# Artificial neural networks in energy applications in buildings

Soteris A. Kalogirou
*Higher Technical Institute, P. O. Box 20423, Nicosia 2152, CYPRUS*
*Tel. +357-22-406466, Fax. +357-22-406480*
*E-mail: skalogir@spidernet.com.cy*

**Abstract** Artificial neural networks (ANNs) are nowadays accepted as an alternative technology offering a way to tackle complex and ill-defined problems. They are not programmed in the traditional way but they are trained using past history data representing the behaviour of a system. They have been used in a number of diverse applications. Results presented in this paper are testimony to the potential of artificial neural networks as a design tool in many areas of building services engineering.

**Keywords** artificial neural networks; energy prediction; building applications

## 1. Introduction

For the estimation of the flow of energy and the performance of energy systems in buildings, 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 building energy systems being inherently noisy are good candidate problems to be handled with artificial neural networks.

When dealing with research and design associated with energy in buildings there are often difficulties encountered in handling situations where there are many variables involved. To adequately model and predict the behaviour of building energy systems requires consideration of nonlinear multivariate inter-relationships, often in a 'noisy' environment. For example, for the prediction of performance of a building energy 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, the performance of a building energy system depends on the environmental conditions such as solar radiation and wind speed, the direction, strength and duration of which are highly variable.

Many of the building energy systems are exactly the types of problems and issues for which the artificial neural network (ANN) approach appear to be most applicable. In these computational models 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 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.

ANN 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. ANN 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 ANNs and to present various applications in energy applications in buildings. The applications are presented in a thematic rather than a chronological or any other order. This will show the capability of ANNs as tools in building energy systems prediction and modelling.

## 2. Artificial neural networks

The concept of neural network analysis was 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 literatures and will not be covered in this paper except for a very brief overview of how neural networks operate. 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, 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.

Artificial neural network 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 [1].

The best example of a neural network is probably the human brain. In fact, the human brain is the most complex and powerful structure known today. Artificial neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. A schematic diagram of typical multilayer feed-forward neural network architecture is shown in Fig. 1. Although two hidden layers are shown, their number can be one or more than two, depending on the problem examined. In its simple form, each single neuron is connected to all 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 functions to determine the output of that neuron. 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).

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

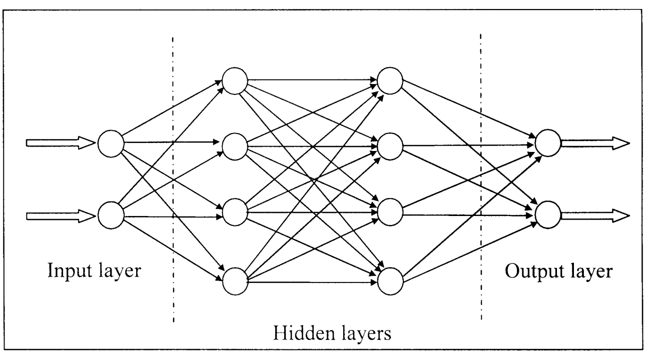


Figure 1. *Schematic diagram of a fully connected multilayer feed-forward neural network.*

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.

The most popular learning algorithms are the back-propagation and its variants [1, 2]. The Back-Propagation (BP) algorithm is one of the most powerful learning algorithms in neural networks. 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 on the BP algorithm can be found in [3]. 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.

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 and 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, number of neurons in each hidden layer and the activation function/s. This is a laborious and time-consuming method. As experience is gathered some parameters can be predicted easily thus shortening tremendously the time required. A procedure for the selection of the different network parameters is given in [4].

## 3. Applications of ANNs in energy applications in buildings

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

### 3.1 Solar water heating systems

The first application of ANNs in this category deals with the performance prediction of a thermosyphon solar domestic water heating systems. A multi-layer feed-forward ANN has been trained using performance data for four types of systems, all employing the same collector panel under varying weather conditions [5]. 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.

In another application the long-term performance prediction of solar domestic water heating systems is presented [6]. 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. From these, data for twenty-seven systems were used for training and testing the network while data for the remaining three were used for validation. Two multi-layer feed-forward 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.

