ARTIFICIAL INTELLIGENCE IN SOLAR ENERGY APPLICATIONS

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ABSTRACT: -Artificial intelligence (AI) systems comprise two major areas, expert systems and artificial neural networks (ANNs). The major objective of this paper is to illustrate how artificial intelligence techniques might play an important role in modelling and prediction of the performance of solar energy systems. The paper outlines an understanding of how expert systems and neural networks operate by way of presenting a number of problems in the different disciplines of solar energy engineering. The various applications of expert systems and neural networks are presented in a thematic rather than a chronological or any other order. Results presented in this paper, are testimony to the potential of artificial intelligence as a design tool in many areas of solar energy engineering.

Keywords: Expert systems, artificial neural networks, renewable energy applications

1. INTRODUCTION

The possibility of developing a machine that would "think" has intrigued human beings since ancient times. In 1637 the French philosopher-mathematician Rene Descartes predicted that it would never be possible to make a machine that thinks as humans do. However, in 1950, the British mathematician and computer pioneer Alan Turing declared that one day there would be a machine that could duplicate human intelligence in every way.

Artificial Intelligence (AI) is a term that in its broadest sense would indicate the ability of a machine or artifact to perform the same kinds of functions that characterise human thought. The term AI has been applied to computer systems and programs which can perform tasks more complex than straightforward programming, although still far from the realm of actual thought. AI consists of two branches, i.e., expert systems and artificial neural networks. Logic programs called expert systems allow computers to "make decisions" by interpreting data and selecting from among alternatives. Expert systems take computers a step beyond straightforward programming, being based on a technique called rule-based inference, in which pre-established rule systems are used to process the data. Despite their sophistication, systems still do not approach the complexity of true intelligent thought.

Artificial neural networks (ANNs) are collections of small individual interconnected processing units. Information is passed between these units along interconnections. An incoming connection has two values associated with it, an input value and a weight. The output of the unit is a function of the summed value. ANNs while implemented on computers are not programmed to perform specific tasks. Instead, they are trained with respect to data sets until they learn the patterns presented to them. Once they are trained, new patterns may be presented to them for prediction or classification.

For the estimation of the flow of energy and performance of solar energy systems, analytic computer codes are often used. The algorithms employed are usually complicated involving the solution of complex differential equations. These programs usually require large computer power and need a lot of time to give accurate predictions. Data from solar energy systems being inherently noisy are good candidate problems to be handled with AI.

AI analysis is based on past history data of a system and is therefore likely to be better understood and appreciated by designers than other theoretical and empirical methods. AI may be used to provide innovative ways of solving design issues and will allow designers to get an almost instantaneous expert opinion on the effect of a proposed change in a design.

The major objective of the paper is to demonstrate the possibilities of applying AI to solar energy applications. This will be done by way of presenting applications of expert systems and neural networks to various solar energy related problems. The problems are presented in a thematic rather than a chronological or any other order. This will show the capability of expert systems and artificial neural networks as tools in solar energy systems prediction and modelling. The majority of the applications presented however are related with ANNs.

2. EXPERT SYSTEMS

An expert system is a computer program in which the knowledge of an expert on a specific subject can be incorporated in order to solve problems or give advice [1]. Thus an expert system is a program capable of emulating human cognitive skills such as problem solving, visual perception and language understanding. An expert system must be distinguished from conventional application programs, as it exhibits certain characteristics that the latter do not have. Specifically an expert system [2]:

1. Can be designed for solving complex problems ordinarily requiring human intelligence.
2. Embody both expert knowledge and logically inferring means; the former should be stored in a symbolic declarative language; the latter would consist of heuristic search and reasoning procedures for utilizing the stored information.
3. Is capable of achieving high performance in narrowly specified domains of incremental development, dealing with incomplete or uncertain data, handling unforeseen situations and explaining or justifying its results.
4. Is limited to a specific area of human expertise.
5. Can be designed to grow on an evolutionary basis, improving its “expertise” as it grows.
6. Can represent the expertise using facts and rules.
7. Is able to use other knowledge representation methods to handle knowledge, which is not well expressed as rules.

What is expected from an expert system is to deal with problems of scientific or commercial nature and to provide correct solutions in a reasonable time. Moreover, similarly to the human expert, it should be able to provide explanations about the conclusions reached, by displaying in some way all the steps of its reasoning process, and it should be able to provide explanations about the course of action it will follow according to the user’s answers to the questions that the system is programmed to ask [1, 2].

