Analysis of Novel Random Neural Network Controller for Residential Building Temperature Control

Abbas Javed, Hadi Larijani, Ali Ahmadinia, Rohinton Emmanuel

School of Engineering and Built Environment
Glasgow Caledonian University
Glasgow, United Kingdom
Email: abbas.javed@gcu.ac.uk, H.Larijani@gcu.ac.uk, Ali.Ahmadinia@gcu.ac.uk
Rohinton.Emmanuel@gcu.ac.uk

***Abstract*—Random neural networks (RNN) have strong generalisation capabilities and are easy to implement on hardware as compared to Artificial Neural Networks (ANN). In this paper, a novel RNN controller is proposed to maintain a comfortable indoor environment in a single zone residential building fitted with radiators for heating. This controller is capable of maintaining a comfortable indoor environment on the basis of a predicted mean vote (PMV)-based set point. The implemented RNN controller is compared with ANN controller for energy consumption, indoor room temperature, and minimum square error. Results show that for same training data and learning algorithm parameters, RNN converges faster and it consumes less energy, results in better comfortable room temperature as compared to ANN controller.**

***Keywords*-random neural network; artificial neural network; building simulation; residential heating system; energy efficient controller**

I. INTRODUCTION

Buildings currently consume 40% of the total energy in most developed countries. The International Energy Agency (IEA) has set a target to reduce energy consumption in buildings by improving energy efficiency. This will result in estimated energy saving of 1509 million tonnes of oil equivalent (Mtoe) by 2050 [1]. The energy efficiency policy of IEA will not only save energy but it will also reduce carbon dioxide (CO_2) emission from the building sector. This will result in possible mitigation of 12.6 gigatonnes (Gt) of CO_2 emissions by 2050. According to Intelligent Energy Executive Agency (IEAE), in European households, 68% of energy consumption is for space heating, 14% for water heating and 13% for electric appliances [2].

The number of homes in UK has increased from 18 million to 26 million during the period of 1970-2011. The energy used in homes is equal to quarter of total energy used and CO_2 emission in UK [3]. UK's carbon emission reduction targets therefore will be impossible to achieve without reducing CO_2 emission in households. While many fabric-based and equipment-based interventions are needed, controllers for residential heating systems could play a useful part without compromising the occupants comfort.

According to [4], 95% of radiators were controlled using thermostatic radiator valves (TRVs). It was found that majority of TRVs failed to reduce the heating output once the room temperature is greater than the setpoint, as a result energy was wasted. The survey further revealed that 32% of TRVs were positioned at "Max" and more than 65% of TRVs were set for greater flowrates than required. If TRVs were kept within 2-3 settings (max 5), about 12.4% reduction of heat consumption could be gained compared with the situation in which the TRVs were kept fully open [5].

In non-domestic buildings for controlling the Heating Ventilation and Air Conditioning (HVAC), the control techniques are categorized in two parts, i.e., Local control and Supervisory control [6]. For local control, ON/OFF and proportional-integral derivative control schemes are normally used. The control settings of these local controllers might be optimal and energy efficient for certain subsystem however they may not be energy efficient for overall system as these control schemes are unable to maintain indoor comfort of the building by taking in to the account the ever changing indoor and outdoor environmental variables.

Supervisory control techniques are used for maintaining comfortable indoor environment by considering indoor and outdoor environment variables. Supervisory control techniques can be implemented by using physical model based techniques and black box techniques. Physical model-based techniques require physical model of the building to predict energy/cost of the concerned system which is computationally expensive and requires lot of memory. Black box techniques are normally implemented by ANN and RNN models. The ANN models are developed on empirical model of the system and are capable to mathematically relate the input and output variables of the system. ANN models are computationally less expensive than physical model based techniques but requires extensive training data to achieve accuracy.

