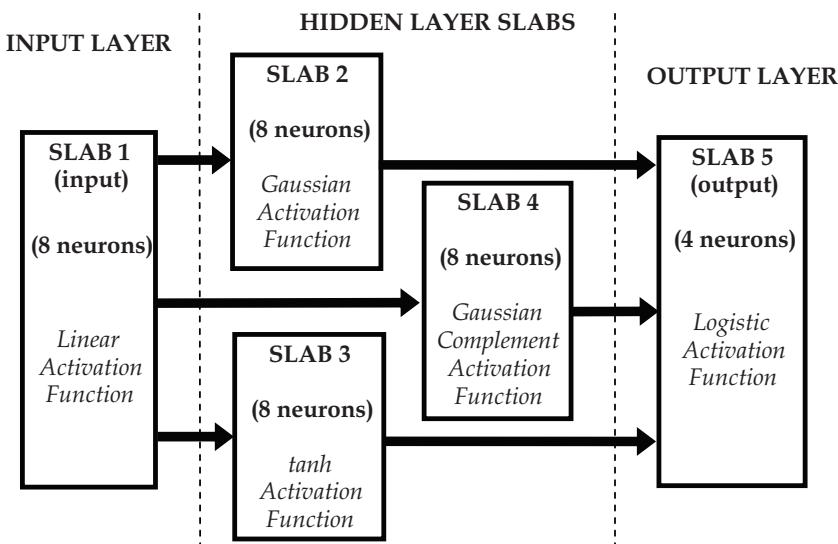


Fig. 7. The selected neural network architecture for modelling the transient heat-up response of a solar steam-generation system (Kalogirou et al., 1998)

Kalogirou and Bojic (2000) used artificial neural networks for the prediction of the energy consumption of a passive solar building. The building's thermal behaviour was evaluated by using a dynamic thermal building model constructed on the basis of finite volumes and time marching. The energy consumption of the building depends on whether all walls have insulation, on the thickness of the masonry and insulation, and on the season. Simulated data for a number of cases were used to train the artificial neural network. The ANN model proved to be much faster than the dynamic simulation programs.

Almonacid et al. (2009) used a neural network for predicting the electrical characteristics of Si-crystalline modules. I-V curves have been generated for Si-crystalline PV modules for a number of irradiance (G) and module temperature (T_m) combinations. The structure of the neural network is shown in Fig. 8. The input layer has two neurons or nodes (T_m and G), the

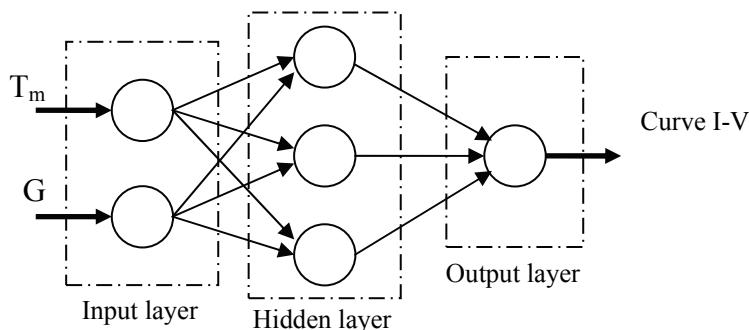


Fig. 8. Proposed neural network architecture for obtaining the I-V curves of PV modules (Almonacid et al., 2009).

second layer (hidden layer) has three nodes, and finally the last layer (output layer) has only one node: the points of the I-V curve. The results show that the proposed ANN introduces an accurate prediction for Si-crystalline PV modules' performance when compared with the measured values.

Sözen et al. (2008) developed a new formula based on artificial neural network techniques to determine the efficiency of flat plate solar collectors. The selected ANN architecture is depicted in Fig. 9.