A similar approach was followed for the long-term performance prediction of three forced circulation type solar domestic water heating (SDWH) systems [7]. The maximum percentage differences obtained when unknown data were used, were 1.9% and 5.5% for the two networks respectively.

## 3.2 Solar radiation and wind speed prediction

### *3.2.1 Prediction of solar radiation*

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.

The first application in this category deals with the prediction of the maximum solar radiation [8]. In this work, artificial neural networks are utilised due to their ability to be trained with past data and 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).

A multilayer recurrent architecture employing the standard back-propagation learning algorithm has been applied. 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 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 predictions to ±20% variation in temperature and RH give correlation coefficients of 0.9858 to 0.9875 respectively, which are considered satisfactory. This is considered as an adequate accuracy for such predictions.

Alawi and Hinai [9] 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.

Mohandes *et al.* [10] used data from 41 collection stations in Saudi Arabia together with an ANN for the estimation of global solar radiation. 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.

Kemmoku *et al.* [11] used a multistage ANN to forecast the daily 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%.

Reddy and Ranjan [12] used ANN based models for the estimation of monthly mean daily and hourly values of solar global radiation. Solar radiation data from 13 stations spread over India 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 network. 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 deviation of predicted hourly global radiation is 4.1%. The results indicate that the ANN model shows promise for evaluating solar global radiation at the places where monitoring stations are not established.

Sozen *et al.* [13] presented a new formula, based on meteorological and geographical data, developed to determine the solar-energy potential in Turkey using 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 training data of the neural network, shown in Fig. 2. 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 were used for validation of the network. These data were not used for training. This study confirms the ability of the ANN to predict solar-radiation values precisely.

In another study Sozen *et al.* [14] have used meteorological data for last three years (2000–2002) from 17 stations (namely cities) spread over Turkey used for training (11 stations) and testing (6 stations). The cities selected can give a general idea about solar radiation in Turkey. Meteorological and geographical data (latitude, longitude, altitude, month, mean sunshine duration, and mean temperature) are used in the input layer of the network. Solar radiation is the output parameter. The maximum mean absolute percentage error was found to be less than 6.7% and $R^2$ values to be about 0.9989 for the testing stations. The results indicate that the ANN model seems promising for evaluating solar resource possibilities at the places where there are no monitoring stations. The results on the testing stations indicate a relatively good agreement between the observed and the predicted values. In another study Sozen *et al.* [15] have used the ANN predicted solar potential values to construct monthly radiation maps in Turkey. These maps are of prime importance for different working disciplines like, scientists, architects, meteorologists and solar

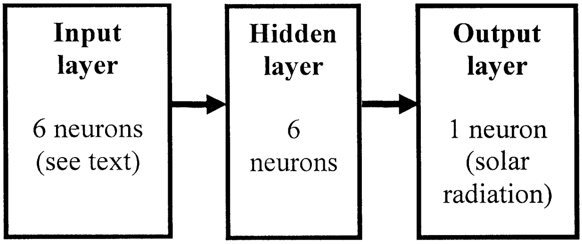


Figure 2. *Neural network architecture for estimating solar radiation.*

engineers. The predictions from the ANN models could enable scientists to locate and design solar energy systems and determine the best solar technology.

Cao and Cao [16] 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 the different effects of different time-step on the accuracy of the forecast when updating the weights and biases of the networks during network training. On the basis of combination of recurrent backpropagation 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, in which a data sample of the historical day-by-day records of solar irradiance in Shanghai was used. The results show that the accuracy of the method is more satisfactory than that of other methods.

Soares *et al.* [17] used a perceptron neural-network technique to estimate hourly values of the diffuse solar-radiation in Sao Paulo City, Brazil, using as input the global solar-radiation and other meteorological parameters measured from 1998 to 2001. The neural network verification was performed using the hourly measurements of diffuse solar-radiation obtained during the year 2002. The neural network was developed based on both feature determination and pattern selection techniques. 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.

