Artificial Intelligence in Renewable Energy Applications in Buildings

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Abstract: - Artificial intelligence (AI) systems comprise three major areas, artificial neural networks (ANNs), genetic algorithms (GA) and fuzzy logic. 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 renewable energy systems in buildings. The paper outlines an understanding of how neural networks, genetic algorithms and fuzzy systems operate by way of presenting a number of problems in the different disciplines of renewable energy applications in buildings. The various applications 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 renewable energy engineering.

1 Introduction

Artificial Intelligence (AI) is a term that in its broadest sense would indicate the ability of a machine or artefact to perform the same kinds of functions that characterise human thought. The term AI has also been applied to computer systems and programs capable of performing tasks more complex than straightforward programming, although still far from the realm of actual thought.

For the estimation of the flow of energy in buildings and the performance of renewable 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 considerable amount of time to give accurate predictions. Data from renewable energy systems being inherently noisy are good candidate problems to be handled with AI.

When dealing with research and design associated with renewable energy (RE) there are often difficulties encountered in handling situations where there are many variables involved. To adequately model and predict the behaviour of RE systems requires consideration of nonlinear multivariate inter-relationships, often in a 'noisy' environment. For example in the prediction of performance of a solar system from the point of view of energy efficiency, there are numerous variables involved and the precise interactions to each other are not fully understood or cannot easily be modelled. In addition RE systems receive their inputs from the sun, wind, waves etc, the strength and duration of which are highly variable.

Analytical techniques have been very successful in the study of the behaviour of engineering systems such as heat transfer, thermal processes, and other areas. While the analytical models have been valuable in understanding principles and useful where less than optimal designs were acceptable with the advent of digital computers, numerical methods became much more attractive than analytical solutions, as they could handle more complex and realistic situations.

Numerical methods have their limitations as well. They cannot easily account for practical limitations, they tend to perform well at analysing a situation but not so well as a designer's tool for quickly looking at options. Additionally, the number of variables that can be considered is still limited and numerical solutions cannot usually be obtained directly. Frequently complex systems for which there is no exact model of behaviour need to be designed. Furthermore, designers have to design or deal with complex systems whose expected performances are completely unknown. Much of the complexity is due to the multi parameter and multi criteria aspects of a system’s design which are not easily handled using rules of thumb, analytical methods, physical models or numerical methods.

Many of the renewable energy problems are exactly the types of problems and issues for which AI approach appear to be most applicable. In these models of computation attempts are made to simulate the powerful cognitive and sensory functions of the human brain and to use this capability to represent and manipulate knowledge in the form of patterns. Based on these patterns neural networks for example model input-output functional relationships and can make predictions about other combinations of unseen inputs. Neural networks have the potential for making better, quicker and more practical predictions than any of the traditional methods. Artificial neural networks (ANNs) are collections of small individually 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 patterns used as inputs. Once they are trained, new patterns may be presented to them for prediction or classification. An ANN can automatically learn to recognize patterns in data from real systems or from physical models, computer programs, or other sources. It can handle many inputs and produce answers that are in a form suitable for designers.

Genetic algorithms (GA) 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 in the process the evolution of population 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.

Approximate reasoning has proven to be in many cases more successful control strategy than classically designed controlled scheme. Fuzzy logic is used mainly in control engineering. It is based on fuzzy logic reasoning which employs linguistic rules in the form of IF-THEN statements. Fuzzy logic and fuzzy control feature a relative simplification of a control methodology description. This allows the application of a “human language” to describe the problems and their fuzzy solutions. In many control applications, the model of the system is unknown or the input parameters are highly variable and unstable. In such cases, fuzzy controllers can be applied. These are more robust and cheaper than conventional PID controllers. It is also easier to understand and modify fuzzy controller rules, which not only use human operator’s strategy but, are expressed in natural linguistic terms.

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 objective of this paper is to briefly introduce the three major areas of AI, i.e., ANNs, GA and fuzzy logic and to present various applications in renewable energy applications in buildings. The applications are presented in a thematic rather than a chronological or any other order. The majority of the applications presented are related with ANNs. This will show the capability of AI as tools in renewable energy systems prediction and modelling.

2 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 (1994) 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 mimic 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 (Rumelhart *et al.*, 1986).

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 processing element, is the basic unit of a neural network and performs summation and activation function to determine the output of that neuron (Fig. 2). 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.

Figure 2 illustrates how information is processed through a single node. The node receives weighted activation of 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 with the specific weight and transferred to the next node.

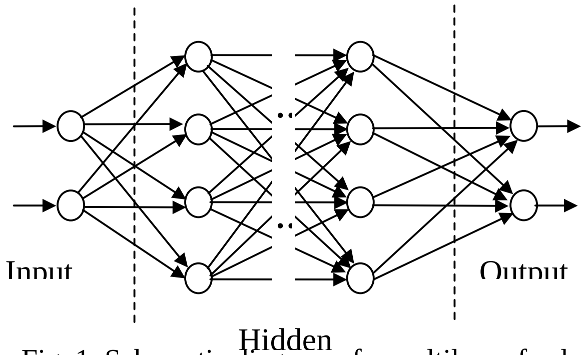


Fig. 1. Schematic diagram of a multilayer feed forward neural network.

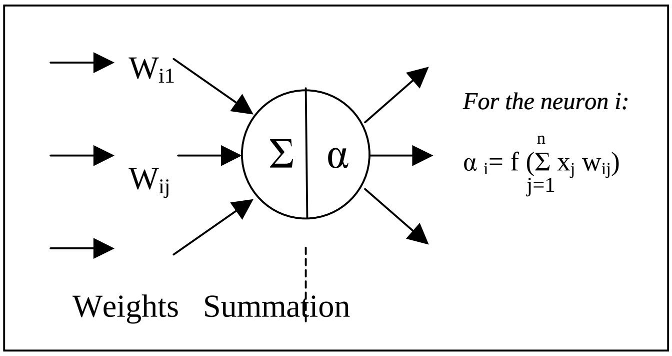


Fig. 2. Information processing in a neural network unit.

A training set is a group of matched input and output patterns used for training the network, usually by suitable adaptation of the synaptic weights. The outputs are the dependent variables that the network produces for the corresponding input. It is important that all the information the network needs to learn is supplied to the network as a data set. Starting from an initially randomised weighted network system, input data is propagated through the network to provide an estimate of the output value. When each pattern is read, the network uses the input data to produce an output, which is then compared to the training pattern, i.e., the correct or desired output. If there is a difference, the connection weights (usually but not always) are altered in such a direction that the error is decreased. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the ANN runs again through all the input patterns repeatedly until all the errors are within the required tolerance. When the training reaches a satisfactory level, the network holds the weights constant and uses the trained network to make decisions, identify patterns, or define associations in new input data sets not used to train it.