An expert system usually consists of a knowledge base, an inference mechanism and a user interface [2]. The knowledge base usually contains two different databases, a static and a dynamic. The static database contains the knowledge about the domain, represented in a certain formalism. It is created once, when the system is being developed by the user, but it can be modified at runtime (with addition of new facts, deletion of some part of the existing knowledge or alteration of some part of it). The dynamic database may be enriched during each execution of the program but the information is lost when the execution is terminated. It is used to store all information obtained from the user, as well as intermediate conclusions (facts) that are inferred during the reasoning process.

The inference mechanism contains the control methods that indicate how the present knowledge is to be processed, in order to obtain solutions and conclusions to the problem. It reflects the way in which the system reasons on the acquired knowledge, and it is interrelated with the human way of reasoning.

The user interface provides the user with the explanations on the system's performance, obtains from the user the information that the system needs in order to perform and presents the results obtained during the reasoning process.

There are only a few applications of expert systems in solar energy systems. Panteliou *et al.* [3] present an expert system developed and used for the selection and design of solar domestic hot water systems (SDHW) in Greece. Frame and class formalism was used for knowledge representation together with forward and backward chaining techniques for drawing conclusions and utilizing the accumulated information present. It was shown that the program performed successfully for 21 SDHW systems available on the Greek market. Apart from the possibility of selection of a SDHW system, the program developed also supports the facility for updating its knowledge database with new data so that it can be adapted to changes appearing on the market. According to the authors the developed program proved to be highly functional and user friendly.

3. ARTIFICIAL NEURAL NETWORKS

The concept of neural network analysis has been discovered nearly 50 years ago, but it is only in the last 20 years that applications software has been developed to handle practical problems. The history and theory of neural networks have been described in a large number of published literature and will not be covered in this paper except for a very brief overview of how neural networks operate. ANNs are good for some tasks while lacking in some others. Specifically, they are good for tasks involving incomplete data sets, fuzzy or incomplete information, and for highly complex and ill-defined problems, where humans usually decide on an intuitional basis. They can learn from examples, and are able to deal with non-linear problems. Furthermore they exhibit robustness and fault tolerance. The tasks that ANNs cannot handle effectively are those requiring high accuracy and precision as in logic and arithmetic.

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 being used in weather and market trends forecasting, in the prediction of mineral exploration sites, in electrical and thermal load prediction, in adaptive and robotic control and many others. Neural networks are used for process control because they can build predictive models of the process from multidimensional data routinely collected from sensors.

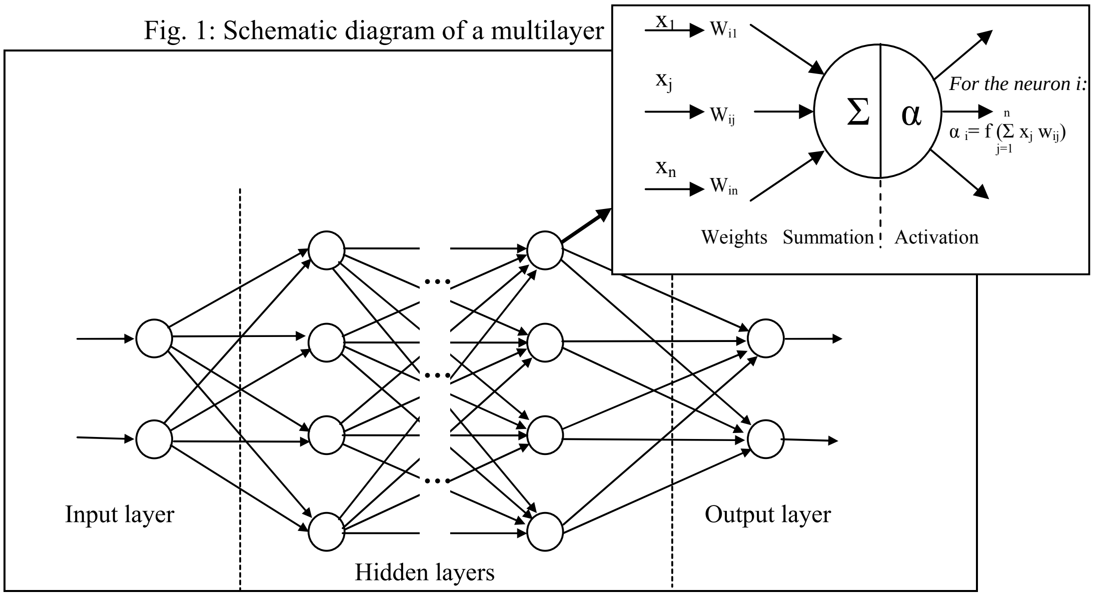
According to Haykin [4] a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects; the knowledge is acquired by the network through a learning process, and inter-neuron connection strengths known as synaptic weights are used to store the knowledge.

