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Neural network predictor for thermal comfort conditions

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Abstract – This paper is investigated thermal comfort conditions having surface and fresh air introduced directly in a room using neural network predictors. The investigation is divided into two steps. First step; experimental room system result is obtained the Building Physics Laboratory of the Department of Building Services, University of Debrecen. The room could be heated by radiator, on the wall, on the floor and on the ceiling heating system methods. During the operation of the heating system a series of measurements are derived, involving 20 students as subjects during education, in order to establish the effects of intermittency on thermal comfort feeling. The second step of the study; according to experimental results, some neural network predictors are used modelling the experimental room. Four types of ANNs are used to compare each other. From the results, it is noted that the proposed Radial Basis Neural Network gives the best results for analyzing thermal comfort conditions.

Keywords: thermal comfort, surface heating, neural networks.

1. INTRODUCTION

Thermal comfort analysis of building is an important field in which mechanical engineers study in order to decrease in total energy consumption. Some of studies have been presented about thermal comfort and ventilation system in a construction. Thermal comfort feeling during the heating-up and cooling down period of surface heating systems has been researched by Kalmár [1]. Wan et al. have been investigated a new method for selecting indoor temperature and indoor relative humidity to achieve minimum energy consumption for a required indoor thermal comfort level which have been evaluated with indoor effective temperature [2]. An investigation of airflow and contaminant transport in an occupied cabin by both experimental measurements and numerical simulations

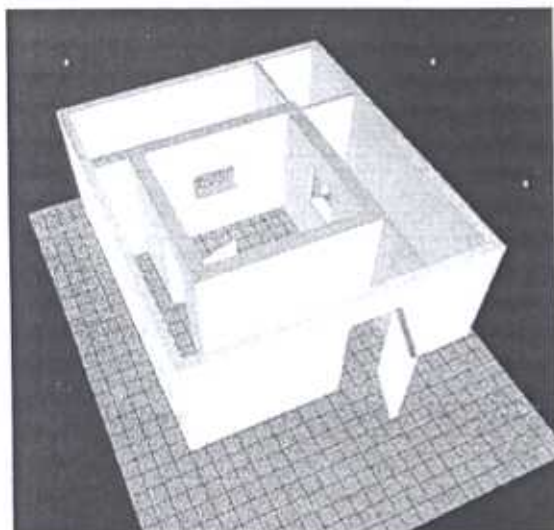
has been presented Zhang et al. [3]. Su et al. have been presented an evaluation method of natural ventilation system based on thermal comfort in China. With the testing result of natural ventilation system of an office building in Shanghai, the irrationality of using energy-utilization coefficient to evaluate one natural ventilation system has been discussed [4]. Ho et al. have been searched a three-dimensional analysis for thermal comfort and contaminant removal in a hospital operating room [5]. Memarzadeh and Manning have been analyzed the performance of a ventilation system in a typical patient room using computational fluids dynamics (CFD) modelling [6]. Shiming et al. have been presented on an experimental study to investigate the indoor thermal comfort characteristics under the control of a direct expansion air conditioning unit having variable-speed compressor and supply fan at a fixed space cooling load but having three different ratios between its sensible part and latent part [7]. Mora et al. have been studied thermal comfort in two operating rooms in a hospital [8].

In this paper, neural networks with different learning algorithms were used to predict thermal comfort conditions parameters having surface and fresh air introduced directly in a room. The paper can be organized in the following manner; Theory of the thermal comfort model and experimentally test room is described in Section 2. Theory of the neural networks is given in Section 3. Theory of learning algorithms of the neural networks are outlined in Sections 3.1 and 3.2. Experimental and Simulation results of the experimental room system and neural network are given and compared in Section 4. The paper is discussed and concluded in Section 5.