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 and its variants (Rumelhart *et al.*, 1986; Werbos, 1974). The Back-Propagation (BP) algorithm is one of the most powerful learning algorithms in neural networks. The training of all patterns of a training data set is called an epoch. The training set has to be a representative collection of input-output examples. Back-propagation training 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 Kalogirou (2001).

Neural networks obviate the need to use complex mathematically explicit formulas, computer models, and impractical and costly physical models. Some of the characteristics that support the success of artificial neural networks and distinguish them from the conventional computational techniques are (Nannariello and Fricke, 2001):

- The direct manner in which artificial neural networks acquire information and knowledge about a given problem domain (learning interesting and possibly non-linear relationships) through the 'training' phase.
- Neural networks can work with numerical or analogue data that would be difficult to deal with by other means because of the form of the data or because there are so many variables.
- Neural network analysis can be conceived of as a 'black box' approach and the user does not require sophisticated mathematical knowledge.
- The compact form in which the acquired information and knowledge is stored within the trained network and the ease with which it can be accessed and used.
- Neural network solutions can be robust even in the presence of 'noise' in the input data.
- The high degree of accuracy reported when artificial neural networks are used to generalize over a set of previously unseen data (not used in the 'training' process) from the problem domain.

While neural networks can be used to solve complex problems they do suffer from a number of shortcomings. The most important of them are:

- The data used to train neural nets should contain information, which ideally, is spread evenly throughout the entire range of the system.
- There is limited theory to assist in the design of neural networks.
- There is no guarantee of finding an acceptable solution to a problem.
- There are limited opportunities to rationalize the solutions provided.

2.1 Network Parameters Selection

When building the neural network model the process has to be identified with respect to the input and output variables that characterise the process. The inputs include measurements of the physical dimensions, measurements of the variables specific to the environment, equipment, and controlled variables modified by the operator. Variables that do not have any effect on the variation of the measured output are discarded. These are estimated by the contribution factors of the various input parameters. These factors indicate the contribution of each input parameter to the learning of the neural network and are usually estimated by the network, depending on the software employed.

The first step 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 to determine accuracy 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.

3 Genetic Algorithms

The genetic algorithm (GA) is a model of machine learning, which derives its behavior from a representation of the processes of evolution in nature. This is done by the creation within a machine/computer of a population of individuals represented by chromosomes. Essentially these are a set of character strings that are analogous to the chromosomes that we see in the DNA of human beings. The individuals in the population then go through a process of evolution.

GAs are used for a number of different application areas. An example of this would be multidimensional optimization problems in which the character string of the chromosome can be used to encode the values for the different parameters being optimized.

In practice, therefore, this genetic model of computation can be implemented by having arrays of bits or characters to represent the chromosomes. Simple bit manipulation operations allow the implementation of crossover, mutation and other operations.

When the GA is executed, it is usually done in a manner that involves the following cycle. Evaluate the fitness of all of the individuals in the population. Create a new population by performing operations such as crossover, fitness-proportionate reproduction and mutation on the individuals whose fitness has just been measured. Discard the old population and iterate using the new population. One iteration of this loop is referred to as a generation. The structure of the standard genetic algorithm is shown in Fig. 3 (Zalzala and Fleming, 1997).

```
Begin (1)
        t = 0
        Initialize Population P(t)
        Evaluate fitness of Population P(t)
        While (Generations < Total Number) do begin (2)
                t = t + 1
                Select Population P(t) out of Population P(t-1)
                Apply Crossover on Population P(t)
                Apply Mutation on Population P(t)
                Evaluate fitness of Population P(t)
        end (2)
end (1)
```

Fig. 3 The structure of standard genetic algorithm

With reference to Fig. 3, in each generation individuals are selected for reproduction according to their performance with respect to the fitness function. In essence, 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. More details on genetic algorithms can be found in Goldberg (1989), Davis (1991) and Michalewicz (1996).

The first generation (generation 0) of this process operates on a population of randomly generated individuals. From there on, the genetic operations, in concert with the fitness measure, operate to improve the population.

During each step in the reproduction process, the individuals in the current generation are evaluated by a fitness function value, 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.

Genetic algorithms (GA) are suitable for finding the optimum solution in problems were 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 genetic algorithm works by selective breeding of a population of “individuals”, each of which could be a potential solution to the problem. The genetic algorithm is seeking to breed an individual, which either maximizes, minimizes or it is focused on a particular solution of a problem.

The larger the breeding pool size, the greater the potential of it producing a better individual. However, as the fitness value produced by every individual must be compared with all other fitness values of all other individuals on every reproductive cycle, larger breeding pools take longer time. After testing all of the individuals in the pool, a new “generation” of individuals is produced for testing.

During the setting up of the GA the user has to specify the adjustable chromosomes, i.e. the parameters that would be modified during evolution to obtain the maximum value of the fitness function.

Additionally the user has to specify the ranges of these values called constraints.

A genetic algorithm is not gradient based, and uses an implicitly parallel sampling of the solutions space. The population approach and multiple sampling means that it is less subject to becoming trapped to local minima than traditional direct approaches, and can navigate a large solution space with a highly efficient number of samples. Although not guaranteed to provide the globally optimum solution, the GAs have been shown to be highly efficient at reaching a very near optimum solution in a computationally efficient manner.

The genetic algorithm is usually stopped after best fitness remained unchanged for a number of generations or when the optimum solution is reached.

4 Fuzzy Logic

Fuzzy logic is a logical system, which is an extension of multi-valued logic. Additionally fuzzy logic is almost synonymous with the theory of fuzzy sets, a theory that relates to classes of objects without sharp boundaries in which membership is a matter of degree. Fuzzy logic is all about the relative importance of precision, i.e., how important is to be exactly right when a rough answer will work. Fuzzy inference systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems and computer vision. Fuzzy logic is a convenient way to map an input space to an output space, as for example, according to how hot the water is required adjust the valve to the right setting, or according to the steam outlet temperature required adjust the fuel flow in a boiler. From these two examples it can be understood that fuzzy logic mainly has to do with the design of controllers.

