Applications of artificial neural-networks forenergy systems

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ABSTRACT

Artificial neural networks offer an alternative way to tackle complex and illdefined problems. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems, and once trained can perform predictions and generalisations at high speed. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimisation, signal processing, and social/psychological sciences. They are particularly useful in system modelling, such as in implementing complex mapping and system identification. This paper presents various applications of neural networks in energy problems in a thematic rather than a chronological or any other way. Errors reported when using these models arewell within acceptable limits, which clearly suggests that artificial neural-networks can be used for modelling in other fields of energy production and use. The work of other researchers in the field of energy is also reported. This includes the use of artificial neural-networks in heating, ventilating and air-conditioning systems, solar radiation, modelling and control of power-generation systems, load-forecasting and refrigeration

Keywords: Artificial neural-networks; System modelling; System-performance prediction

1. Introduction

For the estimation of the flow of energy and the performance of 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. Instead of complex rules and mathematical routines, artificial neural-networks are able to learn the key information patterns within a multi-dimensional information domain. In addition, neural-networks are fault-tolerant, robust and noise-immune [1]. Data from energy systems, being inherently noisy, are good candidate problems to be handled with neural networks. The objective of this paper is to present various applications of neural-networks in energy problems. The problems are presented in a thematic rather than a chron- ological (or any other) way. This will show the capability of artificial neural networks as tools in energy-prediction and modelling

2. Artificial neural-networks

The study of artificial neural-networks (ANNs) is one of the two major branches of artificial intelligence. The other one is expert systems. During the last decade, there has been a substantial increase in interest concerning artificial neural-networks.

The ANNs are good for some tasks, while lacking in some others. Specifically, they are good for tasks involving incomplete-data sets, fuzzy or incomplete infor- mation, 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 withnon-linear problems. Furthermore, they exhibit robustness and fault-tolerance. Thetasks that ANNs cannot handle effectively are those requiring high accuracy and pre- cision, as in logic and arithmetic. ANNs have been applied successfully to a number ofapplications. Some of the most important ones are listed below.

A. Classification
- Pattern recognition.
- Sound and speech recognition.
- Analysis of electromyographs and other medical signatures.
- Identification of military targets.
- Identification of explosives in passenger suitcases.

B. Forecasting
- Weather and market trends.
- Predicting mineral-exploration sites.
- Electrical and thermal load predictions.

C. Control systems
- Adaptive control.
- Robotic control.

D. Optimisation and decision making
- Engineering systems.
- Management.

2.1. Biological and autificial neuuons

A biological neuron is shown in Fig. 1. In the brain, there is a flow of coded information (using electrochemical media, the so-called neurotransmitters) from the synapses towards the axon. The axon of each neuron transmits information to a number of other neurons. The neuron receives information at the synapses from a large number of other neurons. It is estimated that each neuron may receive stimuli from as many as 10,000 other neurons. Groups of neurons are organised into sub-systems and the integration of these subsystems forms the brain. It is estimated that the human brain has around 100 billion interconnected neurons.

Fig. 2 shows a highly simplified model of an artificial neuron, which may be used to simulate some important aspects of the real biological neuron. An ANN is a group of interconnected artificial neurons, interacting with one another in a concerted manner. Insuch a system, excitation is applied to the input of the network. Following some suitable operation, it results in a desired output. At the synapses, there is an accumulation ofsome potential which, in the case of the artificial neurons, is modelled as a connection weight. These weights are continuously modified, based on suitable learning rules.

