A Back-Propagation Neural Network Thermal Model for a Five-Storey Commercial Building

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Artificial neural networks form part of an emerging field that has had considerable success in tasks involving prediction, recognition and control and this has resulted in their being implemented in energy management algorithms. Historical building data was used to train a back propagation artificial neural network to model the thermal performance of a five (5) storey building. Preliminary results show that the neural network model was able to successfully predict building thermal performance to within a low margin of error.

1. Introduction

Research in the area of energy conservation in commercial buildings has focused not only on reducing energy costs, but also on making the energy conservation exercise itself a less onerous one for building operator personnel. Building process automation in the form of energy management and control systems, which are microprocessor-based systems resulting from the integration of direct digital controllers and energy conservation algorithms and which have increasingly complex control strategies that take greater advantage of the speed and precision of electronic controls, have been able to successfully relieve the building operator from many monotonous tasks. Implementation of an energy management system in a building requires the following [1]:

(a) An energy audit (to determine the energy conservation opportunities).
(b) Implementation of energy conservation opportunities.
(c) Monitoring the performance of the building.
(d) Evaluation of the energy performance of the building.

Energy conservation opportunities can be considered 'passive' when associated with maintenance or retrofitting type activities or 'active' when associated with repetitive or sequentially controlled type procedures or cycles. Wherever possible, active energy conservation opportunities should be considered, only after having implemented the passive ones. The active energy conservation opportunities represent that body of activities normally referred to by the term 'energy management', and their repetitive nature makes them well-suited for the automated approach of energy management and control systems.

Energy management can be considered as the study of the optimisation of energy consumption in energy-based systems. Optimisation typically involves modelling a process and experimenting with the model to find operating parameters, with the aid of some parameter selection technique, to minimise power use [4]. This approach of building models for the purpose of evaluating system behaviour under various conditions while avoiding the need to experiment with the actual physical process itself, is common in many engineering fields [13]. A model of a system is a description of some of its properties, suitable for a particular purpose [13]. An analytical approach to building system models can be carried out by examining the basic components of the system and taking into account the physical laws governing them. In many cases, however, the processes are so complex that it is not possible to obtain reasonable models using only physical insight [17]. System identification is an experimental approach to model building which avoids the problems associated with traditional model building [12]. Some experiments are performed on a system, a mathematical model is then fitted to the recorded data by

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assigning suitable numerical values to its parameters and in this way, the need for 'a priori' system information is not necessary. In practice, the estimation of both structure and parameters is often done iteratively [17]. Artificial neural networks represent an alternative approach to modelling that effectively automates the model building task. Though these neural networks make use of experimental (historical) data to derive the model, they do not have recourse to the iterative structure and parameter estimation process that system identification requires.

Artificial neural networks are mathematical models of biological neurons networked together. There are many types of artificial neural networks. What distinguishes one artificial neural network from another are:

(a) The neuroscience theory upon which the modelled neuron is based and
(b) The learning paradigm which is used to determine the way in which the weights are updated.

Learning in neural networks is said to take place by adjustments made in the weights. This learning may be supervised or unsupervised and it may include some degree of feedback in the learning process or not. Output from the artificial neural network is usually produced via a feed-forward process, though some degree of recurrency may be involved [6]. The artificial neural network that has gained widespread application is the Back-Propagation artificial neural network. Back-Propagation is termed a hetero-associative artificial neural network that learns via error correction during the feedback stage of learning - hence the name. A learning event is said to consist of a forward pass followed by a backward pass through the artificial neural network. This hetero-associative property approximates the function that best expresses the relationships between independent and dependent (input and output) variables in a way similar to non-linear regression [4]. This approximation however is stored by the artificial neural network implicity in the internal data structure of the net - i.e., in its weight space - and consequently is not readily available for inspection. Once this functional approximation has been learned, the need for a statistical understanding of the relationships between independent and dependent variables is not needed though improved performance will obviously result if properly chosen variables are used [2]. After training, the artificial neural networks operate like a "Black Box" model [4].

Artificial Neural Networks and Modelling

Artificial neural networks have been successful in applications of prediction. Seem and Braun (1991) used a CMAC Neural Network in conjunction with an auto-regressive model to provide near optimum predictions of building energy demand [16]. Kreider and Wang (1991) who showed that back propagation networks are more accurate and perform better than other building energy demand predictors even with less relevant data and operator knowledge [11]. Anstett and Kreider (1993) found that an artificial neural network performed significantly better than statistical predictors for predicting electricity consumption [2]. Kawashima (1994) was successful in his attempt to accurately predict building energy consumption using a Back-Propagation artificial neural network with three-phase annealing [8] [10], Kawashima et al. (1995) compared Back-Propagation with some statistical techniques and showed that the artificial neural network was the most accurate thermal load predictor [9].