The main contributions of this paper are:

1. Novel variable set point RNN and ANN controllers have been developed for optimisation of energy consumption by residential heating systems without compromising the thermal comfort of the occupants. The gradient descent algorithm is used to train the RNN and ANN controllers for predicting the optimised inflow of hot water in to the radiator. Variable set point estimated by PMV thermal comfort model, indoor environmental variables, and meteorological data have been used

 ISBN: 978-1-61208-332-2

by RNN and ANN controllers to predict the flow rate from the TRVs for optimised energy consumption and comfortable thermal environment.
2. The energy consumption by residential heating system controlled by RNN and ANN controller is compared by simulating the single zone building model in Matlab/Simulink for 100 days. The single zone building model is developed by using International Building Physics Toolbox (IBPT).
3. The training algorithm for RNN and ANN is critically analysed in terms of no. of iterations and minimum square error attained. The percentage of periods when air temperature overshoots the specified range of room temperature set point is calculated for ANN and RNN controller.
The rest of this paper is organized as follows. Brief introduction to RNN and ANN and learning algorithm for RNN are given in Section II. The implemented building model is described in Section III followed by description of intelligent heating control system in Section IV. The experimental results are provided in Section V followed by the discussions and conclusions in Section VI.

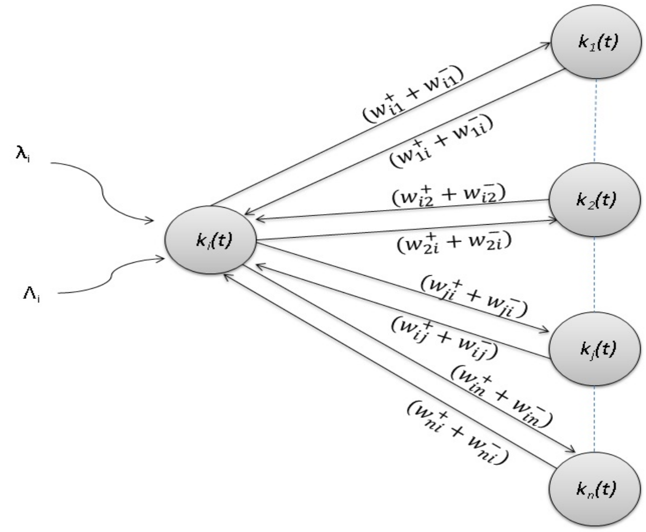

Figure 1. Random Neural Network

II. Related Work

A. Artificial Neural Network

The ANNs have been used in different applications for BEMS such as modeling the thermal dynamics of building space, estimation of heating loads of buildings, control of HVAC, prediction of energy consumption in buildings, and solar radiation predictions for non-domestic buildings [7]-[13]. The above mentioned ANN techniques are difficult to implement on hardware as they are computationally expensive. Residential water heating systems and radiant floor heating systems were effectively controlled by ANN based predictive control methods. In [14], the authors proposed an ANN based predictive control model. The results of their work showed that the performance of proposed predictive control is better than that of the current two-position ON/OFF control. In [15], [16], the authors showed that ANN based predictive control strategies are better than conventional control techniques in terms of energy saving, building thermal control with reduced overheating and overcooling. In [17], the authors developed an ANN based adaptive and predictive control method that ensures more comfortable thermal conditions than typical thermostat systems in terms of increased comfort periods of air temperature, humidity, PMV [18] - the most commonly used indoor thermal comfort index in buildings, and reduced over and undershoots. The ANN based models takes into account not only indoor air temperature but also PMV as a control variable in order to reduce overshoot and undershoot of the temperature which resulted in energy conservation. In [19],the author proposed the PMV index based variable set point control scheme and compared the results with fixed set point control scheme.

B. Random neural network

Gelenbe [20], [21] proposed the new class of ANN as RNN in which signals are either +1 or -1 due to which it is an excellent modeling tool. RNN can give more detailed system state description because the potential of neuron is represented by integer rather than binary value [22]. RNN is easy to implement on hardware as its neurons can be represented by simple counters [23], [24].
Applications of RNN have been reported for modeling, pattern recognition, image processing, classification, and communication systems [22], [25]. However, no such application has been reported so far in implementing control scheme for HVAC in residential/commercial buildings.
In RNN shown in Figure 1, signal travels in the form of impulse between the neurons. If the receiving signal has positive potential (+1) it represents excitation, and if the potential of the input signal is negative (-1) it represents inhibition to the receiving neuron. Each neuron *i* in the random neural network has a state $k_i(t)$ which represents the potential at time *t*. This potential $k_i(t)$ is represented by non-negative integer. If $k_i(t) > 0$ then neuron *i* is in excited state and if $k_i(t) = 0$ then neuron *i* is in idle state. When neuron *i* is in excited state, it transmits impulse according to the poisson rate r_i. The transmitted signal can reach neuron *j* as excitation signal with probability $p^+(i,j)$ or as inhibitory signal with probability $p^-(i,j)$, or can leave the network with probability $d(i)$ such that