Artificial neural network (ANN) models may be used as an alternative method in engineering analysis and predictions. ANN mimics somewhat the learning process of a human brain. They operate like a “black box” model, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data. ANN can also be compared to multiple regression analysis except that with ANN no assumptions need to be made about the system to be modelled. Neural networks usually perform successfully where other methods do not, and have been applied in solving a wide variety of problems, including non-linear problems such as pattern recognition, that are not well suited to classical methods of analysis. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They seem to simply ignore excess data that are of minimal significance and concentrate instead on the more important inputs. Instead of complex rules and mathematical routines, artificial neural networks are able to learn the key information patterns within a multidimensional information domain. In addition, neural networks are fault tolerant, robust, and noise immune [5].

A schematic diagram of a typical multilayer feedforward neural network architecture is shown in Fig. 1. 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. The number of input and output parameters and the number of cases influence the geometry of the network. The network consists of an 'input' layer of neurons, with one neuron corresponding to each input parameter a 'hidden' layer or layers of neurons and an output layer of one neuron for each output. A neuron, also called a processing element, is the basic unit of a neural network and performs summation and activation function to determine the output of that neuron (see Fig. 1 insert). The number of neurons in the hidden layer is approximately the average of the inputs and outputs though it does depend also on the number of training cases. Too many hidden layer neurons can result in 'over-training' (or lack of generalization) and lead to large 'verification' errors. Too few neurons can result in large 'training' and 'verification' errors. 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.

Several algorithms are commonly used to achieve the minimum error in the shortest time. There are also many alternative forms of neural networking systems and, indeed, many different ways in which they may be applied to a given problem. The suitability of an appropriate paradigm and strategy for application is very much dependent on the type of problem to be solved. The most popular learning algorithms are the back-propagation (BP) and its variants [5]. The BP algorithm is one of the most powerful learning algorithms in neural networks and is a gradient descent algorithm. It tries to improve the performance of the neural network by reducing the total error by changing the weights along its gradient. More details of the BP algorithm can be found in [6].

Fig. 1: Schematic diagram of a multilayer



The first step to be followed when dealing with a particular problem is to collect the required data and prepare them in a spreadsheet format with various columns representing the input and output parameters. Three types of data files are required; a training data file, a test data file and a validation data file. The former and the latter should contain representative samples of all the cases the network is required to handle, whereas the test file may contain about 10% of the cases contained in the training file. During training the network is tested against the test file and training should be stopped when the mean average error remains unchanged for a number of epochs. This is done in order to avoid overtraining, in which case, the network learns perfectly the training patterns but is unable to make predictions when an unknown training set is presented to it.

The basic operation that has to be followed to successfully handle a problem with ANNs is to select the appropriate architecture and the suitable learning rate, momentum, number of neurons in each hidden layer and the activation function. This is a laborious and time-consuming method but as experience is gathered some parameters can be predicted easily thus shortening tremendously the time required.

4. APPLICATIONS OF ANN IN SOLAR ENERGY SYSTEMS

ANN’s have been used by many researchers for modelling and predictions in the field of solar energy systems. This paper presents various such applications in a thematic rather than a chronological or any other order. More details are given on the most recent work of the author in the area. A more detailed review can be found in [6].

3.1. Modelling of a Solar Steam Generator

ANN's have been applied to model various aspects of a solar steam generator. The system employs a parabolic trough collector, a flash vessel, a high pressure circulating pump and the associated pipework. Some of the work done on this system is described here.

The intercept factor is defined as the ratio of the energy absorbed by the receiver to the energy incident on the concentrator aperture. From the intercept factor the collector optical efficiency can be determined. This is a very important parameter in the determination of the overall effectiveness of solar concentrating collectors. ANN's have been able to calculate the intercept factor with a difference confined to a less than 0.4% as compared to the much more complex estimation of the Energy DEPosition (EDEP) computer code [7].