Conventional control is based on the derivation of a mathematical model of the plant from which a mathematical model of a controller can be obtained. When a mathematical model cannot be created then there is no way through classical control to develop a controller. Other limitations of conventional control are (Reznik, 1997):

- Plant nonlinearity. Nonlinear models are computationally intensive and have complex stability problems.
- Plant uncertainty. Accurate models can not be created due to uncertainty and lack of perfect knowledge.
- Multi-variables, multi-loops and environmental constrains. Multi-variable and multi-loop systems have complex constrains and dependencies.
- Uncertainty in measurements due to noise.
- Temporal behaviours. Plants, controllers, environments and their constrains vary with time. Additionally, time delays are difficult to model.

The advantages of fuzzy control are (Reznik, 1997):

- Fuzzy controllers are more robust than PID controllers as they can cover a much wider range of operating conditions and can operate with noise and disturbances of different natures.
- Their development is cheaper than that of a model-based or other controller to do the same thing.
- They are customisable since it is easier to understand and modify their rules and also are expressed in natural linguistic terms.
- It is easy to learn how these controllers operate and how to design and apply them in an application.
- They can model nonlinear functions of arbitrary complexity.
- It can be built on top of the experience of experts.
- It can be blended with conventional control techniques.

Fuzzy control should not be used when conventional control theory yields a satisfactory result and when an adequate and solvable mathematical model already exists or can easily be created. Fuzzy logic was initialled in 1965 in the States by Professor Lofti Zateh (1973). In fact, Zadeh's theory not only offered a theoretical basis for fuzzy control, but also establishes a bridge connecting artificial intelligence to control engineering. Fuzzy logic has emerged as a tool for controlling industrial processes, as well as household and entertainment electronics, diagnosis systems and other expert systems. Fuzzy logic is basically a multi-valued logic that allows intermediate values to be defined between conventional evaluations like yes/no, true/false, black/white, large/small, etc. Notions like "rather warm" or "pretty cold" can be formulated mathematically and processed in computers. Thus, an attempt is made to apply a more human-like way of thinking in the programming of computers.

A fuzzy controller design process contains the same steps as any other design process. One needs initially to choose the structure and parameters of a fuzzy controller, test a model or the controller itself and change the structure and/or parameters based on the test results (Reznik, 1997). A basic requirement for implementing fuzzy control is the availability of a control expert who provides the necessary knowledge for the control problem (Nie and Linkens, 1995). More details on fuzzy control and practical applications can be found in (Mamdani, 1974; Sugeno, 1985).

The linguistic description of the dynamic characteristics of a controlled process can be interpreted as a fuzzy model of the process. In addition to the knowledge of a human expert, a set of fuzzy control rules can also be derived by using experimental knowledge. A fuzzy controller avoids rigorous mathematical models and is consequently more robust than a classical approach in cases which cannot be or are with great difficulties precisely modelled mathematically. Fuzzy rules serve to describe in linguistic terms a quantitative relationship between two or more variables. Processing of the fuzzy rules provides a mechanism for using them to compute the response to a given fuzzy controller input.

The basis of a fuzzy or any fuzzy rule system is the inference engine responsible for the inputs fuzzification, fuzzy processing and defuzzification of the output. A schematic of the inference engine is shown in Fig. 4. Fuzzification means that the actual inputs are fuzzified and fuzzy inputs are obtained. Fuzzy processing means that the inputs are processed according to the rules set and produces fuzzy outputs. Defuzzification means to produce a crisp real value for a fuzzy output which is also the controller output. The fuzzy logic controller's goal is to achieve a satisfactory control of a process. Based on the input parameters the operation of the controller (output) can be determined. The typical design scheme of a fuzzy logic controller is shown in Fig. 5 (Reznik, 1997). The design of such a controller contains the following steps:

1. Define the inputs and the control variables.
2. Define the condition interface. Inputs are expressed as fuzzy sets.
3. Design the rule base.
4. Design the computational unit. Many readymade programs are available for this purpose.
5. Determine the rules for defuzzification, i.e., to transform fuzzy control output to crisp control action.

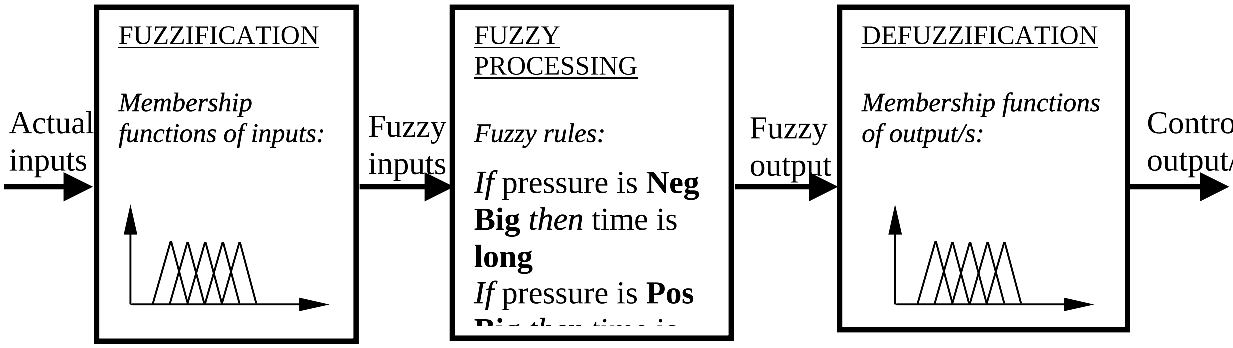


Fig. 4 Operation of a fuzzy controller

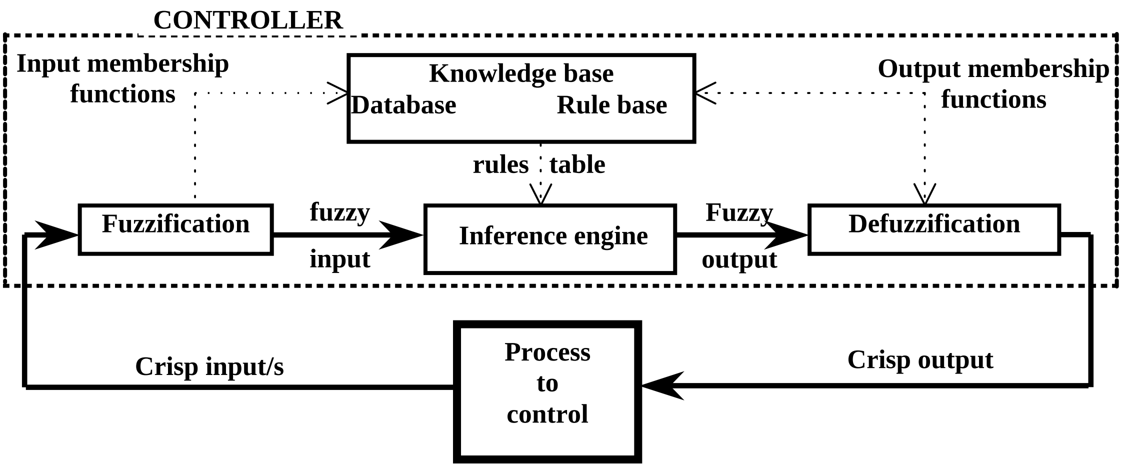


Fig. 5 Basic configuration of fuzzy logic controller

The possibility of integrating neural networks and fuzzy logic was considered quite recently into a new kind of system called neuro-fuzzy control where several strengths of both systems are utilised and combined appropriately.