$$d(i) + \sum_{j=1}^{N} \left[p^+(i,j) + p^-(i,j)\right] = 1 \forall i \tag{1}$$

$$w^+(i,j) = r_i p^+(i,j) \geqslant 0 \tag{2}$$

$$w^-(i,j) = r_i p^-(i,j) \geqslant 0 \tag{3}$$

combining (1)-(3)

$$r(i) = (1 - d(i))^{-1} \sum_{j=1}^{N} \left[w^+(i,j) + w^-(i,j)\right] \tag{4}$$

The firing rate between the neuron is represented by $r(i) = \sum_{j=1}^{N} [w^+(i,j) + w^-(i,j)]$. As *'w'* matrices are the product of firing rate and probabilities, therefore these matrices always hold non-negative values. External positive or negative signal can also reach neuron *i* at poisson rate Λ_i and λ_i respectively. When positive signal is received at neuron *i* its potential $k_i(t)$ will increase to +1. If neuron *i* is in excitation state and it receives negative signal the potential of neuron *i* will decrease

 ISBN: 978-1-61208-332-2

TABLE I
DESCRIPTION OF RNN SYMBOLS

RNN Symbols	Description
q_i	Probability neuron *i* excited at time *t*
$p^+(i,j)$	Probability neuron *j* receives positive signal from neuron *i*
$p^-(i,j)$	Probability neuron *j* receives negative signal from neuron
r_i	Firing rate of neuron *i*
Λ_i	Arrival rate of external positive signals
λ_i	Arrival rate of external negative signals
$d(i)$	Probability a signal from neuron departs from the network
$k_i(t)$	Potential of neuron *i* at time *t*

to zero. Arrival of negative signal will have no effect on neuron *i* if its potential is already 0. The description of symbols used is given in Table 1.
Consider the vector $\mathbf{K}(\mathbf{t})$= $(k_1(t), ...k_n(t))$ where $k_i(t)$ is the potential of neuron *i* and n is the total number of neurons in the network. Let $\mathbf{K}$ is continuous time Markov process. The stationary distribution of $\mathbf{K}$ is represented as:

$$\lim_{t\to\infty} Pr(K(t))) = (k_1(t).......k_n(t)) = \prod_{i=1}^{n}(1-q_i)q_i^{ni} \quad (5)$$

For each node *i*

$$q_i = \frac{G_i^+}{r_i + G_i^-} \quad (6)$$

where

$$G_i^+ = \Lambda_i + \sum_{j=1}^{N} q_j w^+(j,i) \quad (7)$$

$$G_i^- = \Lambda_i - \sum_{j=1}^{N} q_j w^-(j,i) \quad (8)$$

For three layer network, q_i for each layer is calculated as

$$q_{i\varepsilon I} = \frac{\Lambda_i}{r_i + \lambda_i} \quad where\ I is\ input\ layer \quad (9)$$

$$q_{i\varepsilon H} = \frac{\sum_{i\varepsilon I} q_i w^+(i,h)}{r_h + \sum_{i\varepsilon I} q_i w^-(i,h)} \quad where\ H is\ hidden\ layer \quad (10)$$

$$q_{i\varepsilon O} = \frac{\sum_{i\varepsilon H} q_h w^+(h,o)}{r_h + \sum_{i\varepsilon I} q_h w^-(h,o)} \quad where\ O is\ Output\ layer \quad (11)$$

In this paper, we propose a novel variable set-point RNN controller for maintaining comfortable indoor environment in single zone residential building by controlling the motorized TRVs mounted on radiator. RNN controller uses room temperature, error (difference between current room temperature and variable setpoint), and outside temperature as Inputs to predict flow rate m' $(\frac{m^3}{hr})$ from the TRVs for optimized energy consumption while maintaining comfortable thermal environment.