Artificial neural networks have been successful in applications of control. Curtiss et al. (1993) successfully used a Back-Propagation artificial neural network for predictive control of a hot water coil - or more specifically, a back propagation neural network simulated model of a hot water coil - which was used to warm an air stream in a real-world on-line application [5]. Miller and Seem (1991) have also used artificial neural networks in the application of Optimum Start Control of the heating equipment in a commercial building showing that a Back-Propagation artificial neural network performed better than other statistical algorithms used in predicting the Optimum Start Time [14].

In the light of the wide success that the Back-Propagation neural network has had in the modelling of such varied systems, a neural network was chosen to model the thermal performance of a five (5) storey commercial building. This paper discusses the preliminary results of this work.

2. Building Data Collection

The commercial building, located in downtown Port of Spain had three (3) 88-tonne chillers, located on the roof which were used to serve the air-handling units of each floor. The tinted glass faċade together with venetian blinds allowed daylight to be used in conjunction with artificial lighting. There were two flights of stairs, the main staircase which was air-conditioned and could be reached through a swinging glass door (which at times remained open), and the fire escape (not air-conditioned) whose access doors normally remained closed. The water lines serving the air-handling units, passed through a 2′ x 2′ opening in each floor. This opening, located in the area of the Air Handling Room was not sealed off resulting in mixing of air from the different floors which would have influenced the data collected.

An energy management and control system was used to regulate the operation of the air-conditioning system.

The energy management and control system had a data logger incorporated that permitted building data to be recorded. As there was a limit to the amount of data that could be stored by the data logger, a 5-minute sample time was selected. Smaller sampling times recorded fluctuations which were deemed to be more a consequence of over-sensitivity of the thermometer than from unmeasured disturbances. The data logger had the peculiarity of only logging data if (and only if) a change from the last recorded value was noted (see **Figure 1**). Data was collected daily by manually downloading from the energy management and control system unit to a laptop computer. Recorded data was then interpolated, or linearised, so as to produce the comprehensive data set that would be used to train the artificial neural network (see **Figure 2**). The data used for this study was taken for the period 8-6-96 to 13-7-95 and the following parameters were recorded in each day's data: the ambient air temperature (outside air temperature), the state (on or off) of the three (3) chillers and the indoor air temperature, air handler fan state (on or off) and set point temperature of each of the five (5) floors. The total number of data points monitored were therefore 19. The data collected during the period displayed interesting building temperature profiles. These profiles varied with the varying weather conditions experienced during the month, which could be loosely categorised as follows:-

(i) Ambient temperature rising gradually to a maximum temperature, which occurs just after midday, and then gradually falling again.
(ii) Ambient temperature rising gradually to a maximum temperature but falling sharply due to afternoon showers.
(iii) Ambient temperature remaining constantly low all day long due to overcast conditions.
(iv) Indoor air temperature initially high (on days immediately after a weekend or public holiday)

The data set was partitioned into two sets to reserve some of the collected data for the purpose of validation, the training data set used consisted of approximately 70% to 80% of the entire data collected. The rest of the data was used to validate the network. Validation verifies just how well the artificial neural network can generalise from the data it has been presented with during training, ensuring that it has learned the underlying relationship between input and output data, as opposed to over-learning the specific input-output relations to the extent that it becomes incapable of generalising [6].

3. The Artificial Neural Network: Back-Propagation

An artificial neural network was trained with the whole building data collected. The network was a two hidden-layer fully interconnected Back-Propagation neural network, written in C, trained specifically to predict the indoor air temperature of each floor of the building. The output of the model was measured by comparing the model's temperature prediction with the actual indoor temperature of the data set presented to the network. The Back-Propagation network incorporated the 'delta-delta' learning rate modification rule (see [6] and [7]) and a 'momentum' term (see [6] and [15]) both used as a means of speeding up the training process. The learning rates, for the outer and hidden layers, ranged from a factor of 0.05 to 0.1 and a momentum factor of 0.9 was used as suggested in [6]. This arrangement allowed the first hidden-layer to extract the local features proper to the different floors, while the second hidden-layer would reflect features that are common to all floors, i.e., the global features [6]. The input layer consisted of a time history window of the 19 channels of data or inputs. This time history window allows the Back-Propagation network to sense the trends seen in the historical data and to relate such trends to the value to be predicted. Further details of the Back-Propagation neural network parameters can be seen in **Table 1**.