More specifically by neuro-fuzzy control it is meant (Nie and Linkens, 1995):

1. The controller has a structure resulting from a combination of fuzzy systems and artificial neural networks.
2. The resulting control system consists of fuzzy systems and neural networks as independent components performing different tasks, and
3. The design methodologies for constructing respective controllers are hybrid ones coming from ideas in fuzzy and neural control.

In this case a trained neural network can be viewed as a means of knowledge representation. Instead of representing knowledge using IF-THEN localised associations as in fuzzy systems, a neural network stores knowledge through its structure, and more specifically its connection weights and local processing units in a distributed or localized manner. Many commercial software (like Matlab) include routines for neuro-fuzzy modelling.

The basic idea behind a neuro-fuzzy technique is to provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. A neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map. The parameters associated with the membership functions will change through a learning process. Generally, the procedure followed is similar to any neural network technique described in section 2.

5 Applications of ANN in Renewable Energy Applications in Buildings

ANN's have been used by various researchers and by the author for modelling and predictions in the field of renewable energy systems in buildings. This field includes models for predicting solar radiation and wind, renewable energy systems that can be applied in buildings, control of building renewable energy systems and naturally ventilated buildings. This paper presents various such applications in a thematic rather than a chronological or any other order.

5.1 Solar Water Heating Systems

a) Modelling of solar domestic water heating (SDHW) 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 (Kalogirou *et al.*, 1999a). Open and closed systems have been considered both with horizontal and vertical storage tanks. In addition to the above, an attempt was made to consider a large variety of weather conditions. In this way 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 (U-value), tank type, storage volume, type of system, and ten readings from real experiments of total daily solar radiation, mean ambient air temperature, and the water temperature in the storage tank at the beginning of a day for each system. 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. Typical results are shown in Tables 1 and 2 for the useful energy extracted from the system and the stored water temperature rise respectively. These include systems considered for the training of the network at different weather conditions (systems 11 and 12) and completely unknown systems (systems 15, 32 and 43).

Table 1 Comparison between actual and predicted results for the useful energy extracted (Q_{out}).

System	Actual Q_{out} (MJ)	ANN predicted Q_{out} (MJ)	% difference
11	20.6 19.0	20.6 19.3	0.0 1.5
12	22.3 17.1	22.4 18.4	0.4 7.1
15	20.5 12.2	22.4 12.7	8.5 3.9
32	16.2 15.6	16.6 15.4	2.4 -1.3
43	23.1 32.7	22.6 35.9	-2.2 8.9

Predictions within 7.1% and 9.7% were obtained respectively (Kalogirou *et al.,* 1999a). 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. This is done by embedding experiential knowledge in the network.

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.

Table 2 Comparison between actual and predicted results for the temperature rise of the water in the storage tank

System	Actual temperature (°C)	ANN predicted temperature (°C)	% difference
11	64.1 61.0	62.6 60.8	-2.3 -0.3
12	53.0 45.1	52.2 45.6	-1.5 1.1
15	60.9 47.9	62.4 44.8	2.4 -6.9
32	45.7 44.1	42.8 41.5	-6.8 -6.3
43	45.1 56.5	41.1 57.0	-9.7 0.9

b) Performance prediction of a thermosyphon solar domestic water heating system.

An ANN has been trained using performance data for four types of systems, all employing the same collector panel under varying weather conditions (Kalogirou *et al.*, 1999b). The output of the network is the useful energy extracted from the system 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 the experimental measurements and with the artificial neural network to predict the above two parameters. The predicted values thus obtained were very comparable. These results indicate that the proposed method can successfully be used for the estimation of the performance of the particular thermosyphon system at any of the different types of configurations used here.

c) Solar domestic water heating systems long-term performance prediction

Thirty thermosyphon SDWH systems have been tested and modelled according to the procedures outlined in the standard ISO 9459-2 at three locations in Greece (Kalogirou and Panteliou, 2000). 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. Different networks were used due to the nature of the required output, which is different in each case. 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. These were the size and performance characteristics of each system and various climatic data. In the second network the demand temperature was also used as input. The statistical coefficient of multiple determination (R^2-value) obtained for the training data set was equal to 0.9993 for the first network and 0.9848 and 0.9926 for the second for the two output parameters respectively. Unknown data were subsequently used to investigate the accuracy of prediction. Predictions with R^2-values equal to 0.9913 for the first network and 0.9733 and 0.9940 for the second were obtained (Kalogirou and Panteliou, 2000). Comparative graphs are shown in Figs 6 and 7.

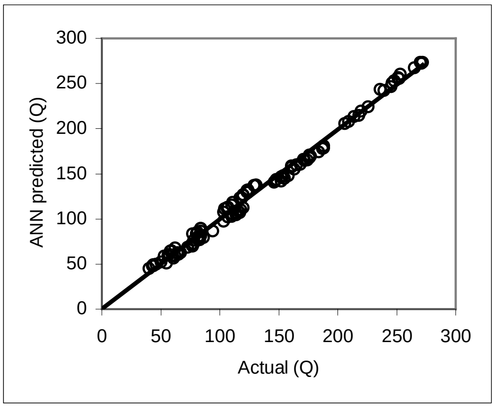
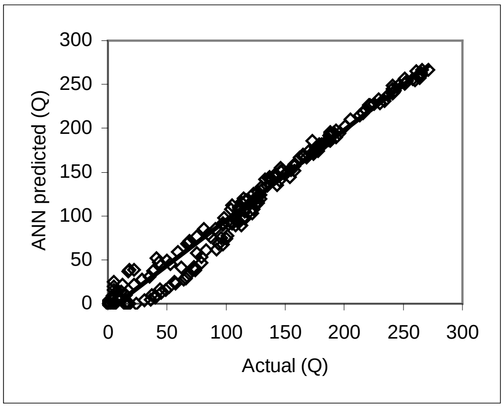
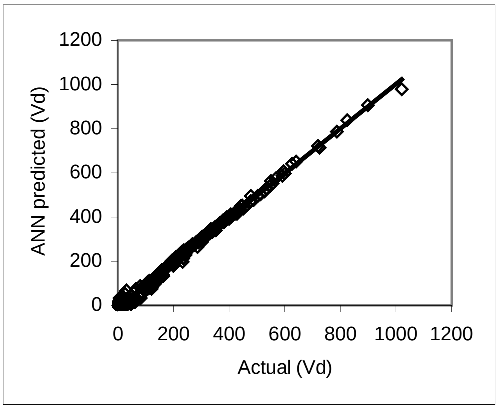