C. Gradient Descent learning algorithm for RNN

Suppose we have data set F composed of M input-output pairs (x^m, y^m) where $m = 1, 2, ...M$ and $x^m = [\Lambda^m \lambda^m]$ such that x^m are pairs of excitation and inhibition signal ow rates entering each neuron from outside of the network. Output $y^m \varepsilon[0..1]$ where $y^m = f(x^m)$. The goal of the learning algorithms is to find parameters for RNN such that difference between q_i^m and y_i^m is minimum. Similarly gradient descent algorithm developed by Gelenbe [26] adjusts the parameters in order to minimize the cost function E_m

$$E_m = \frac{1}{2}\sum_{i=1}^{n} a_i(q_j^m - y_j^m)^2, \quad a_i \geqslant 0 \quad (12)$$

The rule of updating the weights by using m^{th} input-output data pair for connection between neuron *e* and *f* is

$$w_{(e,f)}^{+t} = w_{(e,f)}^{+(t-1)} - \eta \sum_{i=1}^{n} a_i(q_j^m - y_j^m) \left[\frac{\partial q_i}{\partial w_{(e,f)}^+}\right]^{t-1}$$

$$w_{(e,f)}^{-t} = w_{(e,f)}^{-(t-1)} - \eta \sum_{i=1}^{n} a_i(q_j^m - y_j^m) \left[\frac{\partial q_i}{\partial w_{(e,f)}^-}\right]^{t-1} \quad (13)$$

where

$$\left[\frac{\partial q_i}{\partial w_{(e,f)}^+}\right] = \gamma_{e,f}^+ q_e [I-W]^{-1}$$

$$\left[\frac{\partial q_i}{\partial w_{(e,f)}^-}\right] = \gamma_{e,f}^- q_e [I-W]^{-1} \quad (14)$$

$$\gamma_{e,f;i}^+ = \begin{cases} \frac{-1}{r_i+G_i^-} & if\ e=i, f\neq i \\ \frac{1}{r_i-G_i^-} & if\ e\neq i, f=i \\ 0 & else \end{cases}$$

$$\gamma_{e,f;i}^- = \begin{cases} \frac{(-1+q_i)}{r_i+G_i^-} & if\ e=i, f=i \\ \frac{-1}{r_i+G_i^-} & if\ e=i, f\neq i \\ \frac{-q_i}{r_i+G_i^-} & if\ e\neq i, f=i \end{cases}$$

$$W(i,j) = \frac{w_{(i,j)}^+ - w_{(i,j)}^- q_j}{D_j} \quad i,j = 1......,N \quad (15)$$

Steps for gradient descent learning algorithm are as followings:
$a)$ Initialize $w_{(e,f)}^+$ and $w_((e,f))^-$ $\forall$ e, f and choose suitable value for learning rate
$b)$ For all input output pairs, initialize Λ_{im}, λ_{im} according to X_{im}.
$c)$ Solve (6)-(8) by using current weight values
$d)$ Calculate W, $\gamma_{(e,f)}^+, \gamma_{(e,f)}^- \forall e, f$
$e)$ Calculate $\frac{\partial q_i}{\partial w_{(e,f)}^+}$ and $\frac{\partial q_i}{\partial w_{(e,f)}^-}$ by solving (14)
$f)$ Update the weights from (13)
Weights are product of firing rate and probability and can never have negative values. After solving (13) negative weights can either be set to zero or repeat the iteration with smaller value of η. Repeat the procedure (b)-(f) until convergence or maximum number of iterations.

III. IMPLEMENTATION OF MODEL

In this work, a single zone building made of three layered walls/roof, fitted with Intelligent Controllers for heating/cooling system management is modeled in Matlab/Simulink using IBPT.