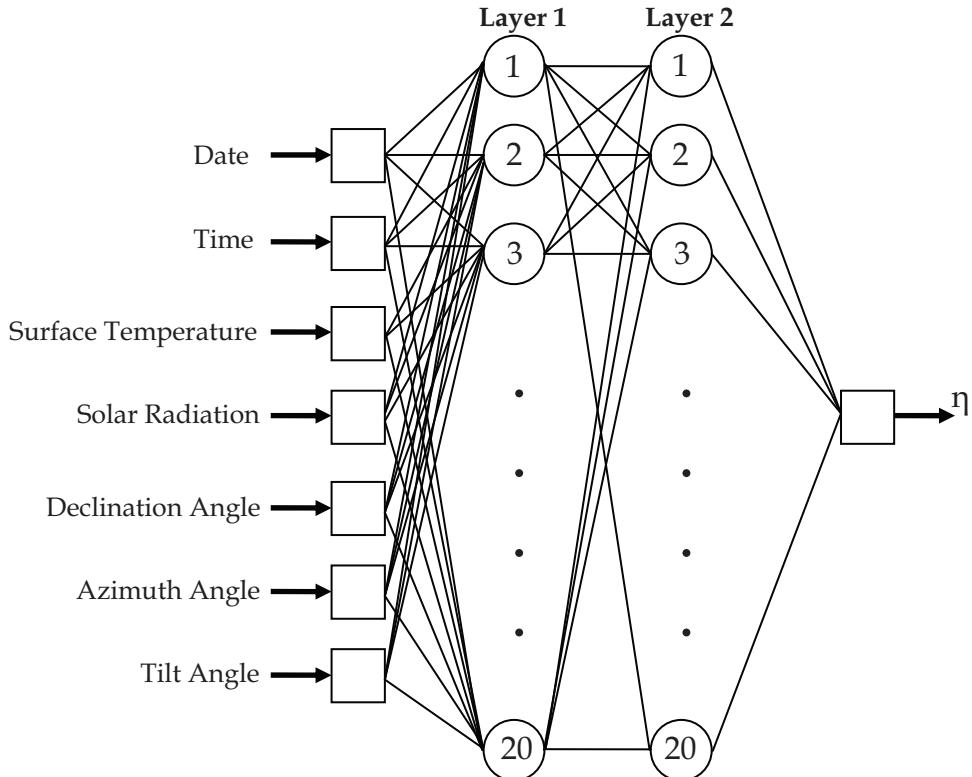


Fig. 9. ANN structure used by Sözen et al. (2008)

Date, time, surface temperature on collector, solar radiation, declination angle, azimuth angle and tilt angle are used as input to the network. The efficiency of flat-plate solar collector is in the output of the ANN. The results show that the maximum and minimum deviations were found to be 2.558484 and 0.001969, respectively. The advantages of the ANN model compared to the conventional testing methods are speed, simplicity and capacity of the ANN to learn from examples.

Argiriou et al. (2000) used ANN in order to control the indoor temperature of a solar building. The performance of the ANN controller has been tested both experimentally and in a building thermal simulation environment. The results showed that the use of the proposed controller can lead to 7.5% annual energy savings in the case of a highly insulated passive solar test cell.

Esen et al. (2009) proposed the modelling of a solar air heater system by using an artificial neural network and wavelet neural network. Two output parameters (collector efficiency and the air temperature leaving the collector unit) were predicted by the models. For this purpose, an experimental solar air heating system was set up and tested in clear day conditions. The data used as inputs to the model were obtained from measurements made on a solar air heater. A neural network-based method was intended to adopt solar air heater system for efficient modelling. Comparison between predicted and experimental results indicates that the proposed neural network model can be used for estimating the efficiency of solar air heaters with reasonable accuracy.

3.2 Applications of fuzzy logic

In recent years, the number and variety of applications of fuzzy logic have increased significantly. Table 3 shows a summary of fuzzy logic applications for solar energy systems.