2.2. Autificial neuual-netwouk puinciples

According to Haykin [2], a neural-network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and

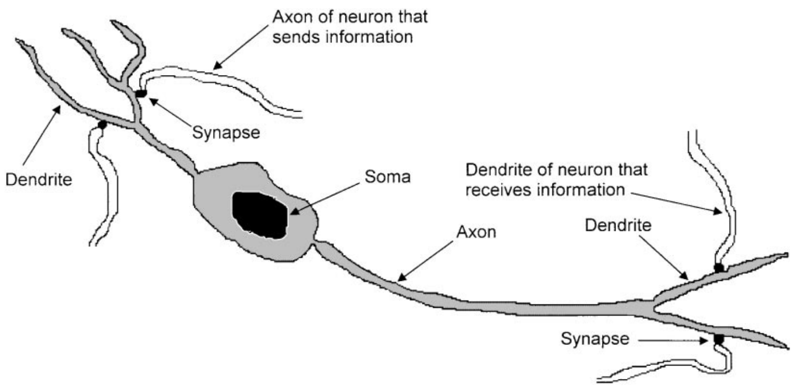

Fig. 1. A simplified model of a biological neuron.

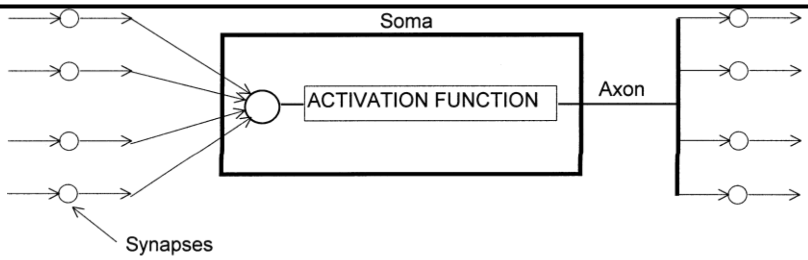

Fig. 2. A simplified model of an artificial neuron.

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 alternative methods in engineering analyses and predictions. ANNs mimic somewhat the learning process of a human brain. They operate like a ''black box'' model, and require 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, in a way similar to how a non-linear regression might be performed.Another advantage of using ANNs is their ability to handle large and complex sys-tems with many interrelated parameters. They seem to simply ignore excess data that are of minimal significance, and concentrate instead on the more important inputs.

A schematic diagram of a typical multilayer feed-forward neural-network archi- tecture is shown in Fig. 3. The network usually consists of an input layer, some hiddenlayers and an output layer. In its simple form, each single neuron is connected to otherneurons of a previous layer through adaptable synaptic weights. Hnowledge is usuallystored as a set of connection weights (presumably corresponding to synapse-eAcacy in biological neural systems). Training is the process of modifying the connection weights, in some orderly fashion, using a suitable learning method. The network usesa 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.

Fig. 4 illustrates how information is processed through a single node. The node receives weighted activations of other nodes through its incoming connections. First, these are added up (summation). The result is then passed through an activation function, the outcome being the activation of the node. For each of the outgoing con- nections, this activation value is multiplied by the specific weight and transferred to thenext node.

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. When each pattern is read, the network uses the input data to produce an output, which is then compared with the training pattern, i.e. the correct