TABLE 1: *Parameters used for Back Propagation Artificial Neural Networks*

Initial weights	Random weights between +0.5 and -0.5
Channels of data	19
Time history window	3 time steps of past
Size of input layer	57 neurons (3 x 19)
1st hidden layer	19 neurons
2nd hidden layer	7 neurons
Output layer	5 neurons (one per floor)
Learning rate:	0.05 for first hidden layer neurons 0.08 for second hidden layer neurons 0.10 for output layer neurons
Momentum	0.9
Stopping criterion	For average sum of squares error Below 0.0005 and within 0.00025 of the two previous average sum of squares error

The training data set contained 22 days of data. Each day consisted of 289 events (actual instances of historical building data) or samples making the total size of the training data set approximately equal to 6,292 events. During training, one presentation of all the events in the data set to the Back-Propagation neural network is called an 'Epoch'. Only four (4) days of data were reserved for validation purposes.

Date	Actual Time	Rounded Time	OSAT	Ground Floor			Mezzanine			1st Floor			2nd Floor			3rd Floor			Chiller 1	Chiller 2	Chiller 3
				Temp	Fan	SP	Temp	Fan	SP	Temp	Fan	SP	Temp	Fan	SP	Temp	Fan	SP			
28 Jun 95	12:00:00 AM	12:00 AM	76																		
28 Jun 95	12:00:00 AM	12:00 AM		75																	
28 Jun 95	12:00:00 AM	12:00 AM			OFF																
28 Jun 95	12:00:00 AM	12:00 AM				75															
28 Jun 95	12:00:00 AM	12:00 AM					76														
28 Jun 95	12:00:00 AM	12:00 AM						OFF													
28 Jun 95	12:00:00 AM	12:00 AM							74												
28 Jun 95	12:00:00 AM	12:00 AM								76											
28 Jun 95	12:00:00 AM	12:00 AM									OFF										
28 Jun 95	12:00:00 AM	12:00 AM										76									
28 Jun 95	12:00:00 AM	12:00 AM											74								
28 Jun 95	12:00:00 AM	12:00 AM												OFF							
28 Jun 95	12:00:00 AM	12:00 AM													70						
28 Jun 95	12:00:00 AM	12:00 AM														77					
28 Jun 95	12:00:00 AM	12:00 AM															OFF				
28 Jun 95	12:00:00 AM	12:00 AM																76			
28 Jun 95	12:00:00 AM	12:00 AM																	OFF		
28 Jun 95	12:00:00 AM	12:00 AM																		OFF	
28 Jun 95	12:00:00 AM	12:00 AM																			OFF
28 Jun 95	12:10:00 AM	12:10 AM	75.4																		
28 Jun 95	12:25:00 AM	12:25 AM		76																	
28 Jun 95	12:30:00 AM	12:30 AM	76																		
28 Jun 95	12:35:00 AM	12:35 AM	75.4																		
28 Jun 95	12:45:00 AM	12:45 AM	76																		
28 Jun 95	12:55:00 AM	12:55 AM	74.7																		
28 Jun 95	1:04:58 AM	1:05 AM	74.1																		
28 Jun 95	1:04:58 AM	1:05 AM								77											
28 Jun 95	1:04:58 AM	1:05 AM														78					
28 Jun 95	1:09:58 AM	1:10 AM	74.7																		
28 Jun 95	1:09:58 AM	1:10 AM								76											
28 Jun 95	1:14:58 AM	1:15 AM	75.4																		
28 Jun 95	1:19:58 AM	1:20 AM														77					
28 Jun 95	1:24:58 AM	1:25 AM	74.1																		
28 Jun 95	1:24:58 AM	1:25 AM														78					
28 Jun 95	1:29:58 AM	1:30 AM	75.4																		
28 Jun 95	1:29:58 AM	1:30 AM														77					
28 Jun 95	1:34:58 AM	1:35 AM	74.7																		
28 Jun 95	1:44:58 AM	1:45 AM	75.4													78					
28 Jun 95	1:44:58 AM	1:45 AM														77					
28 Jun 95	1:49:58 AM	1:50 AM																			
28 Jun 95	1:54:58 AM	1:55 AM	74.7																		
28 Jun 95	1:59:58 AM	2:00 AM	75.4																		
28 Jun 95	2:04:58 AM	2:05 AM	74.7																		
28 Jun 95	2:09:58 AM	2:10 AM	75.4																		
28 Jun 95	2:14:58 AM	2:15 AM								77											
28 Jun 95	2:19:58 AM	2:20 AM	74.7																		
28 Jun 95	2:19:58 AM	2:20 AM								76											
28 Jun 95	2:29:58 AM	2:30 AM														78					
28 Jun 95	2:34:58 AM	2:35 AM	74.1																		
28 Jun 95	2:34:58 AM	2:35 AM														77					