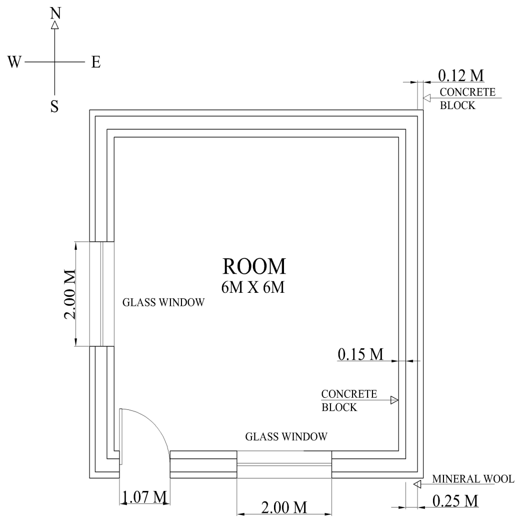

Figure 2. Layout of Walls

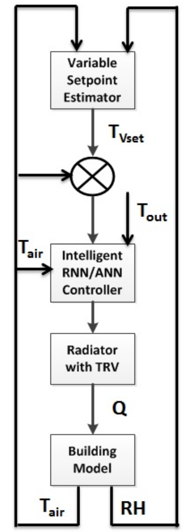

Figure 3. Control Scheme

A. Target Building

A single zone residential house is considered as the target building. The size of the house is 6 x6 x2.7 m^3. The house has a window in south and west wall with flat ceiling and three layered walls. Concrete blocks are used for exterior/interior material on each wall while mineral wool is used for insulation. Thicknesses of the materials are 0.15m, 0.25m and 0.12m respectively shown in Figure 3. Area of the uncoated double-glazed south & west windows is 4 m^2 and U-Value of window is 2.44 and resistance of air gap is 0.23.
In the simulation heat gains from lights, occupants and equipment are ignored. External parameters that affect the building environment such as ambient temperature, dewpoint temperature, global irradiation, diffuse horizontal irradiation, direct normal irradiation, longwave sky radiation, global luminance, diffuse horizontal illuminance, direct normal illuminance, wind direction, and wind speed are included in the weather data file. The building model is affected by meteorological parameters and heat emitted from radiator inside the room. The room is fitted with the radiator and TRV is mounted on inlet pipe of the radiator for controlling the flow rate of hot water entering the radiator. Heat emission from radiator is controlled by changing the flow rate $m^{'}$ of hot water.

B. Radiator Model

The heat transfer from radiator to surrounding is represented by (16). At low mass flow rate the radiator exhaust temperature is nearly equal to room temperature and heat emission from the radiator is linear function of mass flow rate.

$$q = m^{'} c_p (T_{su} - T_{en}) \tag{16}$$

Where,
$q =$ heat flux W
$m^{'} =$ fluid mass flowrate$\frac{Kg}{s}$
$c_p =$ specific heat capacity of fluid $\frac{J}{Kg-K}$
$T_{su} =$ radiator supply temperature °C.
$T_{en} =$ environment temperature °C

C. Thermostatic Radiator Valve Model

The TRV used in this model is 15mm valve whose flow rate Kv varies between 0 to 0.56 ($\frac{m^3}{hr}$) at differential pressure of 0.6 bar. The flowrate through the valve is represented by (17).

$$Kv = \frac{Q}{\sqrt{\triangle P}} \tag{17}$$

$Q =$ the flow rate in $\frac{m^3}{hr}$
$\triangle P =$ differential pressure of 0.6 bar.
The relationship between the position of the thermostatic radiator valve, flow rate and differential pressure is implemented in Simulink. The kv -value as a function of the TRV position is included in a lookup table.

IV. INTELLIGENT HEATING CONTROL SYSTEM

The main goal of the controller design is to reduce energy consumption while maintaining acceptable indoor thermal comfort for occupants. In Figure 4, the block diagram of intelligent heating system controller is shown. The variable set point estimator estimates the variable set point TVset for the building temperature by using PMV index as proposed in [19]. The intelligent controller takes the difference between the T_{Vset} and room air temperature (T_{air}), room air temperature (T_{air}), and outside temperature (T_{out}) as inputs and controls the heat emission from the radiator by changing the flowrate ($m^{'}$) through TRV mounted on the radiator. Two types of intelligent controllers are investigated in this study, i.e., ANN and RNN controller.

A. Variable Set Point Estimator

The Institute for Environmental Research at the Kansas State University conducted the research study under the contract of ASHRAE and defined PMV in terms of easily measured parameters [19].

$$PMV = at + bp_v - c \tag{18}$$

Where a, b, c are constants defined in Kansas State university research, p_v is vapour pressure and t is temperature.