Fig. 6 Actual (modelled) against ANN predicted values for the validation data set for the solar energy output (Q) (Network #1).

A similar approach was followed for the long-term performance prediction of three forced circulation type solar domestic water heating (SDWH) systems (Kalogirou, 2000). The maximum percentage differences obtained when unknown data were used were 1.9% and 5.5% for the two networks respectively.



(a) Solar energy output (Q)



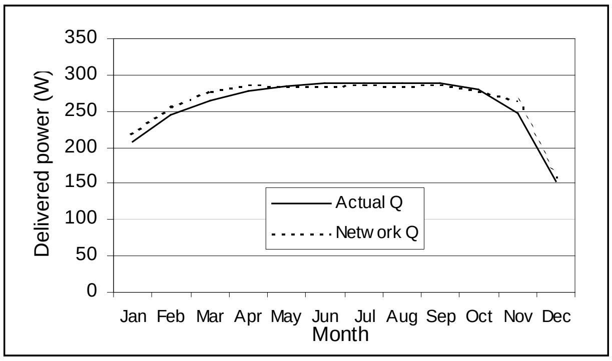
(b) Monthly hot water quantity (V_d)

Fig. 7 Actual (modelled) against ANN predicted values for the validation data set. (Network #2)

d) Thermosyphon system long-term performance prediction using the dynamic system testing method and artificial neural networks

The performance of a solar hot water thermosyphon system was tested with the dynamic system method according to Standard ISO/CD/9459.5. The system is of closed circuit type and consists of two flat plate collectors with total aperture area of 2.74 m^2 and of a 170-litre hot water storage tank. The system was modelled according to the procedures outlined in the standard with the weather conditions encountered in Rome. The simulations were performed for hot water demand temperatures of 45 and 90°C and volume of daily hot water consumption varying from 127 to 200 litres. These results have been used to train a suitable neural network to perform long-term system performance prediction (Kalogirou and Panteliou, 1999). The input data were learned with adequate accuracy with correlation coefficients varying from 0.993 to 0.998, for the four output parameters. When unknown data were used to the network, satisfactory results were obtained. The maximum percentage difference between the actual (simulated) and predicted results is 6.3%. These results prove that artificial neural networks can be used successfully for this type of predictions. A comparison of the actual and ANN predicted results for the delivered power are shown in Fig. 8.

Fig. 8 Comparison of actual (simulated) data with



ANN predicted data for delivered power

e) Identification of the time parameters of solar collectors

Lalot (2000) used ANNs for the identification of time parameters of solar collectors. Two parameters fully describe the static behaviour whereas two other parameters are necessary to fully describe the dynamic behaviour of a flat plate collector. The discrimination ability of the network however was not very high when a second order system was considered. It has been shown that collectors may be considered as third order systems. A radial basis function (RBF) neural network is used to accurately identify pure third order systems. The neural network was validated by the computation of the Euclidean distance between the collectors and their models, depending on the number of learning steps. Finally it was shown that the neural networks are able to discriminate collectors that have close parameters: the proposed network identified a difference of two percent for one parameter.

f) Model of a solar thermal plant

Lopez-Baldan *et al.* (2002) presented an application of modelling and identification techniques for obtaining two fuzzy models of a solar domestic hot water system. The models have been generated in order to estimate the energy supplied by a thermal solar system and the output temperature of the water, respectively. The methods have been applied by using only the experimental input/output data taken from the process.

5.2 Photovoltaic Systems

a) Peak power tracking for PV supplied dc motors

Veerachary and Yadaiah (2000) applied an ANN for the identification of the optimal operating point of a PV water pumping system. A gradient descent algorithm is used to train the ANN controller for the identification of the maximum power point of a solar cell array and gross mechanical energy operation of the combined system. The input parameter to the neural network is solar insolation and the output parameter is the converter chopping ratio corresponding to the maximum power output of the PV cells or gross mechanical energy output of the combined PV system. The error in the ANN predictions is less than 2% for centrifugal and 7% for volumetric pump loads respectively. According to the authors the ANN provides a highly accurate identification/tracking of optimal operating points even with stochastically varying solar insolation.

5.3. Solar Radiation and Wind Speed Prediction

a) Prediction of maximum solar radiation

The prediction of solar radiation is very important for many solar applications. This is particularly important in solar electric generating systems, where accurate predictions of solar radiation allow for a better planning of the operation of an auxiliary system, especially in cases where steam boilers that require many hours to warm-up are used.

Due to the very nature of solar radiation, many parameters can influence both its intensity and its availability and therefore it is difficult to employ analytical methods for such predictions. For this reason, multivariate prediction techniques are more suitable. In this respect, artificial neural networks are utilised due to their ability to be trained with past data in order to provide the required predictions.

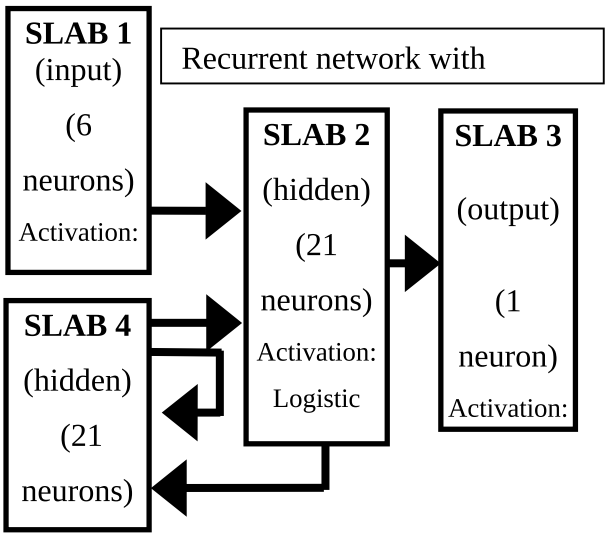
The input data that are used in the present approach are those which influence mostly the availability and intensity of solar radiation, namely, the month, day of month, Julian day, season, mean ambient temperature and mean relative humidity (RH). For example, increased value of relative humidity may mean either increased moisture in the atmosphere or cloudiness, both leading to a reduction of available radiation. Additionally, the input data, i.e. mean temperature and RH can be predicted with other statistical or analytical methods and used in the present modelling approach.