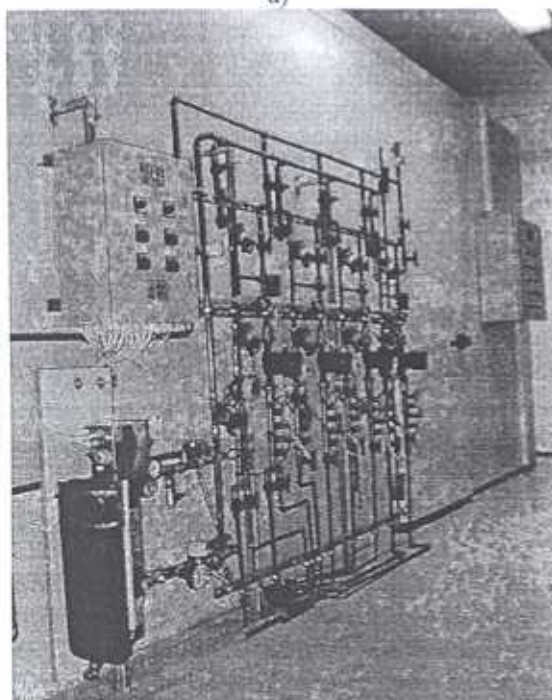
II. THERMAL COMFORT MODEL AND EXPERIMENTALLY TEST ROOM

In the first step of the research is obtained in the Building Physics Laboratory of the Department of Building Services, University of Debrecen (Fig. 1). In this laboratory there is an "adiabatic" room which has its external building elements very well insulated. In this external room the test room is placed (3,0×3,0×2,5 m).

In the space between these rooms temperatures between $-20...+28^{\circ}\text{C}$ can be produced, so a room having one or two external walls can be simulated. The test room has an external window. Using the well known relations the dimensions of the gaps which permit the minimal $\text{ACH}=0.5\text{ h}^{-1}$ (through natural ventilation) even for higher mean temperatures ($+10^{\circ}\text{C}$) are calculated. In the test room radiator, floor, wall and ceiling heating is installed. A series of measurements is derived to determine how the PMV values varies if ceiling and wall heating is used successively.



a)



b)

Figure 1. a) Measuring rooms; b) Experimental heating system

Having inlet/outlet gaps practiced on the window frame, the air mass flow depends mainly on the gaps cross section and indoor outdoor temperature difference. If the external air velocity is zero (no wind), than at the

same surface of the gaps the minimal air change rate during a heating season is obtained when the external temperature is equal to the balance point temperature of the building. In our case the indoor temperature set value is $t_i = 20^{\circ}\text{C}$, the external temperature (considered to be the balance point temperature) is $t_e = 10^{\circ}\text{C}$. The minimal ACH value is 0.5 h^{-1} . Having this input values results the necessary surface of the gaps: $A=0.004873\text{ m}^2$. Considering the gap height equal to 1 cm , the length of the gap could be determined. This value has to be 50 cm . The average value of the gap correction factor μ is 0.8686 . The scope of the measurements is to see if during the dynamic operation successively of the ceiling and floor heating system are there any periods of time when the thermal comfort might be accepted. The duration of the measurements is 3 hours and the external temperature is set to -15°C .

Predicted mean vote (PMV) is a parameter for assessing thermal comfort in an occupied zone based on the conditions of temperature and humidity along with metabolic rate, clothing, and air speed. PMV values refer to the ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) thermal sensation scale that ranges from -3 to 3 . The value of PMV is given by:

$$\text{PMV} = (0.303e^{-0.036M} + 0.028)(M - W) - 3.05 \times 10^{-3} \times [5733 - 6.99(M - W) - p_a] - 0.42 \times [(M - W) - 58.15] - 1.7 \times 10^{-5} M(5867 - p_a) - 0.0014M(34 - t_a) - 3.96 \times 10^{-8} f_{cl} \times [(t_{cl} + 273)^4 - (t_r + 273)^4] - f_{cl} h_c (t_{cl} - t_a); \quad (1)$$

where:

$$h_c = 2.38(t_{cl} - t_a)^{0.25} \quad (2)$$

$$f_{cl} = 1.05 + 0.645I_{cl} \quad (3)$$

During the measurements the external work is considered equal to zero, the metabolic rate equal to 1.2 met , $I_{cl} = 1.0\text{ clo} = 0.155\text{ m}^2\text{ K/W}$ and the surface temperature of the clothing $t_{cl} = 28^{\circ}\text{C}$.