 ISBN: 978-1-61208-332-2

By setting the required PMV (in this work between -0.3 and +0.3) and using the constants (a=0.220, b=0.233, c=5.673) heating setpoint for room temperature varies between room temperature varies between 22.76 ^oC to 23.77 ^oC and cooling setpoint varies between 26.59 ^oC to 27.58 ^oC.

B. Training Data

The training dataset have been generated by simulating the single zone building for 30 days in Matlab/Simulink using IBPT toolbox. During this period the outside temperature of the building varies between -20 ^oC and 10.2 ^oC. The building has radiator fitted with motorized TRV and simple ON/OFF controller to control the TRV for maintaining the required flow rate ($m^{'}$) of hot water entering the radiator. The training data is recorded after every 30 seconds and both ANN and RNN controllers are trained with this data.

C. Artificial Neural Network Controller

Feed forward neural network (FFNN) consists of simple neuron like processing unit and is organised in layers. In this network all neurons in *i*th layer are connected to all neuron in (i-1)th layer. In FFNN, the learning rule tries to adjust the weights and biases of the network in order to move the network output closer to the target. The output of each neuron in the hidden layer and output layer is the result of non linear transfer function f represented by (19).

$$y_i = f(\sum_{j=1}^{m} w_{ij}x_j + b_i) \tag{19}$$

Where x is the input presented to the network, w are the weights of the network, b is the constant term which is referred as bias, and y is the output predicted by the network.
The intelligent ANN controller is three layered neural network model and it has three neurons in input layer, eight neurons in hidden layer and one neuron in the output layer. The ANN controller is trained by using gradient descent algorithm with learning rate η = 0.01. It took 20000 iterations by gradient descent algorithm to converge with minimum square error (MSE) of 2.3e-04.

D. Random Neural Network Controller

Similar to ANN controller the proposed RNN controller is three layer random neural network model with three neurons in the input layer, eight neurons in the hidden layer and one neuron in the output layer. When random neural network is trained by using gradient descent algorithm it took only 500 iterations to achieve the MSE of 1.6288e-06 at learning rate η = 0.01.

V. RESULTS AND DISCUSSION

The single zone building is simulated for 100 days for testing the performance of RNN and ANN controller. During this period of 100 days the outside temperature varies between -20.89 ^oC to 14 ^oC. The indoor air temperature of the building with RNN and ANN controller is shown in Figure 5. The heat supplied by the RNN controller is shown in Figure 6. Similarly, Figure 7 represents the heat supplied by the ANN controller. The variable heating set point for room temperature varies

