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RESEARCH PAPER ON ARTIFICIAL NEURAL NETWORKS IN ENERGY APPLICATIONS IN BUILDINGS

Salver Sruthilaya
Student
Department of CSE
St. Martin's Engineering college
Secundarabad, Telangana, India
sruthilaya.salver@gmail.com

Dr. G. Govinda Rajulu
Professor
Department of CSE
St. Martin's Engineering College
Secundarabad, Telangana, India
drgovindacsecse@smec.ac.in

Abstract-- Artificial neural networks (ANNs) are nowadays accepted as an alternative technology offering a way to tackle complexand 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 tobe handled with artificial neural networks. When dealing with research and design associated with energy in buildings there areoften 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 performanceof a building energy system depends on the environmental conditions such as solar radiationand 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 manipulateknowledge 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.

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

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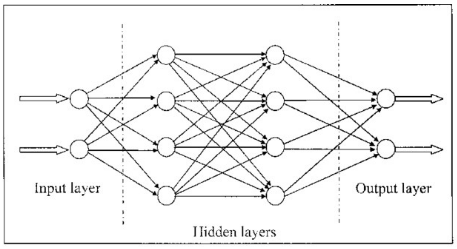
described in a large number of published literatures and will not be covered in this paper except for a very brief overview of how neural networks operate. ANNs have been applied successfully in various fields of mathematics, engineering, medicine, economics, meteorology,psychology, neurology, and many others. Some of the most important ones are; in pattern, sound and speech recognition, in the analysis ofelectromyographs and other medical signatures, in the identification of military targets and in theidentification 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. The best example of a neural network is probably thehuman brain. In fact, the human brain is themost 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 . Although two hidden layers areshown, 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 neuralsystems). 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 issupplied 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 outputvalue. 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 allthe input patterns, if the error is still greater thanthe maximum desired tolerance, the ANN runs again through all the input patterns repeatedly until all the Artificial neural networks in energy applications in buildings.



The most popular learning algorithms are the back-propagation and its variants . The Back-Propagation (BP) algorithm is one of the most powerful learning algorithms in neuralnetworks. Back-propagation training is agradient 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 . The training of allpatterns 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 outputare 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.

3. Applications of ANNs in energy applications in buildings:

ANN's have been used by various researchers and by the author for modelling and predictionin the field of energy systems in buildings. This field includes models for predicting solar radiation and wind, solar energy systems thatcan 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 feedforward ANN has been trained using performance data for four types of systems, all employing the same collector panel under varying weather conditions . 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 wereobtained for the two output parametersrespectively. Random data were also used both with the performance equations obtained from the experimental measurements and with the artificial neural network to predict the abovetwo 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. The first network was trained to estimate the solar energy output of thesystem (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 (Vd) at demand temperatures of 35°Cand 40°C. The input data in both networks are similar to the ones used in the program supplied with the

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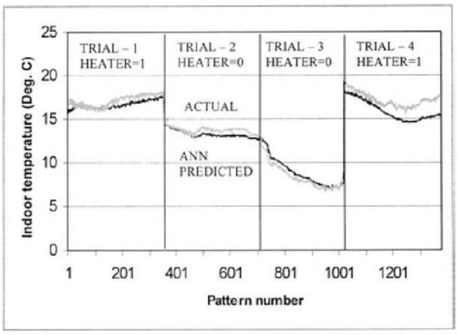

standard. These were the size and performance characteristics of each system and various climatic data. In the second network the demand temperature was also used as input. The statistical coefficient of multiple determination (R2 - value) obtained for the training data set was equal to 0.9993 for the 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 R2 - 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. The maximum percentage differences obtained when unknown data were used, were 1.9% and 5.5% for the two networks respectively.

3.2. Naturally ventilated buildings:

The air flow distribution inside a lightweighttest room, which is naturally ventilated, was predicted using artificial neural networks . 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 beencollected. 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 minuteintervals and the length of each trial varied but were generally 12 hours in duration. A multi layer feedforward neural network was employedwith three hidden slabs. Satisfactory results for the indoor temperature and combined velocity have been obtained when unknown data wasused as input to the network. A comparison between the actual and the ANN predicted data for the indoor air temperature are shown.

3.3. Prediction of energy consumption:

ANN method to model residential end-useenergy consumption at the national and regionallevel. 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 estimatethe space and domestic hot-water heating energy consumptions in the Canadian residential sector. 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, forheating and cooling the building, were estimatedfor several years using feed forward back propagation neural networks. Various neural network architectures were designed and trainedfor the output estimation, which is the building'senergy consumption. The results are tested with extensive sets of non-training measurements andit is found that they correspond well with the actual values. Furthermore, 'multilag' output predictions of ambient air temperature and total solar radiation were used as inputs to the neural network models for modelling and predictingthe future values of energy consumption with sufficient accuracy.

3.4. 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 m2) to large spaces of 100 m2 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 m2 and another with floor areas from 7 to 100 m2 . The statistical R2 -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.

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 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. Basedon the work presented here it is believed that ANNs offers an alternative method which should not be underestimated.

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