III. NEURAL NETWORKS

Neural networks unlike traditional computing are considered as computational paradigms based on mathematical models having a structure and operation similar to that of the human brain. Neural networks are composed by a series of interconnected processing elements that operate in parallel and hence are also called as connectionist systems, parallel distributed systems or adaptive systems. The main aim of neural networks was to understand and shape the functional characteristics and the computational properties of the brain when it performs cognitive processes such as sensorial perception, concept categorization, concept association and learning [9].

The used learning algorithms for updating the weights of the neural network can be described in the following sub sections. Figure 2 shows schematic representation of neural network predictors. Structural and training parameters of the neural network predictors are listed in Table 1.

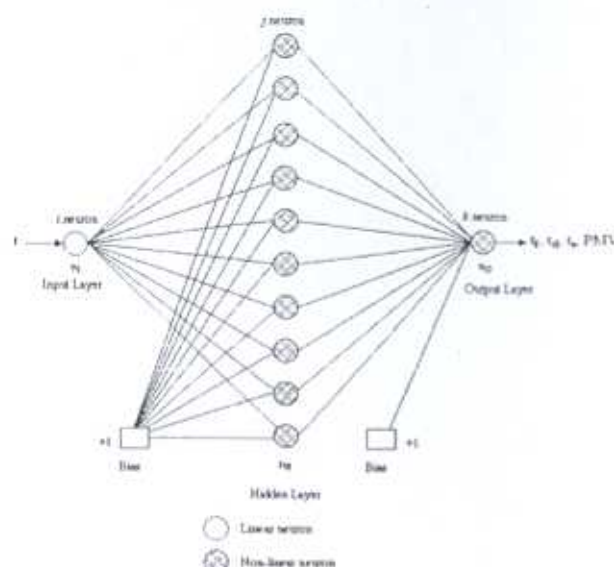


Figure 2. Schematic representation a feedforward neural network predictors

TABLE 1. RMS Errors for different neural network predictors

Results	η	α	N	n_i	n_H	n_o	NN Type	RMSEs
The result of floor surface temperature	0.25	0.4	90000	1	10	1	BPNN	0.0172
							GRNN	0.0204
							MRNN	0.0826
							RBNN	0.0001
The result of ceiling surface temperature	0.25	0.4	90000	1	10	1	BPNN	0.007
							GRNN	0.040
							MRNN	0.0083
							RBNN	0.0001
The result of external temperature	0.25	0.4	90000	1	10	1	BPNN	0.0185
							GRNN	0.0797
							MRNN	0.015
							RBNN	0.0034
The result of mean PMV values	0.25	0.4	9000000	1	10	1	BPNN	0.1056
							GRNN	0.1431
							MRNN	0.0637
							RBNN	0.0001

In the subsections the neural networks which are employed to predict thermal comfort conditions having surface and fresh air introduced directly in a room.

A. Back Propagation Neural Network (BPNN)

The BPNN is a method of supervised neural network learning. During training, the network is presented with a large number of input patterns. The desired corresponding outputs are then compared to the actual network output nodes. The error between the experimental and neural network response is used to update the weights of the network inter-connections. This update is performed after each pattern presentation. One run through the entire pattern set is termed an epoch. The training process continues for multiple epochs, until a satisfactorily small error is produced. The test phase uses a different set of input patterns. The corresponding outputs are again compared to a set of experimental outputs. This error is used to evaluate the networks ability to generalize.