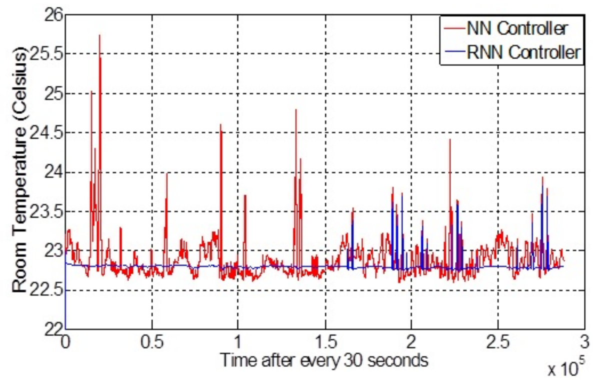

Figure 4. Indoor Air Temperature during testing

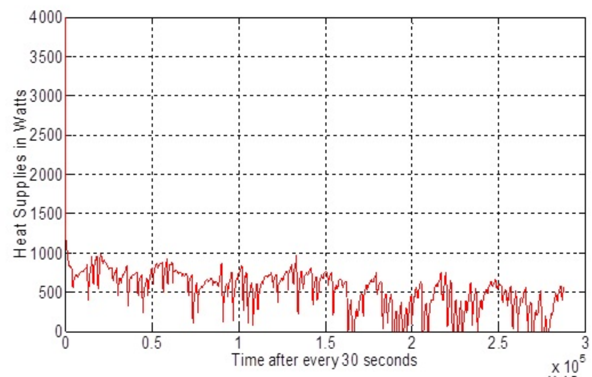

Figure 5. Heat Supplied by the RNN controller

between 22.66 ^oC to 23.00 ^oC in order to maintain the PMV of at least -0.3. As shown from Figure 5, ANN controller failed to keep the temperature within the specified range of variable set point while RNN controller achieved more accurate results than ANN controller.
In Figure 7, it is shown that ANN controller caused frequent oscillation between maximum and minimum flow rate as a result heat supplied to the rooms oscillate between 0 and 4000 watts. The RNN controller kept the stable flow rate due to which the heat suplied to the room didnt oscillate between minimum and maximum. In Table 2, the comparison of RNN and ANN in terms of MSE, no. of iterations, energy consumption, maximum overshoot and percentage of overshoot periods is given. The percentage of overshoot periods is percentage of instances when air temperature T_{air} exceeds the specified range of room temperature set point during 100 days simulation. From Table 2, it is shown that percentage of overshoot periods is only 4.27% for RNN controller while for ANN it is 45.96%. Similarly the energy consumption by heating system with RNN controller is 1282.4 MWh while with ANN controller energy consumption is 1292.5 MWh.

VI. CONCLUSION

In this paper, two variable set point intelligent heating system controllers are developed and their performances are compared for energy efficiency, and accuracy for maintaining the comfortable room temperature. To compare the performance of RNN and ANN controller, both controllers were trained

Copyright (c) IARIA, 2014. ISBN: 978-1-61208-332-2

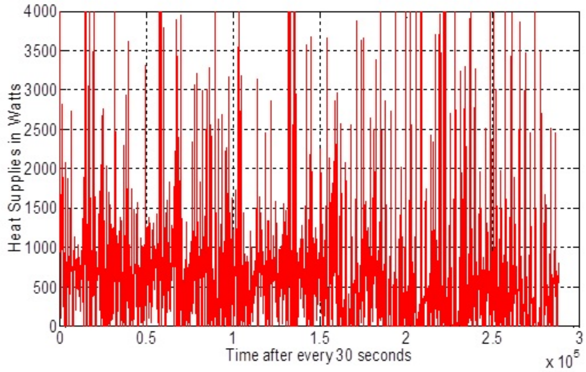

Figure 6. Heat Supplied by the ANN controller

TABLE II
COMPARISON OF RNN AND ANN CONTROLLER

	RNN	ANN
Learning Algorithm	Gradient Descent	Gradient Descent
No. of Iterations	500	20000
MSE	1.8266e-06	2.3 e-04
Energy Consumption 100 days (MWh)	1282.4	1292.5
Max Overshoot (^{o}C)	0.81	2.73
Percentage of overshoot periods	4.27%	45.90%

with same dataset and same training algorithm i.e., gradient descent algorithm. During training RNN showed impressive generalization capabilities and gradient descent algorithm for RNN converges in 500 iterations while gradient descent algorithm of ANN took 20000 iterations to converge. The RNN controller outperformed the ANN controller in testing phase where both controllers were tested for unknown data set. The heating system with RNN controller consumes 10 MWh less energy than with ANN controller. The RNN controller stopped the flowrate of hot water to the radiator by sensing the increase in outside temperature at correct time as a result percentage of overshoot periods is less compared to the ANN controller. The PMV index based variable set point control scheme ensured the comfortable indoor environment by suggesting the variable set points for maintaining PMV index of 0.3. The performance of RNN controller can further be improved by training the RNN with Levenberg Marquardt algorithm [27].

REFERENCES

[1] O. Publishing and I. E. Agency, Energy Technology Perspectives 2010: Scenarios and Strategies to 2050. Organisation for Economic Co-operation and Development, 2010.

[2] A. I. Dounis and C. Caraiscos, “Advanced control systems engineering for energy and comfort management in a building environment: A review,” Renewable and Sustainable Energy Reviews, vol. 13, no. 6, 2009, pp. 1246–1261.

[3] U. Parliament, Climate Change Act 2008. London: The Stationery Office Limited, 2008.

[4] Z. Liao, M. Swainson, and A. Dexter, “On the control of heating systems in the uk,” Building and Environment, vol. 40, no. 3, 2005, pp. 343–351.

[5] B. Xu, L. Fu, and H. Di, “Dynamic simulation of space heating systems with radiators controlled by trvs in buildings,” Energy and buildings, vol. 40, no. 9, 2008, pp. 1755–1764.