FIGURE 1: *Raw Data for June 28th, 1995 collected from Data Logger*

Date	Time	CSAT	Ground Floor Temp	Ground Floor Fan	Ground Floor SP	Mezzanine Temp	Mezzanine Fan	Mezzanine SP	1st Floor Temp	1st Floor Fan	1st Floor SP	2nd Floor Temp	2nd Floor Fan	2nd Floor SP	3rd Floor Temp	3rd Floor Fan	3rd Floor SP	Chiller 1	Chiller 2	Chiller 3
28 Jun 95	12:00 AM	76	75	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	12:05 AM	75.7	75	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	12:10 AM	75.4	75	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	12:15 AM	75.6	76	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	12:20 AM	75.7	76	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	12:25 AM	75.9	76	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	12:30 AM	76	76	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	12:35 AM	75.4	76	0	75	76	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	12:40 AM	75.7	76	0	75	76	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	12:45 AM	76	76	0	75	76	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	12:50 AM	75.4	76	0	75	76	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	12:55 AM	74.7	76	0	75	76	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	1:00 AM	74.4	76	0	75	76	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	1:05 AM	74.1	76	0	75	76	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	1:10 AM	74.7	76	0	75	76	0	74	76	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	1:15 AM	75.4	76	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	1:20 AM	74.8	76	0	75	76	0	74	76	0	76	74	0	70	77	0	76	0	0	0
28 Jun 95	1:25 AM	74.1	76	0	75	77	0	74	76	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	1:30 AM	75.4	76	0	75	77	0	74	76	0	76	75	0	70	77	0	76	0	0	0
28 Jun 95	1:35AM	74.7	76	0	75	77	0	74	76	0	76	75	0	70	77	0	76	0	0	0
28 Jun 95	1:40 AM	75.1	76	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	1:45 AM	75.4	76	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	1:50 AM	75.1	76	0	75	77	0	74	77	0	76	75	0	70	77	0	76	0	0	0
28 Jun 95	1:55 AM	74.7	76	0	75	77	0	74	77	0	76	75	0	70	77	0	76	0	0	0
28 Jun 95	2:00 AM	75.4	76	0	75	77	0	74	77	0	76	75	0	70	77	0	76	0	0	0
28 Jun 95	2:05 AM	74.7	76	0	75	77	0	74	77	0	76	75	0	70	77	0	76	0	0	0
28 Jun 95	2:10 AM	75.4	76	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:15 AM	75.1	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:20 AM	74.7	77	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:25 AM	74.5	77	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:30 AM	74.3	77	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:35 AM	74.1	77	0	75	77	0	74	76	0	76	75	0	70	77	0	76	0	0	0
28 Jun 95	2:40 AM	74.7	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:45 AM	74.5	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:50 AM	74.3	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	2:55 AM	74.1	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:00 AM	74.7	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:05 AM	74.1	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:10 AM	74.7	77	0	75	77	0	74	76	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	3:15 AM	74.9	77	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:20 AM	75.2	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:25 AM	75.4	77	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:30 AM	74.7	77	0	75	77	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	3:35 AM	74.1	77	0	75	77	0	74	77	0	76	74	0	70	78	0	76	0	0	0
28 Jun 95	3:40 AM	74.7	77	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:45 AM	74.1	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:50 AM	74.7	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	3:55 AM	74.5	77	0	75	77	0	74	76	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	4:00 AM	74.3	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0
28 Jun 95	4:05 AM	74.1	77	0	75	77	0	74	77	0	76	75	0	70	78	0	76	0	0	0

FIGURE 2: *Interpolated Data for June 28th, 1995*

The network took about two hours to complete 45 training epochs which means that the artificial neural network would have undergone approximately 283,140 forward and backward passes during the training process. During training, the data was presented to the network in a random fashion as opposed to a sequential one and the weights were updated at the end of each training cycle. The stopping criterion halted the training process when the average sum of squares error fell below the predetermined value (0.0005) for three consecutive cycles [6].