Lopez *et al.* [18] used the Bayesian framework for ANN, called automatic relevance determination method (ARD) to obtain the relative relevance of a large set of atmospheric and radiometric variables used for estimating hourly direct solar irradiance. In addition, the viability of this novel technique, applied to select the optimum input parameters to the neural network, was analysed. A multi-layer feed-forward perceptron was trained. The results reflect the relative importance of the inputs selected. Clearness index and relative air mass were found to be the more relevant input variables to the neural network, as it was expected, proving the reliability of the ARD method. Moreover, the authors showed that this novel methodology can be used in unfavourable conditions, in terms of limited amount of available data, providing successful results.

### *3.2.2 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

Table 1. *Maximum percentage differences of the annual results of the two networks*

| | Mean wind speed (Actual) | | Mean wind speed (ANN predicted) | | % difference | |
|---|---|---|---|---|---|---|
| Network | H-2m | H-7m | H-2m | H-7m | H-2m | H-7m |
| 11-input neurons | 2.4 | 3.35 | 2.43 | 3.52 | 1.2 | 5 |
| 5-input neurons | | | 2.4 | 3.41 | 0 | 1.8 |

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 2 m and 7 m 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 (2 m and 7 m) for the two networks is shown in Table 1. As can be seen the network using only 5 input parameters is more successful, giving a maximum percentage difference of only 1.8% [19].

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 latter, the station can be located within the area marked by the three stations (interpolation) or outside (extrapolation).

### 3.3 Naturally ventilated buildings

The air flow distribution inside a lightweight test room, which is naturally ventilated, was predicted using artificial neural networks [20]. 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 is 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 was recorded at 2 minute intervals and the length of each trial varied but were generally 12 hours in duration. 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 was 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. 3.

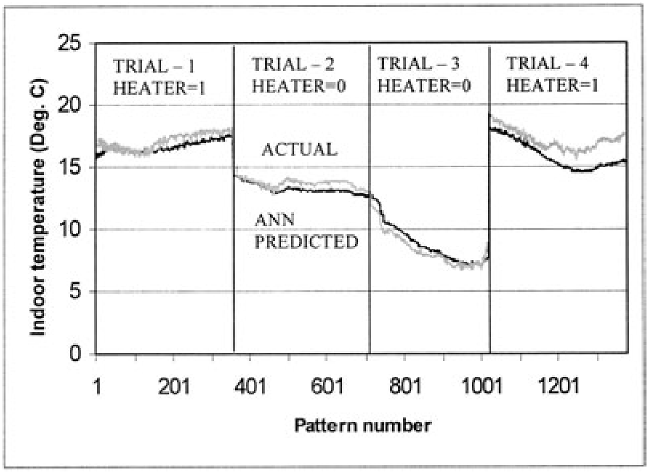


Figure 3. *Comparison between actual and ANN predicted data for indoor air temperature.*

### 3.4 Energy consumption and conservation

#### *3.4.1 Heating and cooling loads estimation*

The first application in this area deals with the heating load estimation. The objective of this work is to train an artificial neural network (ANN) to learn to predict the required heating load of buildings with the minimum of input data [21]. An ANN has been trained based on 250 known cases of heating load, varying from very small rooms (1–2 $m^2$) to large spaces of 100 $m^2$ floor area. The type of rooms varied from small toilets to large classroom halls, while the room temperatures varied from 18°C to 23°C. In addition to the above, an attempt was made to use a large variety of room characteristics. In this way the network was trained to accept and handle a number of unusual cases. The data presented as input were, the areas of windows, walls, partitions and floors, the type of windows and walls, the classification on whether the space has roof or ceiling, and the designed room temperature. The network output is the heating load. Preliminary results on the training of the network showed that the accuracy of the prediction could be improved by grouping the input data into two categories, one with spaces of floor areas up to 7 $m^2$ and another with floor areas from 7 to 100 $m^2$. The statistical $R^2$-value for the training data set was equal to 0.9880 for the first case and 0.9990 for the second. Unknown data were subsequently used to investigate the accuracy of prediction. Predictions within 10% for the first group and 9% for the second were obtained. These results indicate that the proposed method can successfully be used for the prediction of the heating load of a building. The advantages of this approach compared to the conventional algorithmic methods are (i) the speed of calculation, (ii) the simplicity, and (iii) the capacity of the network to learn from examples and thus gradually improve its performance. This is done by embedding experiential knowledge in the network and thus the appropriate U-values are considered. Such an approach is very useful for countries where accurate thermal properties of building materials are not readily available.