Usually, the training set and/or architecture needs to be assessed at this point. The BPNN is the most commonly used to update the weights of the neural networks. The weights between input layer and the hidden layer are updated as follows:

$$\Delta W_{ij}(t) = -\eta \frac{\partial E_2(t)}{\partial W_{ij}(t)} + \alpha \Delta W_{ij}(t-1) \quad (4)$$

The weights between the hidden layer and the output layer are updated in the following equation:

$$\Delta W_{jk}(t) = -\eta \frac{\partial E_1(t)}{\partial W_{jk}(t)} + \alpha \Delta W_{jk}(t-1) \quad (5)$$

where η is the learning rate, and α is the momentum term. $E_2(t)$ is the propagation error between hidden layer and input layer. $E_1(t)$ is the error between output layer and hidden layer.

B. General Regression Neural Network (GRNN)

GRNN are paradigms of the Probabilistic and Radial Basis Function (RBF) used in functional approximation. To apply GRNN to analyze, a vector f_j is formed. The output y is the weighted average of the target values t_n of training cases f_n close to a given case f_j , as given by:

$$y_k = \frac{\sum_{j=1}^{10} z_j W_{jk}}{\sum_{j=1}^{10} W_{jk}} \quad (6)$$

where:

$$W_{jk} = \exp \left[\frac{-|f_j - f_k|^2}{2h^2} \right] \quad (7)$$

The only weights that need to be learned are the smoothing parameters, h of the RBF units in Eq. (7), which are set using a simple grid search method. The distance between the computed value n and each value in the set of target values T is given by:

$$T = \{1, 2\} \quad (8)$$

The values 1 and 2 correspond to the training class and all other classes respectively. The class corresponding to the target value with the minimum distance is chosen. As, GRNN exhibits a strong bias towards the target value nearest to the mean value ξ of T so we used target values 1 and 2 because both have the same absolute distance from ξ .

C. Modular Neural Network (MNN)

MNN refer to the adaptive mixtures of local experts. The most attractive point of MNN architecture is that different experts handle different parts of the data. The problem of pattern interference can be alleviated by this type of architecture. Each local network receives the same input vector applied to the network. A gating network determines the contribution of each local network to the total output as well as what range of the input space each network should learn. The back propagation algorithm is used to train the gating and local networks. The outputs of the local networks are combined to give the network output such that:

$$y_k = \sum_{j=1}^{10} g_{jk} y_{jk} \quad (9)$$

where y_{jk} are the output of the j^{th} local network and y_k are the normalized output vector elements of the gating network given by:

$$y_{jk} = \frac{e^{u_{jk}}}{\sum_{j=1}^{10} e^{u_{jk}}} \quad (10)$$

where u_{jk} are the weighted input received by the j^{th} output unit of the gating network. In Eq. (9), $\sum y_{jk} = 1$ and $0 \leq y_{jk} \leq 1$. The gating and local experts are trained to maximize the following function using the back propagation learning rule:

$$L = \ln \left[\sum_{j=1}^{10} y_{jk} e^{-\frac{1}{2} |N_f - N_{fk}|^2} \right] \quad (11)$$

where N_f is the experimentally obtained number of cycles to failure and N_{fk} are the corresponding output given by the neural network. The neural network simultaneously adjusts the connection and threshold of the local networks as well as the connection weights and thresholds of the gating networks. The error for the j^{th} output of the gating network is calculated as:

$$\frac{\partial L}{\partial u_{jk}} = h_{jk} - y_{jk} \quad (12)$$

where h_{jk} are a posterior probability that the j^{th} local network is responsible for the current output such that:

$$h_{jk} = \frac{y_{jk} e^{-\frac{1}{2} |N_f - N_{fk}|^2}}{\sum_{j=1}^{10} y_{jk} e^{-\frac{1}{2} |N_f - N_{fk}|^2}} \quad (13)$$

while the error for the j^{th} local network is calculated as:

$$\frac{\partial L}{\partial I_{jk}} = h_{jk} \left[(N_f - y_{jk}) \frac{\partial y_{jk}}{\partial I_{jk}} \right] \quad (14)$$

The training process is terminated either when the mean square error between the observed data and the NN outcomes for all elements in the training set has reached a pre-specified threshold or after the completion of a pre-specified number of learning epochs.