A multilayer recurrent architecture employing the standard back-propagation learning algorithm has been applied as shown in Fig. 9. This methodology is considered suitable for time series predictions. Using the hourly records for one complete year, the maximum value of radiation and the mean daily values of temperature and relative humidity (RH) were calculated. The respective data for 11 months were used for the training and testing of the network, whereas the data for the remaining one month, consisting of values for the first two weeks of July and the last two weeks of December, were used for the validation of the network.

The training of the network was performed with adequate accuracy. Subsequently, the “unknown” validation data set produced very accurate predictions, with a correlation coefficient between the actual and the ANN predicted data of 0.9867. Also, the sensitivity of the predictions to ±20% variation in temperature and RH give correlation coefficients of 0.9858 to 0.9875, which are considered satisfactory (Kalogirou *et al.*, 2002). This is considered as an adequate accuracy for such predictions.

As the Meteorological Service collects more data in the coming years, these will be used to retrain the network so as to produce a useful operational tool for radiation prediction. It is anticipated that this prediction methodology will be improved further, as the training database expands covering more unusual cases.

Fig. 9 multilayer recurrent architecture



b) Determination of solar irradiance

Negnevitsky and Le (1995) combined an expert system and an ANN for the evaluation of the thermal rating and temperature rise of overhead power lines. The ANN has been used to determine the hourly solar irradiance depending on astronomic and meteoroclimatic conditions.

c) Prediction of global radiation in locations with no direct measurement instrumentation

Alawi and Hinai (1998) have used ANNs to predict solar radiation in areas not covered by direct measurement instrumentation. The input data to the network are the location, month, mean pressure, mean temperature, mean vapour pressure, mean relative humidity, mean wind speed and mean duration of sunshine. The ANN model predicts solar radiation with an accuracy of 93% and mean absolute percentage error of 7.3.

d) Estimation of global solar radiation
Mohandes *et al.* (1998) used data from 41 collection stations in Saudi Arabia. From these data for 31 stations were used to train a neural network and the data for the other 10 for testing the network. The input values to the network are latitude, longitude, altitude and sunshine duration. The results for the testing stations obtained are within 16.4% and indicate the viability of this approach for spatial modelling of solar radiation.

e) Daily insolation forecasting
Kemmoku *et al.* (1999) used a multistage ANN to predict the insolation of the next day. The input data to the network are the average atmospheric pressure, predicted by another ANN, and various weather data of the previous day. The results obtained shown a prediction accuracy of 20%.

f) Solar resource estimation
Reddy and Ranjan (2003) used Artificial Neural Network based models for estimation of monthly mean daily and hourly values of solar global radiation. Solar radiation data from 13 stations spread over India around the year have been used for training and testing the ANN. The solar radiation data from 11 locations (six from South India and five from North India) were used for training the neural networks and data from the remaining two locations (one from South India and one from North India) were used for testing the estimated values. The results of the ANN model have been compared with other empirical regression models. The solar radiation estimations by ANN are in good agreement with the actual values and are superior to those of other available models. The maximum mean absolute relative deviation of predicted hourly global radiation tested is 4.07%. The results indicate that the ANN model shows promise for evaluating solar global radiation possibilities at the places where monitoring stations are not established.

g) Solar energy potential
Sozen *et al.* (2005) presented a new formula based on meteorological and geographical data was developed to determine the solar-energy potential in Turkey using artificial neural-networks (ANNs). Scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) learning algorithms and a logistic sigmoid transfer function were used in the network. Meteorological data for four years (2000-2003) from 18 cities spread over Turkey were used as data in order to train the neural network, shown in Fig. 10. Meteorological and geographical data (latitude, longitude, altitude, month, mean sunshine duration, and mean temperature) were used in the input layer of the network. Solar radiation is the output parameter. One-month test data for each city was used, and these month data were not used for training. The ANN models show greater accuracy for evaluating solar-resource possibilities in regions where a network of monitoring stations has not been established in Turkey. This study confirms the ability of the ANN to predict solar-radiation values precisely.

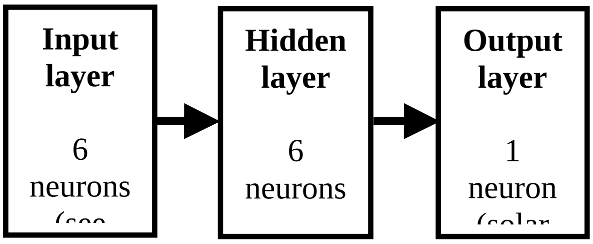


Fig. 10 Neural network architecture for estimating solar radiation

h) Forecast of solar irradiance
Cao and Cao (2005) used artificial neural network combined with wavelet analysis for the forecast of solar irradiance. This method is characteristic of the pre-processing of sample data using wavelet transformation for the forecast, i.e., the data sequence of solar irradiance as the sample is first mapped into several time-frequency domains, and then a recurrent BP network is established for each domain. The forecasted solar irradiance is exactly the algebraic sum of all the forecasted components obtained by the respective networks, which correspond respectively to the time-frequency domains. Discount coefficients are applied to take account of different effect of different time-step on the accuracy of the ultimate forecast when updating the weights and biases of the networks in network training. On the basis of combination of recurrent BP networks and wavelet analysis, a model is developed for more accurate forecasts of solar irradiance. An example of the forecast of day-by-day solar irradiance is presented, the historical day-by-day records of solar irradiance in Shanghai constituting the data sample. The results show that the accuracy of the method is more satisfactory than that of the methods reported before.

i) Wind speed prediction
A suitable artificial neural network was trained to predict the mean monthly wind speed in regions of Cyprus where data are not available. Data for the

period 1986-1996 (11 years) have been used to train the network whereas data for the year 1997 were used for validation. Both learning and prediction were performed with an acceptable accuracy. Two multilayered artificial neural network architectures of the same type have been tried one with five neurons in the input layer (month, wind speed at 2m and 7m for two stations) and one with eleven. The additional input data for the 11-inputs network are the x and y coordinates of the meteorological stations. The 5-inputs network proved to be more successful in the prediction of the mean wind speed.