In another application the daily heating and cooling loads were estimated with ANNs. Initially the daily loads of nine different building structures have been estimated using the TRNSYS program and a typical meteorological year of Cyprus. This set of data has been used to train a neural network [22]. For each day of the year the maximum and minimum loads were obtained from which heating or cooling loads can be determined. All the buildings considered had the same areas but different structural characteristics. Single and double walls have been considered as well as a number of different roof insulations. A multi-slab feedforward architecture having 3 hidden slabs has been employed. Each hidden slab comprised of 36 neurons. For the 'training data set' the $R^2$-values obtained were 0.9896 and 0.9918 for the maximum and minimum loads respectively. The method was validated by using actual (modeled) data for one building, for all days of the year, which the network has not seen before. The $R^2$-values obtained in this case are 0.9885 and 0.9905 for the two types of loads respectively. The results indicate that the proposed method can be used for the required predictions for buildings of different constructions. At present the method was used primarily to investigate its suitability for this kind of predictions.

Ben-Nakhi and Mahmoud [23] used general regression neural networks (GRNN) designed and trained to investigate the feasibility of using this technology to optimize HVAC thermal energy storage in public buildings as well as office buildings. The state of the art building simulation software, ESP-r, was used to generate a database covering the years 1997–2001. The software was used to calculate hourly cooling loads for three office buildings using climate records in Kuwait. The cooling load data for 1997–2000 was used for training and testing the ANN, while the robustness of the trained ANN was tested by applying them to a validation data set (year 2001) that the networks have never seen before. Three buildings of various densities of occupancy and orientational characteristics were investigated. Parametric studies were performed to determine the optimum GRNN design parameters that best predict cooling load profiles for each building. External hourly temperature readings for a 24 hour period were used as network inputs, and the hourly cooling load for the next day is the output. The performance of the ANN analysis was evaluated using $R^2$-value and by statistical analysis of the error patterns, including confidence intervals of regression lines, as well as by examination of the error patterns. The results show that a properly designed ANN is a powerful instrument for optimizing thermal energy storage in buildings based only on external temperature records.

### *3.4.2 Prediction of the indoor air temperature*

Mechaqrane and Zouak [24] used a neural network auto regressive with exogenous input (NNARX) model to predict the indoor temperature of a residential building. Firstly, the optimal regressor of a linear ARX model is identified by minimising Akaike's final prediction error (FPE). This regressor is then used as the input vector of a fully connected feedforward neural network with one hidden layer of ten units and one output unit. Results show that the NNARX model outperforms the linear model considerably; the sum of the squared error (SSE) is 15.0479 with the ARX model and 2.0632 with the NNARX model. The optimal network topology is subsequently determined by pruning the fully connected network according to the optimal brain surgeon (OBS) strategy. With this procedure, nearly 73% of connections were removed and as a result, the performance of the network has been improved as the SSE was reduced to 0.9060.

### *3.4.3 Prediction of energy consumption*

Aydinalp *et al*. [25] used an ANN method to model residential end-use energy consumption at the national and regional level. It was found that the ANN is capable of accurately modelling the behaviour of the appliances, lighting, and space-cooling energy consumption in the residential sector. As a continuation of the work on the use of the ANN method for modelling residential end-use energy-consumption, two ANN based energy-consumption models were developed to estimate the space and domestic hot-water heating energy consumptions in the Canadian residential sector.

Michalakakou *et al.* [26] used a neural network approach for the modelling and estimation of the energy consumption time series for a residential building in Athens. The inputs used are several climatic parameters. The hourly values of the energy consumption, for heating and cooling the building, were estimated for several years using feed forward back propagation neural networks. Various neural network architectures were designed and trained for the output estimation, which is the building's energy consumption. The results are tested with extensive sets of non-training measurements and it is found that they correspond well with the actual values. Furthermore, 'multi-lag' output predictions of ambient air temperature and total solar radiation were used as inputs to the neural network models for modelling and predicting the future values of energy consumption with sufficient accuracy.