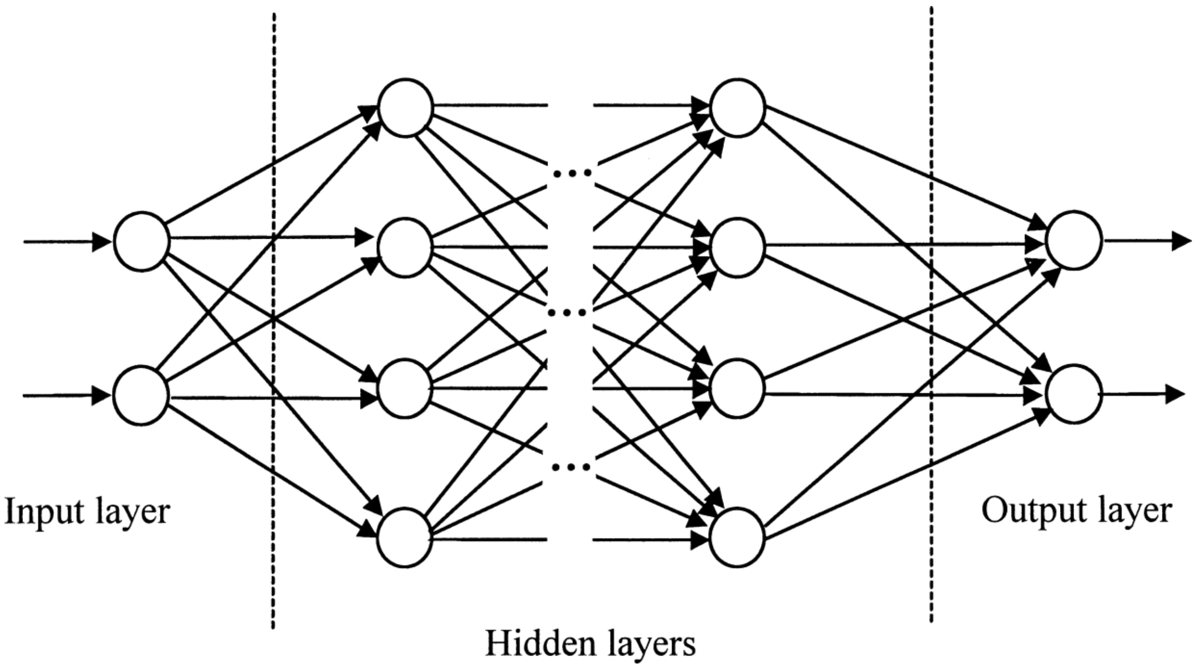

Fig. 3. Schematic diagram of a multilayer feed-forward neural-network.

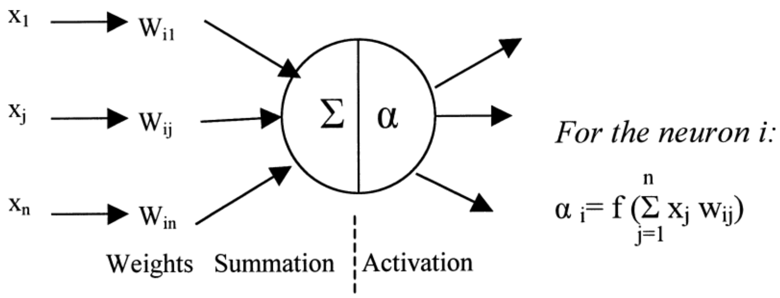

Fig. 4. Information processing in a neural-network unit.

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 networkhas run through all the input patterns, if the error is still greater than the maximumdesired tolerance, the ANN runs again through all the input patterns repeatedly until all the errors are within the required tolerances. When the training reaches a satisfactory level, the network holds the weights constant and uses the trained net- work to make decisions, identify patterns or define associations in new input data sets which were not used to train it.

The most popular learning algorithms are back-propagation and its variants [1,3]. 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 exam- ples. Back-propagation training is a gradient-descent algorithm. It tries to improvethe performance of the neural-network by reducing the total error by changing the weights along its gradient. The error is expressed by the root-mean-square (RMS) value, which can be calculated by:

$$E = \frac{1}{2}\left[\sum_p * \sum_i * [t_{ip} - o_{ip}]^2\right]^{\frac{1}{2}} \quad (1)$$

where (E) is the RMS error, t the network output (target), and o the desired output vectors over all the pattern (p). An error of zero would indicate that all the output patterns computed by the ANN perfectly match the expected values and the net- work is well trained. In brief, BP training is performed by initially assigning randomvalues to the weight terms (w_{ij})[1] in all nodes. Each time a training pattern is presented to the ANN, the activation for each node, α_{pi}, is computed. After the outputof the layer is computed, the error term, 6_{pi}, for each node is computed backwards through the network. This error term is the product of the error function, E, and the derivative of the activation function and, hence, is a measure of the change in the network output produced by an incremental change in the node-weight values. For the output-layer nodes, and for the case of the logistic-sigmoid activation, the error term is computed as:

$$\delta_{pi} = (t_{pi} - \alpha_{pi})\alpha_{pi}(1 - \alpha_{pi}) \quad (2)$$

For a node in a hidden layer:

$$\delta_{pi} = \alpha_{pi}(1 - \alpha_{pi}) \sum_k \delta_{pk} W_{kj} \quad (3)$$