4. Results

The performance of the Back-Propagation neural network was measured using standard deviation, the expected percentage error, the coefficient of variation and the mean bias error which are defined below:-

Definitions of the statistics used to measure the performance of the Back-Propagation neural network. The statistics used were the standard deviation, the expected percentage error, the coefficient of variation and the mean bias error which are defined as follows:

(1) Standard Deviation given by:

$$= \sqrt{\sum\left(y_{pred} - y_{data}\right)^2 / n}$$

(2) Estimated Error Percentage given by:

$$EEP = \frac{\sqrt{\sum\left(y_{pred} - y_{data}\right)^2 / n}}{y_{\max}} x\,100$$

Coefficient of Variation given by:

$$CV = \frac{\sqrt{\sum\left(y_{pred} - y_{data}\right)^2 / n}}{y_{mean}} x\,100$$

Mean Bias Error given by:

$$MBE = \frac{\sum\left(y_{pred} - y_{data}\right) / n}{y_{mean}} x\,100$$

where: y_{data} = measured data at instant
y_{pred} = predicted data at instant
y_{max} = maximum measured data
y_{mean} = mean value of measured data

These statistics for the training data set and for the validation data set are presented in **Tables 2** and **3** respectively.

On comparison of the statistics, we see, as expected, those for the training data set showed a slightly better performance than those for the validation data set. The value of the percentage error appears to be reasonably good. When looking at graphical plots of data, however, the following features become apparent. Firstly, though the output of the network seems to follow the general trend of temperature variation, there are instances of considerable deviation, especially on the 1st and 3rd floor temperature profiles. Secondly, the existence of slight fluctuations in the output of the artificial neural network, for all floors, especially around the period of fan start-up, shut down as well as at other times during the day.

The fluctuations at the start-up and shut-off periods could be due to switching action (i.e., the sudden start up of chillers and fans), a difficult encounter by Curtiss et al. (1993) who, on experiencing mild perturbations in neural network control of an actuator as the network attempted to model a reverse acting process, solved the problem by constraining the weights, in the input layer, of the "driving variables" to negative values, while constraining all other weights to positive values. It should be noted that unlike Curtiss et al. (1993), the prediction of the present indoor temperatures was not used recurrently in the prediction of the temperatures of the future times step [5].

TABLE 2: *Showing Statistics of Performance of Back-Propagation Artificial Neural Network after Training when presented again with the Training Data Set*

Floor	1	2	3	4	5
Standard Deviation	0.185 °F	0.253 °F	0.310 °F	0.256 °F	0.358 °F
Expected Error Percentage:	0.225 %	0.309 %	0.378 %	0.312 %	0.421 %
Coefficient of Variation:	0.241 %	0.331 %	0.406 %	0.343 %	0.457 %
Mean Bias Error	-0.037 %	0.190 %	-0.136 %	-0.002 %	-0.298 %

TABLE 3: *Showing Statistics of Performance of Back-Propagation Artificial Neural Network after Training when presented again with the Validation Data Set*

Floor	1	2	3	4	5
Standard Deviation	0.201 °F	0.143 °F	0.325 °F	0.232 °F	0.4858 °F
Expected Error Percentage:	0.245 %	0.174 %	0.396 %	0.283 %	0.5701 %
Coefficient of Variation:	0.263 %	0.189 %	0.430 %	0.3163 %	0.629 %
Mean Bias Error	-0.168 %	0.047 %	-0.339 %	-0.100 %	-0.531 %

Improved performance may be possible by:

(1) Increasing the time history window.
(2) Increasing the size of the hidden layers.
(3) The collection and use of more data in the training and testing of the network.
(4) Decreasing the sample time of the collected data.
(5) Increasing the number of points or data channels in each day's data.
(6) Train smaller networks to model the temperature performance of just one floor each.

(1) to (3) would certainly increase the training time required for the model and may make the training process too long for it to be a practical means of modelling. Decreasing the sample time, however, as suggested by (4) has the constraint of the memory capacity of the data logger. Increasing the number of data channels as suggested by (5) may require the replacement of the energy management and control system at the building, to be able to measure other, possibly relevant, channels of data. It would also be instructive to undertake a study of the performance of different size artificial neural networks used to model all five floors and compare results with the performance of five (5) smaller artificial neural networks each trained with data corresponding to a particular floor.

5. Conclusion

Data from five (5) storey commercial building was collected and used to train a two (2) hidden layer Back-Propagation artificial neural network, which used the delta training weight modification together with a momentum factor to accelerate the training process. Preliminary results, judging from the standard deviation, the expected percentage error, the coefficient neural network performs reasonably well at predicting the thermal performance of the building to within a very small margin of error.

On considering the graphical results plotting thermal performance, it is clear that the Back-Propagation neural network predictive model generally follows the trend of temperature variation very well. Instances of considerable deviation were noted especially on the first and third floors. Further work to improve performance could be achieved by, varying the time history window, the size of the hidden layers and the samples time of the collected data. The collection and use of a greater number of days of data both to train and test the network, as well as using separate Back-Propagation neural networks to model one floor at a time could also prove useful in improving prediction of thermal performance.

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