## 3.5 Heating, ventilating and air conditioning systems

The first application in this category deals with the model of discharge air temperature system. Zaheer-uddin and Tudoroiu [27] developed a nonlinear neuro-model of a discharge air temperature (DAT) system. Experimental data gathered in a heating, ventilating and air conditioning (HVAC) test facility were used to develop multi-input multi-output (MIMO) and single-input single-output (SISO) neuro-models of a cooling coil. Results show that a three layer second order neural network structure is necessary to achieve good accuracy of the predictions.

In another application, Yang *et al.* [28] presented an application of the ANN in a building control system. The objective of this study is to develop an optimized ANN model to determine the optimal start time for a heating system in a building. For this, programs for predicting the room air temperature and the learning of the ANN model based on back propagation algorithm were developed. Learning data for various building conditions were collected through program simulation for predicting the room air temperature.

Lee *et al.* [29] described a scheme for on-line fault detection and diagnosis (FDD) at the subsystem level in an Air-Handling Unit (AHU). The approach consists of the process estimation, the residual generation, and the fault detection and diagnosis. The schematic of the system is shown in Fig. 4. Residuals are generated using general regression neural-network (GRNN) models. The GRNN is a regression technique and uses a memory-based feed forward network to produce estimates of continuous variables. The main advantage of the GRNN is that no mathematical model is needed to estimate the system. Also, the inherent parallel structure of the GRNN algorithm makes it attractive for the real-time fault detection and diagnosis. Several abrupt and performance degradation faults were considered. Because performance degradations are difficult to introduce artificially in real or experimental systems, simulation data are used to evaluate the method. The simulation results show that the GRNN models are accurate and reliable estimators of highly non-linear and complex AHU processes, and demonstrate the effectiveness of the proposed method for detecting and diagnosing faults in an AHU.

Ben-Nakhi and Mahmoud [30] used general regression neural networks (GRNNs) to optimize the air conditioning setback scheduling in public buildings. To save energy, the temperature inside these buildings is allowed to rise after business hours by setting back the thermostat. The objective is to predict the time of the end of thermostat setback (EoS) such that the design temperature inside the building is restored in time for the start of business hours. State-of-the-art building simulation software, ESP-r, was used to generate a database that covered the past 5 years. The software was used to calculate EoS for two office buildings using the climate records in Kuwait. The EoS data for 1995 and 1996 were used for training and testing the ANNs. The robustness of the trained ANNs was tested by applying them to a validation data set (1997–1999) which the networks have never seen before. A parametric study showed that the optimum GRNN design is one that uses a genetic adaptive algorithm, a so-called City Block distance metric, and a linear scaling function for the input data. External hourly temperature readings were used as network inputs, and the thermostat end of setback (EoS) is the output. The ANN predictions

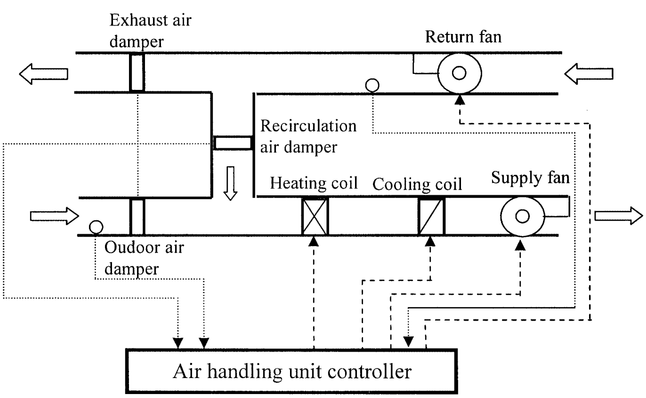


Figure 4. *AHU system diagrammatic.*

were improved by developing a neural control-scheme. This scheme is based on the use of the temperature readings as they become available. Six ANNs were designed and trained for this purpose. The performance of the ANN analysis was evaluated using $R^2$-value and by examination of the error patterns. The results show that the neural control-scheme is a powerful instrument for optimizing air conditioning setback scheduling based on external temperature records.