Authors	Year	Subject
Altas and Sharaf Salah et al.	2008 2008	Photovoltaic solar energy systems
Alata et al.	2005	Sun tracking system
Sen Paulescu et al. Gomez and Casanovas Gomez and Casanovas Iqdour and Zeroual	1998 2008 2002 2003 2005	Prediction of solar radiation
Gouda et al.	2006	Control of solar buildings
Lygouras et al. Lygouras et al.	2007 2008	Controller of a solar air-conditioning system

Table 3. Summary of solar energy applications of fuzzy logic

Altas and Sharaf (2008) carried out a study of a stand-alone photovoltaic energy utilization system feeding a hybrid mix of electric loads which is fully controlled by a novel and simple on-line fuzzy logic-based dynamic search, detection and tracking controller that ensures maximum power point (MPP) operation under variations in solar insolation, ambient temperature and electric load fluctuations. The proposed MPP detection algorithm and dual fuzzy logic MPP tracking controller are tested using the Matlab/Simulink software environment by digitally simulating the PV array scheme feeding hybrid DC loads. Besides the MPP detector and dual fuzzy logic MPP tracking controller, the scheme includes two more control units, one for the voltage control of the common DC load bus, and the other for the speed control of the permanent magnet DC motor (PMDC) using DC/DC choppers. The MPP is detected and tracked with minimum error as the solar irradiation level change resulting in different maximum power operating points.

Salah et al. (2008) used a fuzzy algorithm for energy management of a domestic photovoltaic panel. The algorithm is validated on a 1kW peak (kW_p) photovoltaic panel and domicile apparatus of different powers installed at the Energy and Thermal Research Centre in the north of Tunisia. Criteria are verified on the system behaviour during days covering different seasons of the year. The power audit, established using measures, confirms that the energy save during daylight reaches 90% of the photovoltaic panel available energy.

Alata et al. (2005) developed a multipurpose sun tracking system using fuzzy control. Sugeno fuzzy inference system was utilized for modelling and controller design. In addition, an estimation of the insolation incident on a two axis sun tracking system was determined by fuzzy IF-THEN rules. The simulations, along with the virtual reality 3-D, are regarded as powerful tools to investigate the behaviour of the systems prior to installation. Thus, the need for real values of the simulation parameters makes it closer to real applications. The step tracking that is considered in the design of multi-purpose sun tracking systems is taken every four minutes (one degree movement by the sun), and hence, less energy is needed for driving the sun trackers.

Şen (1998) used a fuzzy logic algorithm for estimating the solar irradiation from sunshine duration measurements. The fuzzy approach has been applied for three sites with monthly averages of daily irradiances in the western part of Turkey. The fuzzy algorithm developed herein does not provide an equation but can adjust itself to any type of linear or nonlinear form through fuzzy subsets of linguistic solar irradiation and sunshine duration variables. It is also possible to augment the conditional statements in the fuzzy implications used in this paper to include additional relevant meteorological variables that might increase the precision of solar irradiation estimation. The application of the proposed fuzzy subsets and rule bases is straightforward for any irradiation and sunshine duration measurements in any part of the world.

Paulescu et al. (2008) used fuzzy logic algorithms for atmospheric transmittances prediction for use in solar energy estimation. Two models for solar radiation attenuation in the atmosphere were presented. The first model encompasses self-dependent fuzzy modelling of each characteristic transmittance, while the second is a proper fuzzy logic model for beam and diffuse atmospheric transmittances. The results lead to the conclusion that developing parametric models along the ways of fuzzy logic is a viable alternative to classical parameterization. Due to the heuristic nature of the fuzzy model input-output map, it has led to more flexibility in adapting to local meteo-climatic conditions.

Gomez and Casanovas (2002) considered solar irradiance as a case study for physical fuzzy modelling of a climate variable. The uncertainty of the solar irradiance is treated as a fuzzy uncertainty whilst other variables are considered crisp. The approach is robust as it does not rely on statistical assumptions, and it is a possible alternative to modelling complex systems. When compared with non-fuzzy models of solar irradiance, the fuzzy model shows an improved performance, and when compared with experimental data, the performance can be evaluated by fuzzy indices that take into account the uncertainty of the data and the model output.