A comparison of the mean wind speed at the two levels (2m and 7m) for the two networks is shown in Table 3. As can be the network using only 5 input parameters is more successful, giving a maximum percentage difference of only 1.8% (Kalogirou *et al.,* 1999d).

Table 3 Maximum percentage differences of the annual results of the two networks

<table>
<tr><th rowspan="2">Network</th><th colspan="2">Mean wind speed (Actual)</th><th colspan="2">Mean wind speed (ANN predicted)</th><th colspan="2">% difference</th></tr>
<tr><th>H= 2m</th><th>H= 7m</th><th>H= 2m</th><th>H= 7m</th><th>H= 2m</th><th>H= 7m</th></tr>
<tr><td>11-input neurons</td><td rowspan="2">2.4</td><td rowspan="2">3.35</td><td>2.43</td><td>3.52</td><td>1.2</td><td>5</td></tr>
<tr><td>5-input neurons</td><td>2.4</td><td>3.41</td><td>0</td><td>1.8</td></tr>
</table>

The two networks can be used for different types of jobs, i.e., the network having five inputs can be used to fill missing data from a database whereas the one having eleven inputs can be used for predicting mean wind speed in other nearby locations. In the former, the station can be located within the area marked by the three stations (interpolation) or outside (extrapolation).

5.4 Optimisation of buildings

a) Optimisation of building thermal design and control

Wright *et al.* (2002) showed that the design of buildings is a multi-criterion optimization problem where there is always a trade-off that needs to be made between capital expenditure, operating cost, and occupant thermal comfort. This paper investigates the application of a multi-objective genetic algorithm (MOGA) search method in the identification of the optimum pay-off characteristic between the energy cost of a building and the occupant thermal discomfort. Results are presented for the pay-off characteristics between energy cost and zone thermal comfort, for three design days and three building weights. Inspection of the solutions indicates that the MOGA is able to find the optimum pay-off characteristic between the daily energy cost and zone thermal comfort. It can be concluded that multi-criterion genetic algorithm search methods offer great potential for the identification of the pay-off between the elements of building thermal design, and as such can help the building design process.

5.5 Naturally ventilated buildings

a) Predicting air flow in a naturally ventilated test room

The air flow distribution inside a lightweight test room, which is naturally ventilated was predicted using artificial neural networks (Kalogirou *et al.*, 1999). The test room is situated in a relatively sheltered location and is ventilated through adjustable louvres. Indoor air temperature and velocity are measured at four locations and six different levels. The outside local temperature, relative humidity, wind velocity and direction are also monitored. The collected data are used to predict the airflow across the test room. Experimental data from a total of 32 trials have been collected. Data for 28 of these were used for the training of the neural network whereas the data for 4 trials were used for validation of the network. The data were recorded at 2 minutes intervals and the length of each trial varied but were generally 12 hours duration (Kalogirou *et al.*, 1999c). A multi layer feedforward neural network was employed with three hidden slabs. Satisfactory results for the indoor temperature and combined velocity have been obtained when unknown data were used as input to the network. A comparison between the actual and the ANN predicted data for the indoor air temperature are shown in Fig. 11.

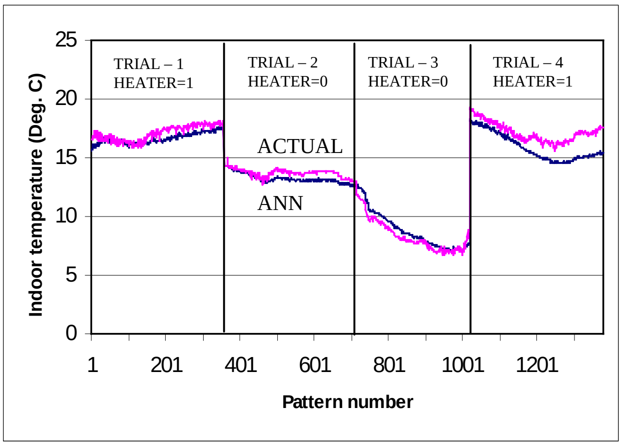


Fig. 11 Comparison between actual and ANN predicted data for indoor air temperature

b) Control in naturally ventilated buildings for summer conditions

Eftekhari and Marjanovic (2003) developed a fuzzy controller for naturally ventilated buildings. The process of designing a supervisory control to provide thermal comfort and adequate air distribution inside a single-sided naturally ventilated test room is described. The controller is based on fuzzy logic reasoning and sets of linguistic rules in forms of IF-THEN rules are used. The inputs to the controller are the outside wind velocity, direction, outside and inside temperatures. The output is the position of the opening. A selection of membership functions for input and output variables are described and analysed. The control strategy consisting of the expert rules is then validated using experimental data from a naturally ventilated test room. The test room is located in a sheltered area and air flow inside the room, the air pressures and velocities across the openings together with indoor air temperature and velocity at four locations and six different levels were measured. Validation of the controller is performed in the test room by measuring the air distribution and thermal comfort inside the room with no control action. These data are then compared to the air temperature and velocity with the controller in action. The initial results presented show that the controller is capable of providing better thermal comfort inside the room.

6 Conclusions

From the above system descriptions one can see that ANNs, GAs and fuzzy systems have been applied in a wide range of fields for modelling and prediction in renewable energy systems. What is required for setting up such systems is data that represents the past history and performance of the real system and a suitable selection of AI model. The selection of this model is done empirically and after testing various alternative solutions. The performance of the selected models is tested with the data of the past history and performance of the real system.

Surely the number of applications presented here is neither complete nor exhaustive but merely a sample of applications that demonstrate the usefulness of artificial intelligence models. Artificial intelligence models like all other approximation 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 work presented here it is believed that AI offers an alternative method which should not be underestimated.

References:

[1]Alawi S.M. and Hinai H.A. An ANN-Based Approach for Predicting Global Radiation in Locations with No Direct Measurement Instrumentation. *Renewable Energy*, Vol. 14, No. 1-4, 1998, pp. 199-204.

[2]Cao, S. and Cao, J., Forecast of solar irradiance using recurrent neural networks combined with wavelet analysis, *Applied Thermal Engineering*, Vol. 25, No. 2-3, 2005, pp. 161-172.