D. Radial Basis Neural Network (RBNN)

Traditionally, RBNN which model functions $y(x)$ mapping $x \in R^n$ to $y \in R$ have a single hidden layer so that the model:

$$\hat{f}_{ij}(x) = \sum_{j=1}^{10} W_{ij} h_{ij}(x) \quad (15)$$

is linear in the hidden layer to output weight W_{ij} . The characteristic feature of RBNN is the radial nature of the hidden unit transfer functions, h_{ij} , which depend only on the distance between the input x and the centre c_{ij} of each hidden unit, scaled by a metric R_{ij} :

$$h_{ij}(x) = \phi \left[(x - c_{ij})^T R_{ij}^{-1} (x - c_{ij}) \right] \quad (16)$$

where ϕ is some function which is monotonic for non negative numbers. Gaussian basis function so that the transfer functions can be written:

$$h_{ij}(x) = \exp \left(- \sum_{k=1}^1 \frac{(x_k - c_{jk})^2}{r_{jk}^2} \right) \quad (17)$$

Using the Gaussian approximation, the output network is approximately:

$$f(x) = \sum_{j=1}^{10} w_{jk} \exp \left(- \sum_{k=1}^1 \frac{(x_k - c_{jk})^2}{r_{jk}^2} \right) \quad (18)$$

where r_j is the radius vector of the j^{th} hidden unit. A direct approach to the model complexity issue is to select a subset of centres from a larger set which, if used in its entirety, would over fit the data.

IV. EXPERIMENTAL AND SIMULATION RESULTS

Four types of neural networks are employed to predict the thermal comfort conditions parameters for comparison in simulation approach. Fig. 3 illustrates the results of variation of floor surface temperature using Neural Network. Fig. 3 (a), (b) and (c) show the result of BPNN, MRNN and GRNN approach for variation of floor surface temperature. It is clear to see from graphs, there are differences between experimental measuring results and neural network results for both cases. Fig. 3 (d) indicates the results of the RBNN are exactly match to experimental results.

The same network structures (BPNN, MRNN, GRNN and RBNN) are used to estimate variation of ceiling surface temperature using Neural Network (see Fig. 4 (a), (b), (c) and (d)).

As can be described from Fig. 4 (d), the RBNN result is exactly match to experimental results.

Fig. 5 (a) shows the BPNN result for variation of external temperature and BPNN does not follow experimental result. The results of MRNN and GRNN are shown in Fig. 5 (b) and (c). The result of variation of external temperature for the RBNN approach is shown in Fig. 5 (d). As can be seen figure, the result of RBNN approach has the best performance for thermal comfort conditions analysis. The responses of experimental results and Neural Network for mean PMV values are shown Fig. 6 (a), (b), (c) and (d). These results are also similar to previous results of Figures. It can be observed that these values are quite higher than the expected -3, and almost half of measuring period this values are higher than -1. It can be seen that the subjects react immediately to the switching off/on of the heating system and the reaction is slow in the case of floor heating. Because of Gaussian function structure of RBNN, the best results in nearly the same experimental approach are given.

V. DISCUSSION AND CONCLUSION

In this paper, we have proposed a neural network predictor for thermal comfort conditions having surface and fresh air introduced directly in a room.