A fuzzy model of solar irradiance on inclined surfaces has been developed by Gomez and Casanovas (2003). The fuzzy model includes concepts from earlier models, though unlike these, it considers non-disjunctive sky categories. The proposed model offers performance similar to that of the models with the best results in the comparative analysis of literature, such as the Perez model.

Iqdour and Zeroual (2005) used the Takagi-Sugeno fuzzy systems for modelling daily global solar radiation recorded in Marrakesh, Morocco. The results obtained from the proposed model have been compared with two models based on higher order statistics; the fuzzy model provides better results in the prediction of the daily solar radiation in terms of statistical indicators.

Gouda et al. (2006) investigated the development of a quasi-adaptive fuzzy logic controller for space heating control in solar buildings. The main aim of the controller is to reduce the

lagging overheating effect caused by passive solar heat gain to a room space. The quasi-adaptive fuzzy logic controller is shown in Fig. 10. The fuzzy controller is designed to have two inputs: the first is the error between the set-point temperature and the internal air temperature and the second is the predicted future internal air temperature. The controller was implemented in real-time using a test cell with controlled ventilation and a modulating electric heating system. Results compared with validated simulations of conventionally controlled heating, confirm that the proposed controller achieves superior tracking and reduced overheating when compared with the conventional method of control.

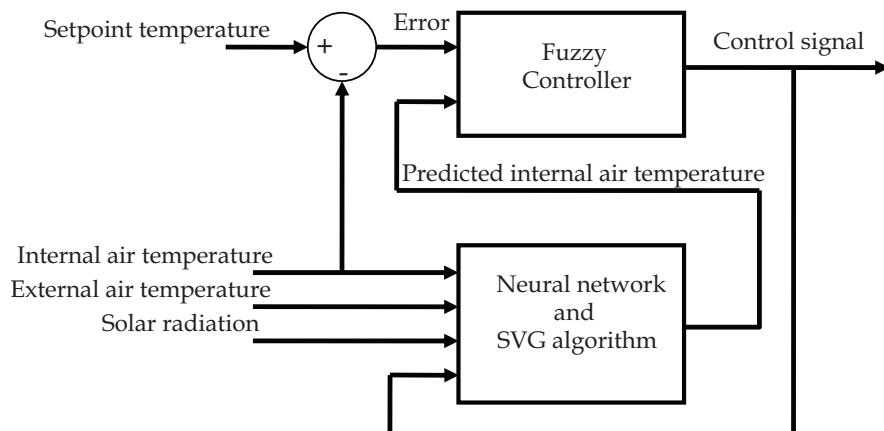


Fig. 10. Quasi-adaptive fuzzy logic controller developed by Gouda et al. (2006).

Lygouras et al. (2007) investigated the implementation of a variable structure fuzzy logic controller for a solar powered air conditioning system and its advantages. Two DC motors are used to drive the generator pump and the feed pump of the solar air-conditioner. Two different control schemes for the DC motors rotational speed adjustment are implemented and tested. The first one is a pure fuzzy controller, its output being the control signal for the DC motor driver. The second scheme is a two-level controller. The lower level is a conventional PID controller, and the higher level is a fuzzy controller acting over the parameters of the low level controller. Comparison of the two control schemes presented in this paper shows that the two-level controller behaves better in all situations.

Lygouras et al. (2008) used a fuzzy-logic controller to adjust the rotational speed of two DC motors of a solar-powered air-conditioner. Initially, a traditional fuzzy-controller has been designed; its output being one of the components of the control signal for each DC motor driver. Subsequently, according to the characteristics of the system's dynamics coupling, an appropriate coupling fuzzy-controller (CFC) is incorporated into a traditional fuzzy-controller (TFC) to compensate for the dynamic coupling among each degree of freedom. This control strategy simplifies the implementation problem of fuzzy control, but can also improve the controller performance. This mixed fuzzy controller (MFC) can effectively improve the coupling effects of the systems, and this control strategy is easy to design and implement.