The radiation profile on the receiver of the collector has a “bell” type shape. This is represented in terms of the local concentration ratios at 10° intervals on the periphery of the receiver. It is very important to be able to measure this profile because in this way the collector optical efficiency can be determined. This measurement must be carried out at various incidence angles and also at normal incidence angle ($\theta=0°$). This is usually very difficult to perform due to the size of the collector. ANN's have been used to learn the radiation profile from readings at angles that experiments could be performed and make prediction for the other angles including the normal incidence angle [8]. The predictions of ANN as compared to the actual experimental values have a maximum difference of 3.2%, which is considered satisfactory.

ANN's have been used also to model the starting-up of the system [9]. It is very important for the designer of such systems to be able to make such predictions because the energy spent during starting-up in the morning has a significant effect on the system performance. This problem is very difficult to handle with analytic methods as the system operates under transient conditions. ANN's could predict the profile of the temperatures at various points of the system to within 3.9%, which is considered adequate for design purposes. From the profiles the energy invested during the heat-up period can be easily estimated.

An important parameter required for the design of such systems is the mean monthly average steam production of the system. A network was trained with performance values for a number of collector sizes ranging from 3.5 to 2160 m^2 and was able to make predictions both within and outside the training range [10]. The ANN was able to predict the mean monthly average steam production with a maximum difference confined to less than 5.1%, compared to simulated values, which is considered acceptable.

3.2 Solar Water Heating Systems

An ANN has been trained based on 30 known cases of systems, varying from collector areas between $1.81m^2$ and $4.38m^2$. Open and closed systems have been considered both with horizontal and vertical storage tanks. Also an attempt was made to consider a large variety of weather conditions thus the network was trained to accept and handle a number of unusual cases. The data presented as input were the collector area, storage tank heat loss coefficient and volume, tank type, type of system, and ten readings from experiments of total daily solar radiation, mean ambient air temperature, and water temperature in the storage tank at the beginning of a day. The network output is the useful energy extracted from the system and the stored water temperature rise. Unknown data were used to investigate the accuracy of prediction. Predictions within 7.1% and 9.7% were obtained respectively [11]. These results indicate that the proposed method can successfully be used for the estimation of the useful energy extracted from the system and the stored water temperature rise. The advantages of this approach compared to the conventional algorithmic methods are the speed, the simplicity, and the capacity of the network to learn from examples. Additionally, actual weather data have been used for the training of the network, which leads to more realistic results as compared to other modelling programs, which rely on typical meteorological year (TMY) data that are not necessarily similar to the actual environment in which a system operates.

The same systems described above have been tested and modelled according to the procedures outlined in the standard ISO 9459-2 at three locations in Greece in order to determine their long-term performance. From these, data for twenty-seven systems were used for training and testing the network while data for the remaining three for validation. Two ANNs have been trained using the monthly data produced by the modelling program supplied with the standard. The first network was trained to estimate the solar energy output of the system (Q) for a draw-off quantity equal to the storage tank capacity and the second one to estimate the solar energy output of the system (Q) and the average quantity of hot water per month (V_d) at demand temperatures of 35°C and 40°C. The input data in both networks are similar to the ones used in the program supplied with the standard, i.e., the size and performance characteristics of each system and various climatic data. In the second network the demand temperature was also used as input. When unknown data were used to investigate the accuracy of prediction statistical R^2-values equal to 0.9913 for the first network and 0.9733 and 0.9940 for the second were obtained [12].

A similar approach was followed for the long-term performance prediction of three forced circulation type solar domestic water heating systems The maximum percentage differences obtained when unknown data were used, were 1.9% and 5.5% for the two networks respectively [13].

In another work, an ANN has been trained using performance data for four types of systems, all employing the same collector panel under varying weather conditions and configurations [14]. The output of the network is the useful energy extracted and the stored water temperature rise. Predictions with maximum deviations of 1MJ and 2.2°C were obtained for the two output parameters respectively. Random data were also used both with the performance equations obtained from experimental measurements and with the ANN model to predict the above parameters. The predicted values thus obtained were very comparable which indicates that the proposed method can be used successfully for the estimation of the performance of the particular thermosyphon system at any of the different configurations used.

5. CONCLUSIONS

From the above problem descriptions one can see that both expert systems and ANNs have been applied in a wide range of fields for modelling and prediction in solar energy systems. What is required for setting up such systems is data that represents the past history and performance of a real system and selection of a suitable expert system or neural network model. Surely the number of applications presented here is neither complete nor exhaustive but merely a sample of applications that demonstrate the usefulness of AI methods. AI models like all other approximation techniques have relative advantages and disadvantages. There are no rules as to when this particular technique is suitable for an application. Based on the work presented here it is believed that AI offers an alternative method which should not be underestimated.

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