In the latter expression, the k subscript indicates a summation over all nodes in the downstream layer (i.e. the layer in the direction of the output layer). The j subscriptindicates the weight position in each node. Finally, the 6 and α terms for each node are used to compute an incremental change to each weight term via:

$$\Delta W_{ij} = \varepsilon\left(\delta_{pi}\alpha_{pj}\right) + mw_{ij}(old) \quad (4)$$

The term s is referred to as the learning rate and determines the size of the weight adjustments during each training iteration. The term m is called the momentum factor. It is applied to the weight change used in the previous training iteration, w_{ij}(old). Both of these constant terms are specified at the start of the training cycle and determine the speed and stability of the network.

3 Applications in energy systems

ANNs have been used by various researchers for modelling and predictions in the field of energy-engineering systems. This paper presents various such applications in a thematic rather than a chronological (or any other) way. More details are given on the most recent work of the author in the area.

3.1. Modelling of a solau steam-geneuatou

The system employs a parabolic trough collector, a flash vessel, a high pressure circulating pump and the associated pipework, as shown in Fig. 5.

3.1.1. Local concentuation uatios

The radiation profile on the receiver of the collector has a "bell"-type shape. This is represented in terms of the local concentration ratios at 10° intervals on the per-iphery of the receiver. It is very important to be able to measure this profile because
in this way the collector's optical eAciency can be determined. This measurement must be carried out for various incidence angles and also at normal incidence. Thisis usually diAcult to perform due to the size of the collector. ANNs have been usedto deduce the radiation profile from readings at angles at which experiments could be performed and make prediction for the other angles, including normal incidence[5]. The predictions of ANNs as compared with the actual experimental values havea maximum difference of 3.2%, which is considered satisfactory.

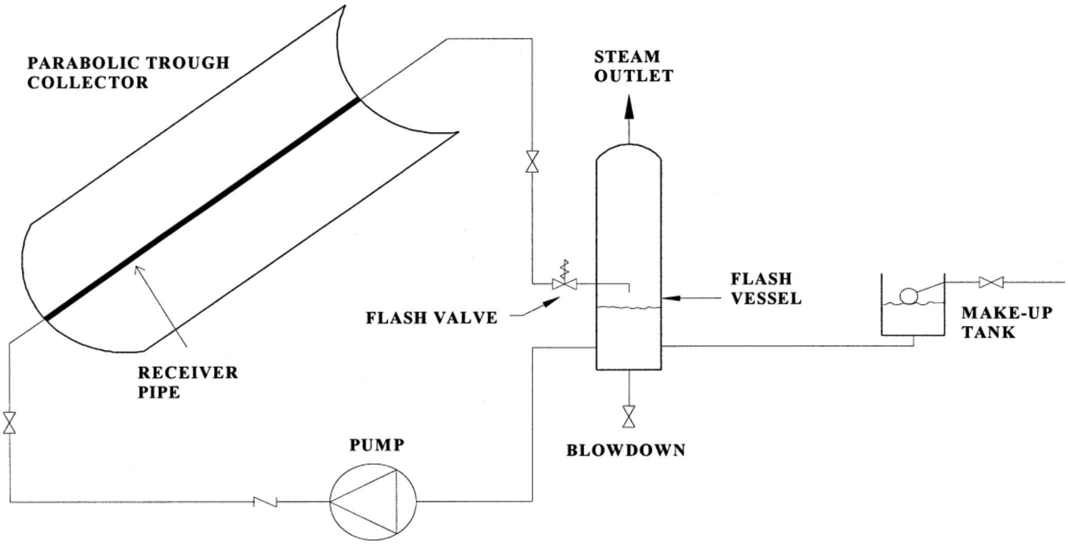

Fig. 5. The steam-generation system

3.1.1. Stauting-up of the solau steam-geneuating plant

ANNs have been used to model the starting-up of the system described above [6]. It is very important for the designer of such systems to be able to make such beha-vioural predictions because the energy spent during starting-up in the morning has a significant effect on the system's performance. It should be noted that this energy is lost due to the diurnal cycle of the Sun and the resulting cooling down of the systemduring the night. This problem is very diAcult to handle with analytic methods as the system operates under transient conditions. ANNs could predict the profile of the temperatures at various points of the system, as shown in Table 1, to within 3.9%, which is considered adequate for design purposes. From the profiles of twosets of flash-vessel top and bottom temperatures versus time, the energy invested during the heating-up period can be estimated.