3.3 Applications of Adaptive Network based Fuzzy Inference System (ANFIS)

Table 4 lists the applications of Adaptive Network based Fuzzy Inference System for solar energy systems.

Authors	Year	Subject
Chaabene and Ammar	2008	Prediction of solar radiation
Moghaddamnia et al.	2009	
Mellit et al.	2008	

Table 4. Summary of solar energy applications of ANFIS

Chaabene and Ammar (2008) used a neuro-fuzzy dynamic model for forecasting irradiance and ambient temperature. The medium term forecasting (MTF) gives the daily meteorological behaviour. It consists of a neuro-fuzzy estimator based on meteorological parameters' behaviour during the days before, and on time distribution models. As for the short term forecasting (STF), it estimates for a 5 min time step ahead, the meteorological parameters evolution. According to normalized root mean square error (NRMSE) and the normalized mean bias error (NMBE) computation, the meteorological estimator carries out satisfactory estimation of the meteorological parameters.

Moghaddamnia et al. (2009) estimated daily solar radiation from meteorological data sets with local linear regression (LLR), multi-layer perceptron (MLP), Elman, NNARX (neural network auto-regressive model with exogenous inputs) and adaptive neuro-fuzzy inference system (ANFIS). They used five relevant variables for estimating the daily solar radiation (extraterrestrial radiation, daily maximum temperature, daily mean temperature, precipitation and wind velocity). In general, they have concluded that the ANFIS model does not have the ability to estimate solar radiation precisely, but LLR and NNARX models are the most suitable models for the area under study.

Mellit et al. (2008) proposed a new model based on neuro-fuzzy for predicting the sequences of monthly clearness index and applied it for generating solar radiation, which has been used for the sizing of a PV system. The authors proposed a hybrid model for estimating sequences of daily clearness index by using an ANFIS; the proposed model has been used for estimating the daily solar radiation. An application for sizing a PV system is presented based on the data generated by this model. Fig. 11 shows the proposed ANFIS-based prediction for the monthly clearness index.

3.4 Applications of genetic algorithms

Table 5 summarizes various applications of genetic algorithms for solar energy systems.

Larbes et al. (2009) investigated the use of intelligent control techniques for maximum power point tracking in order to improve the efficiency of PV systems, under different temperature and irradiance conditions. Initially, the design and simulation of a fuzzy logic-based maximum power point tracking controller was proposed. Compared to the perturbation and observation controller, the proposed fuzzy logic controller has improved the transitional state and reduced the fluctuations in the steady state. To improve the design and further improve the performances of the proposed fuzzy logic-based maximum power point tracking controller, genetic algorithms were then used to obtain the best subsets of the membership functions as they are very fastidious to be achieved by the designer. The obtained optimized fuzzy logic maximum power point tracking controller was then simulated under different temperature and irradiance conditions. Compared to the fuzzy logic controller, this optimized controller showed much better performance and robustness. It has not only improved the response time in the transitional state but has also reduced considerably the fluctuations in the steady state.