[6] S. Wang and Z. Ma, “Supervisory and optimal control of building hvac systems: A review,” HVAC&R Research, vol. 14, no. 1, 2008, pp. 3–32.

[7] S. A. Kalogirou, “Applications of artificial neural networks in energy systems,” Energy Conversion and Management, vol. 40, no. 10, 1999, pp. 1073–1087.

[8] M. Gouda, S. Danaher, and C. Underwood, “Application of an artificial neural network for modelling the thermal dynamics of a building’s space and its heating system,” Mathematical and Computer Modelling of Dynamical Systems, vol. 8, no. 3, 2002, pp. 333–344.

[9] S. A. Kalogirou and M. Bojic, “Artificial neural networks for the prediction of the energy consumption of a passive solar building,” Energy, vol. 25, no. 5, 2000, pp. 479–491.

[10] S. A. Kalogirou, “Artificial neural networks in renewable energy systems applications: a review,” Renewable and sustainable energy reviews, vol. 5, no. 4, 2001, pp. 373–401.

[11] A. A. Argiriou, I. Bellas-Velidis, and C. A. Balaras, “Development of a neural network heating controller for solar buildings,” Neural Networks, vol. 13, no. 7, 2000, pp. 811–820.

[12] S. A. Kalogirou, “Applications of artificial neural-networks for energy systems,” Applied Energy, vol. 67, no. 1, 2000, pp. 17–35.

[13] A. E. Ben-Nakhi and M. A. Mahmoud, “Energy conservation in buildings through efficient a/c control using neural networks,” Applied Energy, vol. 73, no. 1, 2002, pp. 5–23.

[14] J.-Y. Lee, M.-S. Yeo, and K.-W. Kim, “Predictive control of the radiant floor heating system in apartment buildings,” Journal of Asian Architecture and Building Engineering, vol. 1, no. 1, 2002, pp. 105–112.

[15] M. Gouda, S. Danaher, and C. Underwood, “Quasi-adaptive fuzzy heating control of solar buildings,” Building and Environment, vol. 41, no. 12, 2006, pp. 1881–1891.

[16] A. Ruano, E. Crispim, E. Conceição, and M. Lucio, “Prediction of building’s temperature using neural networks models,” Energy and Buildings, vol. 38, no. 6, 2006, pp. 682–694.

[17] J. W. Moon and J.-J. Kim, “Ann-based thermal control models for residential buildings,” Building and Environment, vol. 45, no. 7, 2010, pp. 1612–1625.

[18] P. Fanger, “Thermal comfort: analysis and applications in environmental engineering,” 1972.

[19] J. A. Orosa, “A new modelling methodology to control hvac systems,” Expert Systems with Applications, vol. 38, no. 4, 2011, pp. 4505–4513.

[20] E. Gelenbe, “Random neural networks with negative and positive signals and product form solution,” Neural computation, vol. 1, no. 4, 1989, pp. 502–510.

[21] ——, “Stability of the random neural network model,” Neural computation, vol. 2, no. 2, 1990, pp. 239–247.

[22] S. Timotheou, “The random neural network: a survey,” The computer journal, vol. 53, no. 3, 2010, pp. 251–267.

[23] C. Çerkez, I. Aybay, and U. Halici, “A digital neuron realization for the random neural network model,” in Neural Networks, 1997., International Conference on, vol. 2. IEEE, 1997, pp. 1000–1004.

[24] H. Abdelbaki, E. Gelenbe, and S. E. El-Khamy, “Analog hardware implementation of the random neural network model,” in Neural Networks, 2000. IJCNN 2000, Proceedings of the IEEE-INNS-ENNS International Joint Conference on, vol. 4. IEEE, 2000, pp. 197–201.

[25] H. Bakırcıoğlu and T. Koçak, “Survey of random neural network applications,” European journal of operational research, vol. 126, no. 2, 2000, pp. 319–330.

[26] E. Gelenbe, “Learning in the recurrent random neural network,” Neural Computation, vol. 5, no. 1, 1993, pp. 154–164.

[27] S. Basterrech, S. Mohammed, G. Rubino, and M. Soliman, “Levenbergmarquardt training algorithms for random neural networks,” The Computer Journal, vol. 54, no. 1, 2011, pp. 125–135.