Gouda *et al.* [31] used ANNs for modelling the thermal dynamics of a building's space, its water heating system and the influence of solar radiation. A multi-layered feed-forward neural network using Levenberg-Marquardt backpropagation training algorithm, has been applied to predict the future internal temperature. Real weather data for a number of winter months, together with a validated model (based on the building construction data), were used to train the network in order to generate a mapping between the easily measurable inputs (outdoor temperature, solar irradiance, heating valve position and the building indoor temperature) and the desired output, i.e., the predicted indoor temperature. The objective of this work was to investigate the potential of using an ANN with singular value decomposition method (SVD), as shown in Fig. 5, to predict the indoor temperature to shut down the heating system controller early for saving the energy consumption for heating inside the building.

Zmeureanu [32] proposed a new approach for evaluating the Coefficient of Performance (COP) of existing rooftop units, using the General Regression Neural Networks. This approach reduces the installation cost of monitoring equipment since only a minimum number of sensors is needed and also reduces the costs for re-calibration or replacement of sensors during the operation. The new approach was developed and tested using measurements taken on two existing rooftop units in Montreal, Canada.

## 4. Conclusions

From the above system descriptions one can see that ANNs have been applied in a wide range of fields for modelling, prediction and control of building energy

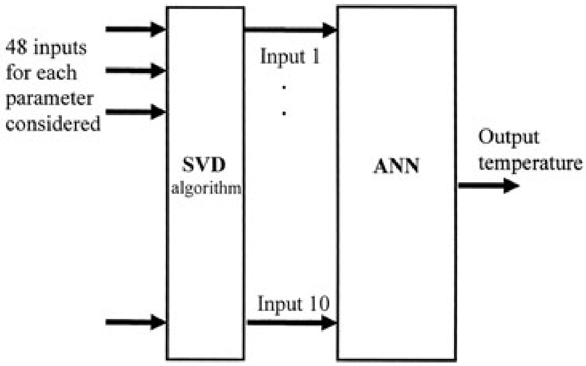


Figure 5. *Feed-forward neural network with SVD algorithm.*

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 ANN models. The selection of this model is done empirically and after testing various alternative solutions. The accuracy 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 ANN models. ANN 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 ANNs offers an alternative method which should not be underestimated.

## References

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

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

[3] S. A. Kalogirou, 'Application of Artificial Neural Networks for Energy Systems', *Applied Energy*, 67(1–2) (2001), 17–35.

[4] S. A. Kalogirou, 'Artificial Neural Networks in Renewable Energy Systems: A Review', *Renewable & Sustainable Energy Reviews*, 5(4) (2001), 373–401.

[5] S. A. Kalogirou, S. Panteliou and A. Dentsoras, 'Artificial Neural Networks used for the Performance Prediction of a Thermosyphon Solar Water Heater', *Renewable Energy*, 18(1) (1999), 87–99.

[6] S. A. Kalogirou and S. Panteliou, 'Thermosyphon Solar Domestic Water Heating Systems Long-Term Performance Prediction Using Artificial Neural Networks', *Solar Energy*, 69(2) (2000), 163–174.

[7] S. A. Kalogirou, 'Forced Circulation Solar Domestic Water Heating Systems Long-Term Performance Prediction Using Artificial Neural Networks', *Applied Energy*, 66(1) (2000), 63–74.

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

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

[10] M. Mohandes, S. Rehman and T. O. Halawani, 'Estimation of Global Solar Radiation Using Artificial Neural Networks', *Renewable Energy*, 14(1–4) (1998), 179–184.

[11] Y. Kemmoku, S. Orita, S. Nakagawa and T. Sakakibara, 'Daily Insolation Forecasting Using a Multi-Stage Neural Network', *Solar Energy*, 66(3) (1999), 193–199.

[12] K. S. Reddy and M. Ranjan, 'Solar resource estimation using artificial neural networks and comparison with other correlation models', *Energy Conversion and Management*, 44(15) (2003), 2519–2530.