[3]Davis L. Handbook of Genetic Algorithms. New York, Van Nostrand, 1991.

[4]Eftekhari M.M. and Marjanovic L.D., Application of fuzzy control in naturally ventilated buildings for summer conditions, *Energy and Buildings*, Vol. 35, No. 7, 2003, pp. 645-655.

[5]Goldberg DE. *Genetic Algorithms in Search Optimization and Machine Learning*. Reading, MA, Addison-Wesley, 1989.

[6]Haykin S. *Neural Networks: A Comprehensive Foundation*, Macmillan, New York, 1994.

[7]Kalogirou S.A. and Panteliou S. Dynamic System Testing Method and Artificial Neural Networks for Solar Water Heater Long-Term Performance Prediction, *Proceedings of the European Symposium on Intelligent Techniques ESIT'99 on CD-ROM*, Crete, Greece, 1999.

[8]Kalogirou S.A., Panteliou S. and Dentsoras A. Modelling of Solar Domestic Water Heating Systems Using Artificial Neural Networks, *Solar Energy,* Vol. 65, No. 6, 1999a, pp. 335-342.

[9]Kalogirou S.A., Panteliou S., and Dentsoras A. Artificial Neural Networks used for the Performance Prediction of a Thermosyphon Solar Water Heater, *Renewable Energy*, Vol. 18, No. 1, 1999b, pp. 87-99.

[10]Kalogirou S., Eftekhari M. and Pinnock D. Prediction of Air Flow in a Single-Sided Naturally Ventilated Test Room Using Artificial Neural Networks. *Proceedings of Indoor Air'99, The 8th International Conference on Indoor Air Quality and*

Climate, Edinburgh, Scotland, Vol. 2, 1999c, pp. 975-980.

[11]Kalogirou S.A., Neocleous C., Paschiardis S. and Schizas C. Wind Speed Prediction Using Artificial Neural Networks, *Proceedings of the European Symposium on Intelligent Techniques ESIT'99* on CD-ROM, Crete, Greece, 1999d.

[12]Kalogirou, S.A. and Panteliou, S. Thermosyphon Solar Domestic Water Heating Systems Long-Term Performance Prediction Using Artificial Neural Networks. *Solar Energy*, Vol. 69, No. 2, 2000, pp. 163-174.

[13]Kalogirou S.A. Forced Circulation Solar Domestic Water Heating Systems Long-Term Performance Prediction Using Artificial Neural Networks. *Applied Energy,* Vol. 66, No. 1, 2000, pp. 63-74.

[14]Kalogirou S.A. Application of Artificial Neural Networks for Energy Systems, *Applied Energy*, Vol. 67, No. 1-2, 2001, pp. 17-35.

[15]Kalogirou, S., Michaelides, S. and Tymvios, F., 2002. Prediction of Maximum Solar Radiation Using Artificial Neural Networks, *Proceedings of the World Renewable Energy Congress VII on CD-ROM*, Cologne, Germany.

[16]Kemmoku Y., Orita S., Nakagawa S. and Sakakibara T. Daily Insolation Forecasting Using a Multi-Stage Neural Network, *Solar Energy*, Vol. 66, No. 3, 1999, pp. 193-199.

[17]Lalot S. Identification of the Time Parameters of Solar Collectors Using Artificial Neural Networks, *Proceedings of Eurosun 2000* on CD-ROM, 2000.

[18]Lopez-Baldan, M.J., Garcia-Cerezo, A., Lopez, J.M.C. and Gallero, A.R., Fuzzy modelling of a solar thermal plant, *International Journal of Intelligent Systems*, Vol. 17, No. 4, 2002, pp. 369-379.

[19]Mamdani EH. Application of fuzzy algorithms for control of simple dynamic plant. IEE proceedings, Vol. 121, 1974, pp. 1585-1588.

[20]Michalewicz Z. *Genetic algorithms+Data Structures=Evolution Programs*. (3^{rd} Ed.), Springer, Berlin, 1996.

[21]Mohandes M., Rehman S. and Halawani T.O. Estimation of Global Solar Radiation Using Artificial Neural Networks, *Renewable Energy*, Vol. 14, No. 1-4, 1998, pp. 179-184.

[22]Nannariello J, Frike FR. Introduction to neural network analysis and its applications to building services engineering. *Building Services Engineering Research & Technology*, Vol. 22, No. 1, 2001, pp. 58-68.

[23]Negnevitsky M. and Le T.L. Artificial Neural Networks Application for Current Rating of Overhead Lines. *IEEE Trans. on Neural Networks*, 1995, pp. 418-422.

[24]Nie J. and Linkens DA. *Fuzzy-Neural Control: Principles, Algorithms and Applications*. Prentice Hall. 1995.

[25]Reddy K.S. and Ranjan M., Solar resource estimation using artificial nueral networks and comparison with other correlation models, *Energy Conversion and Management*, Vol. 44, No. 15, 2003, pp. 2519-2530.

[26]Reznik L. *Fuzzy Controllers*. Newnes, Oxford. 1997.

[27]Rumelhart D.E., Hinton G.E.and Williams R.J. Learning Internal Representations by Error Propagation. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, Vol. 1, Chapter 8, Cambridge, MA, MIT Press, 1986.

[28]Sozen, A., Arcaklioglu, E., Ozalp, M. and Kanit, E.G., Solar-energy potential in Turkey, *Applied Energy,* Vol. 80, No. 4, 2005, pp. 367-381.

[29]Sugeno M. Industrial Applications of Fuzzy Control. Amsterdam: North-Holland. 1985.

[30]Veerachary M. and Yadaiah N. ANN Based Peak Power Tracking for PV Supplied dc Motors, *Solar Energy,* Vol. 69, No. 4, 2000, pp. 343-350.

[31]Werbos P.J. *Beyond Regression: New Tools for Prediction and Analysis in the behavioural Science*, PhD Thesis, Harvard University, Cambridge, MA, 1974.

[32]Wright J.A., Loosemore H.A. and Farmani R., Optimisation of building thermal design and control by multi-criterion genetic algorithm, *Energy and Building*, Vol. 34, No. 9, 2002, pp. 959-972.

[33]Zalzala A, Fleming P. *Genetic Algorithms in Engineering Systems.* The Institution of Electrical Engineers, London, UK, 1997.

[34]Zadeh LA. Outline of a new approach to the analysis of complex systems and decision processes. *IEEE Trans. Syst. Man Cyber.* Vol. 3, 1973, pp. 28-44.