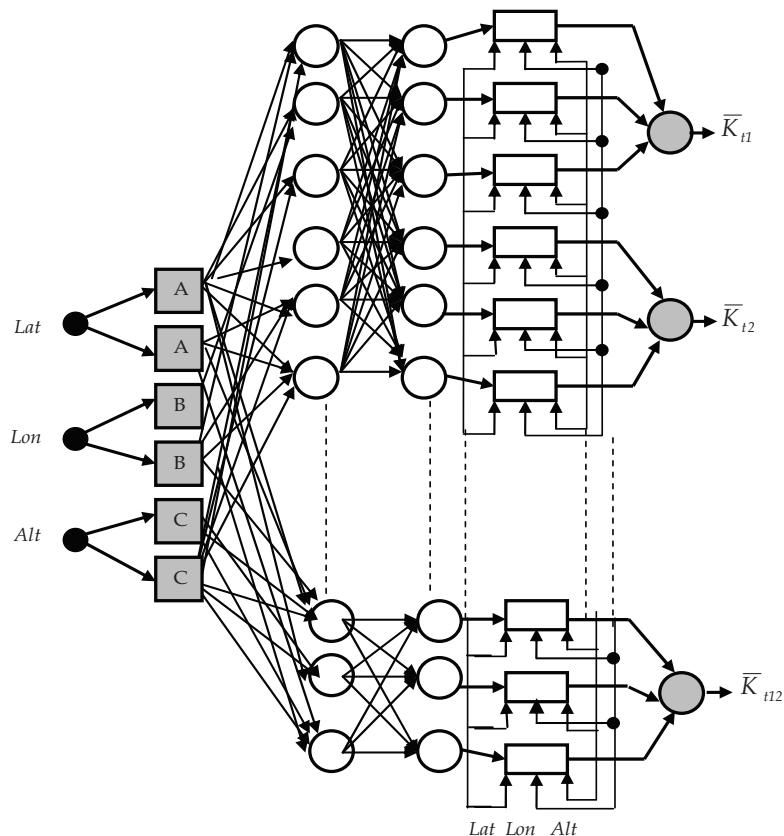


Fig. 11. The proposed ANFIS-based prediction for monthly clearness index proposed by Mellit et al. (2008)

Authors	Year	Subject
Larbes et al.	2009	Photovoltaic solar energy systems
Zagrouba et al.	2010	
Şen et al.	2001	Determination of Angström equation coefficients
Loomans and Visser	2002	Solar hot water systems
Kalogirou	2004	
Koutroulou et al.	2006	Hybrid solar-wind system
Yang et al.	2008	
Bala and Siddique	2009	PV-diesel hybrid system
Dufo-Lopez and Bernal-Agustin	2005	
Lin and Phillips	2008	Solar cell
Varun	2010	Flat plate solar air heater

Table 5. Summary of solar energy applications of genetic algorithms

Zagrouba et al. (2010) proposed to perform a numerical technique based on genetic algorithms (GAs) to identify the electrical parameters of photovoltaic (PV) solar cells and modules. These parameters were used to determine the corresponding maximum power point from the illuminated current-voltage (I-V) characteristic. The one diode type approach is used to model the AM1.5 I-V characteristic of the solar cell. To extract electrical parameters, the approach is formulated as a non convex optimization problem. The GAs approach was used as a numerical technique in order to overcome problems involved in the local minima in the case of non convex optimization criteria. Compared to other methods, they found that the GAs is a very efficient technique to estimate the electrical parameters of PV solar cells and modules. The electrical parameters resulting from the use of the GA-based fitting procedure, with those given by the Pasan cell tester software is shown in Table 6.

Electrical parameters	Pasan software	Genetic algorithms
I_s (A)	Not performed	1.2170×10^{-2}
I_{ph} (A)	0.1360	0.1360
R_s (Ω)	0.2790	0.0363
R_{sh} (Ω)	99999	99050
n	Not performed	1.0196

Table 6. Comparison between the electrical parameters of the solar cell determined using GAs and those given by the Pasan software (Zagrouba et al., 2010)

Şen et al. (2001) used a genetic algorithm for the determination of Angström equation coefficients. Good correlation is obtained in all the cases, showing the validity of the Angström equation for Turkish locations. The authors have presented a new way of estimating the Angström equation parameters using GAs.

Loomans and Visser (2002) used a genetic algorithm for the optimization of large solar hot water systems. The genetic algorithm 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. The applicability of the genetic algorithm was tested for the optimization of large solar hot water systems. Among others, the sensitivity of the optimum system design to the tap water draw-off and the draw-off pattern has been determined using the optimization algorithm. As the genetic algorithm is a discrete optimization tool and is implemented in the design tool through the use of databases, the number of variables in principle is free of choice.