3.1.2. Mean monthly aveuage steam puoductions

An important parameter required for the design of such systems is the mean monthly average steam-production of the system. A network was trained with per-formance values for a number of collector sizes, ranging from 3.5 to 2160 m^2, andwas able to make predictions both within and outside the training range [7]. A neural- network was used to predict the mean monthly average steam production of the sys- tem, as shown in Fig. 6, with a maximum difference confined to less than 5.1% as compared with simulated values, which is considered acceptable. The matching of the predicted and actual values in each case is excellent. In fact, the pairs of two lines,shown in Fig. 6, are almost indistinguishable.

3.2. Solau Nateu Heating Systems

3.2.1. Modelling of solau domestic wateu heating (SDHN) systems

An ANN has been trained based on 30 known cases of systems, varying from collector areas between 1.81 and 4.38 m^2 [8]. 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 coeAcient (U- value), tank type, storage volume, type of system, and 10 readings from real experi- ments of total daily solar radiation, mean ambient air temperature, and the water temperature in the storage-tank at the beginning of a day. The network output is the

Table 1
Statistical analysis of program predictions and resulting maximum percentage errors

Temperature	Correlation coeAcient	R^2-value	Maximum % error
Collector outlet	0.999	0.9987	3.9
Collector inlet	1.000	0.999	1.3
Flash vessel bottom	1.000	0.9992	2.3
Flash vessel top	1.000	0.9992	3.3

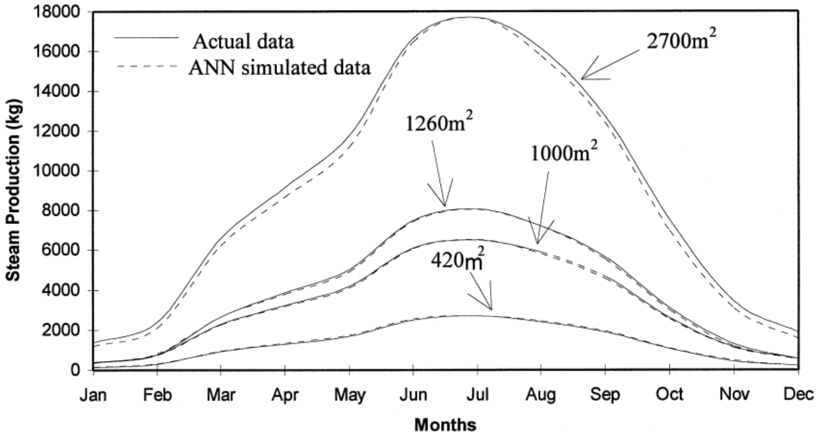

Fig. 6. Comparison of predicted and actual (simulated) results for different collector areas.

Useful energy extracted from the system and the stored-water temperature rise. New data were used to investigate the accuracy of prediction. These include systems considered for the training of the network under different weather conditions and completely unknown systems. Predictions within 7.1 and 9.7% were obtained, respectively [8]. 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 with the conventional algorithmic methods are the speed, the simplicity and the capacity ofthe 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 with 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.

3. Conclusions

From the above system descriptions, one can see that ANNs have been applied over a wide range of fields for modelling and prediction in energy-engineering sys- tems. What are required for setting up such ANN systems are data that representthe past history and performance of the real system and a suitable selection of neural-network models. The selection is accomplished empirically and after testing various alternative-solutions. The performance of the selected model is tested with the data of the past history and performance of the real system.

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