[13] A. Sozen, E. Arcaklioglu, M. Ozalp and E. G. Kanit, 'Solar-energy potential in Turkey', *Applied Energy*, 80(4) (2005), 367–381.

[14] A. Sozen, M. Ozalp, E. Arcaklioglu and E. G. Kanit, 'A study for estimating solar resources of Turkey using artificial neural networks', *Energy Resources*, 26(14) (2004), 1369–1378.

[15] A. Sozen, E. Arcaklioglu and M. Ozalp, 'Estimation of solar potential in Turkey by artificial neural networks using meteorological and geographical data', *Energy Conversion and Management*, 45(18–19) (2004), 3033–3052.

[16] S. Cao and J. Cao, 'Forecast of solar irradiance using recurrent neural networks combined with wavelet analysis', *Applied Thermal Engineering*, 25(2–3) (2005), 161–172.

[17] J. Soares, A. P. Oliveira, M. Z. Boznar, P. Mlakar, J. F. Escobedo and A. J. Machado, 'Modelling hourly diffuse solar-radiation in the city of Sao Paulo using artificial neural-network technique', *Applied Energy*, 79(2) (2004), 201–214.

[18] G. Lopez, F. J. Batlles and J. Tovar-Pescador, 'Selection of input parameters to model direct solar irradiance by using artificial neural networks', *Energy*, 30(9) (2005), 1675–1684.

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

[20] S. A. Kalogirou, M. Eftekhari and D. Pinnock, '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, 2 (1999), 975–980.

[21] S. A. Kalogirou, C. Neocleous and C. Schizas, 'Artificial Neural Networks Used for Estimation of Building Heating Load', *Proceedings of the CLIMA 2000 International Conference*, Brussels, Belgium, Paper Number P159, (1997).

[22] S. A. Kalogirou, G. Florides, C. Neocleous and C. Schizas, 'Estimation of the Daily Heating and Cooling Loads Using Artificial Neural Networks', *Proceedings of CLIMA 2000 International Conference on CD-ROM*, Naples, Italy, (2001).

[23] A. E. Ben-Nakhi and M. A. Mahmoud, 'Cooling load prediction for buildings using general regression neural networks', *Energy Conversion and Management*, 45(13–14) (2004), 2127–2141.

[24] A. Mechaqrane and M. Zouak, 'A comparison of linear and neural network ARX models applied to a prediction of the indoor temperature of a building', *Neural Computing and Applications*, 13(1) (2004), 32–37.

[25] M. Aydinalp, V. I. Ugursal and A. S. Fung, 'Modelling of the space and domestic hot-water heating energy-consumption in the residential sector using neural networks', *Applied Energy*, 79(2) (2004), 159–178.

[26] G. Michalakakou, M. Santamouris and A. Tsagrassoulis, 'On the energy consumption in residential buildings', *Energy and Buildings*, 34(7) (2002), 727–736.

[27] M. Zaheer-uddin and N. Tudoroiu, 'Neuro-models for discharge air temperature system', *Energy Conversion and Management*, 45(6) (2004), 901–910.

[28] I. Yang, M. Yeo and K. Kim, 'Application of artificial neural network to predict the optimal start time for heating system in building', *Energy Conversion and Management*, 44(17) (2003), 2791–2809.

[29] W. Lee, J. M. House and N. Kyong, 'Subsystem level fault diagnosis of a building's air-handling unit using general regression neural networks', *Applied Energy*, 77(2) (2004), 153–170.

[30] A. E. Ben-Nakhi and M. A. Mahmoud, 'Energy conservation in buildings through efficient A/C control using neural networks', *Applied Energy*, 73(1) (2002), 5–23.

[31] M. M. Gouda, S. Danaher and C. P. Underwood, 'Application of artificial neural network for modelling the thermal dynamics of a building's space and its heating system', *Mathematical and Computer Modelling of Dynamical Systems*, 8(3) (2002), 333–344.

[32] R. Zmeureanu, 'Prediction of the COP of existing rooftop units using artificial neural networks and minimum number of sensors', *Energy*, 27(9) (2002), 889–904.