Kalogirou (2004) used artificial intelligence methods like artificial neural-networks and genetic algorithms, to optimize a solar-energy system in order to maximize its economic benefits. The system is modelled using a TRNSYS computer program and the climatic conditions of Cyprus, included in a typical meteorological year (TMY) file. An artificial neural-network is trained using the results of a small number of TRNSYS simulations, to learn the correlation of collector area and storage-tank size on the auxiliary energy required by the system from which the life-cycle savings can be estimated. Subsequently, a genetic algorithm is employed to estimate the optimum size of these two parameters, for

maximizing life-cycle savings; thus the design time is reduced substantially. As an example, the optimization of industrial process heat-system employing flat-plate collectors is presented. The results are shown in Table 7, where the actual results of the genetic algorithm program are presented together with the results of the traditional method. The optimum solutions obtained from the present methodology give increased life-cycle savings of 4.9 and 3.1% when subsidized and non-subsidized fuel prices are used respectively, as compared to solutions obtained by the traditional trial-and-error method.

Fuel price	Parameter	Optimum system obtained from GA	Practical selection to that of GA (1)	Traditional method (2)	Percentage difference between (1) and (2)
29.6 €/L (Subsidized)	Area (m ²) Volume (m ³) LCS (€)	301.6 14.1 13,990	300 14 13,987	300 20 13,336	4.9
48.4 €/L (non-subsidized)	Area (m ²) Volume (m ³) LCS (€)	410 29.9 60,154	410 30 60,156	400 30 58,337	3.1

Table 7. Results of the solar-system optimization (Kalogirou, 2004)

Koutroulis et al. (2006) developed a methodology for the optimal sizing of stand-alone photovoltaic (PV)/wind-generator (WG) systems using genetic algorithms. The cost (objective) function minimization was implemented using genetic algorithms, which, compared to conventional optimization methods such as dynamic programming and gradient techniques, have the ability to attain the global optimum with relative computational simplicity. The proposed method has been applied for the design of a power generation system which supplies electricity to a residential household. The simulation results verify that hybrid PV/WG systems feature lower system cost compared to the cases where either exclusively WG or exclusively PV sources are used.

An optimal sizing method used to optimize the configurations of a hybrid solar-wind system employing battery banks is proposed by Yang et al. (2008). Based on a genetic algorithm, which has the ability to attain the global optimum with relative computational simplicity, an optimal sizing method was developed to calculate the optimum system configuration that can achieve the customers required loss of power supply probability (LPSP) with a minimum annualized cost of system (ACS). The decision variables included in the optimization process are the PV module number, wind turbine number, battery number, PV module slope angle and wind turbine installation height. The proposed method has been applied to the analysis of a hybrid system which supplies power to a telecommunication relay station, and good optimization performance has been found. Furthermore, the relationships between system power reliability and system configurations were also given. Although a solely solar or a wind turbine solution can also achieve the same desired LPSP, it represents a higher cost. The relationships between system power reliability and system configurations have been studied, and the hybrid system with 3–5 days' battery storage is found to be suitable for the desired LPSP of 1% and 2% for the studied case.

Bala and Siddique (2009) carried out the optimal sizing of PV array, storage battery capacity, inverter capacity, backup diesel generator set capacity and operational strategy of a solar-diesel mini-grid of an isolated island-Sandwip in Bangladesh using genetic algorithms. This study reveals that the major share of the costs is for solar panels and batteries. Technological development in solar photovoltaic technology and development in batteries production technology make rural electrification in isolated islands more promising and demanding.

Dufo-Lopez and Bernal-Agustin (2005) developed the HOGA (hybrid optimization by genetic algorithms), which is a program that uses a genetic algorithm (GA) to design a PV-diesel system (sizing, operation and control of a PV-diesel system). The program has been developed in C++. A PV-diesel system optimized by HOGA is compared with a stand-alone PV-only system that has been dimensioned using a classical design method based on the available energy under worst-case conditions. In both cases, the demand and solar irradiation are the same. The computational results show the economical advantages of the PV-hybrid system. HOGA is also compared with a commercial program for optimization of hybrid systems.

Lin and Phillips (2008) used a genetic algorithm to optimize the multi-level rectangular and arbitrary gratings. Solar cells with optimized multi-level rectangular gratings exhibit a 23% improvement over planar cells and 3.8% improvement over the optimal cell with periodic gratings. Solar cells with optimized arbitrarily shaped gratings exhibit a 29% improvement over planar cells and 9.0% improvement over the optimal cell with periodic gratings. The enhanced solar cell efficiencies for multi-level rectangular and arbitrary gratings are attributed to improved optical coupling and light trapping across the solar spectrum.

Varun (2010) used GAs for estimating the optimal thermal performance of a flat plate solar air heater having various system and operating parameters. The present work facilitates the domain of optimized values for different parameters which are decisive for ultimately finding the best performance of such a system. The basic values like number of glass covers, irradiance and Reynolds number are the key inputs on the basis of which the entire set of optimized values of parameters like wind velocity, panel tilt angle, emissivity of plate and ambient temperature are estimated by the proposed algorithm and finally the efficiency is calculated. Different optimized parameters for Reynold numbers ranging from 2000 to 20000 have been evaluated.

3.5 Applications of data mining

Table 8 summarizes various applications of data mining for solar energy systems.

Authors	Year	Subject
Kusama et al.	2007	Solar cell

Table 8. Summary of solar energy applications of data mining

Only one application is found in this area. This is by Kusama et al. (2007) who used data mining assisted by theoretical calculations for improving dye-sensitized solar cell performance. This method led to new knowledge about the influence of imidazole (crystalline heterocyclic compound used mainly in organic synthesis) derivatives as additives in an electrolytic solution on the cell performance. It was found that the solar energy conversion efficiency is strongly correlated to the Mulliken charge of the carbon

atom at position 4 in the imidazole group. This result indicates that data mining assisted by theoretical calculations should facilitate the rate that cell performance is improved. Data mining combined with theoretical calculations successfully elucidated a new research direction for developing an improved electrolytic solution for dye-sensitized solar cell using base additives.

4. Conclusions

From the description of the various applications presented in this chapter, one can see that artificial intelligence techniques have been applied in a wide range of fields for modelling, prediction and control of solar energy systems. What is required for setting up such an AI system is data that represents the past history and performance of the real system and a selection of a suitable model. The selection of this model is usually done empirically and after testing various alternative solutions. The performance of the selected models is tested with the data of the past history of the real system.

In this chapter, various AI techniques used in a number of solar energy systems have been reviewed. Available literature summaries published in this area is also presented. AI techniques are becoming useful as alternate approaches to conventional techniques. AI have been used and applied in different areas, such as engineering, economics, medicine, military, marine, etc. They have also been applied for modelling, identification, optimization, prediction and control of complex systems. As can be seen from the applications presented, AI techniques have been applied successfully in a wide range of solar energy applications.

Surely, the number of applications presented here is neither complete nor exhaustive but merely a sample of applications that demonstrate the usefulness and possible applications of artificial intelligence techniques. Like all other approximation techniques, artificial intelligence techniques have relative advantages and disadvantages. There are no rules as to when this particular technique is more or less suitable for an application. Based on the works presented here it is believed that artificial intelligence techniques offer an alternative method, which should not be underestimated.

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This book provides a quick read for experts, researchers as well as novices in the field of solar collectors and panels research, technology, applications, theory and trends in research. It covers the use of solar panels applications in detail, ranging from lighting to use in solar vehicles.

How to reference

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