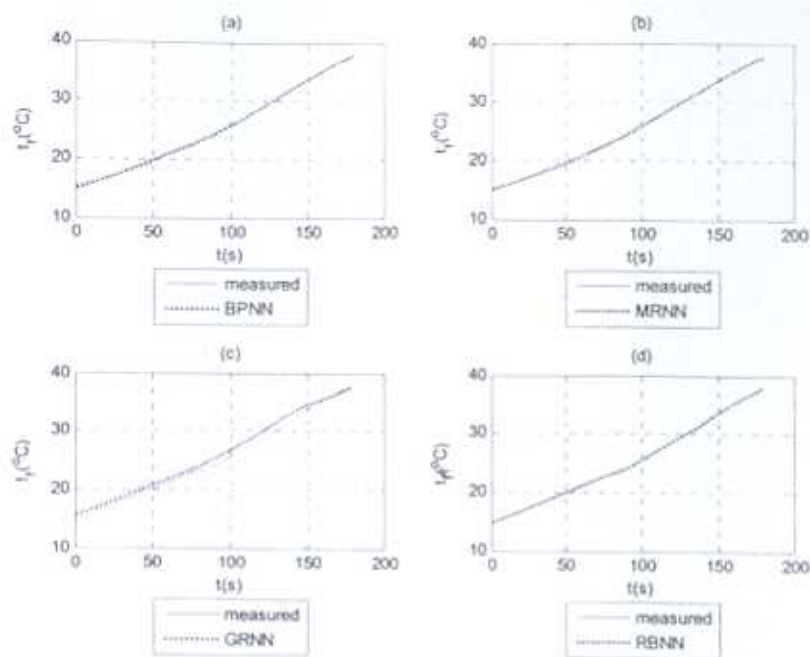


Figure 3. The result of variation of floor surface temperature using neural network predictors ($t(s)$ = collected samples in 3 hours)

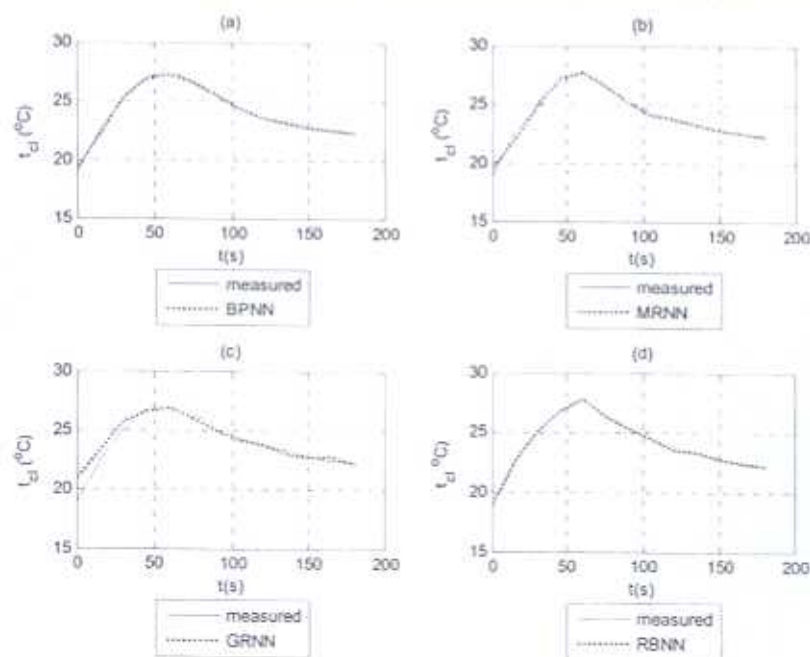


Figure 4. The result of variation of ceiling surface temperature using neural network predictors ($t(s)$ = collected samples in 3 hours)

From the experiments, the measurements have shown that having surface heating in dynamic operation the occupants might accept the microclimate even though, theoretical, $PMV=-3$ should be obtained. However if we would like to exploit a part of the heating up time as exploitation time of the operative temperature should be higher than 17°C when the process starts. During the measurements the fresh air flow enters directly in the room having very low temperatures. Using a mechanical ventilation system with heat recovery the results would be better both from energy and thermal comfort point of view.

The four types of the neural networks were used for

finding exact model of the room heating system. The use of RBNN structure was given the best results in nearly the same experimental approach. Because, RBNN structure is unusual in that the constitution of its hidden units is entirely different from that of its output units. With radial basis functions providing the foundation for the design of the hidden units, the theory RBNN is linked closely with that radial-basis functions, which is one of the main fields of study in numerical analysis. Finally, the results of prediction improved that the RBNN has superior prediction for thermal comfort conditions parameters having surface and fresh air introduced directly in a room.

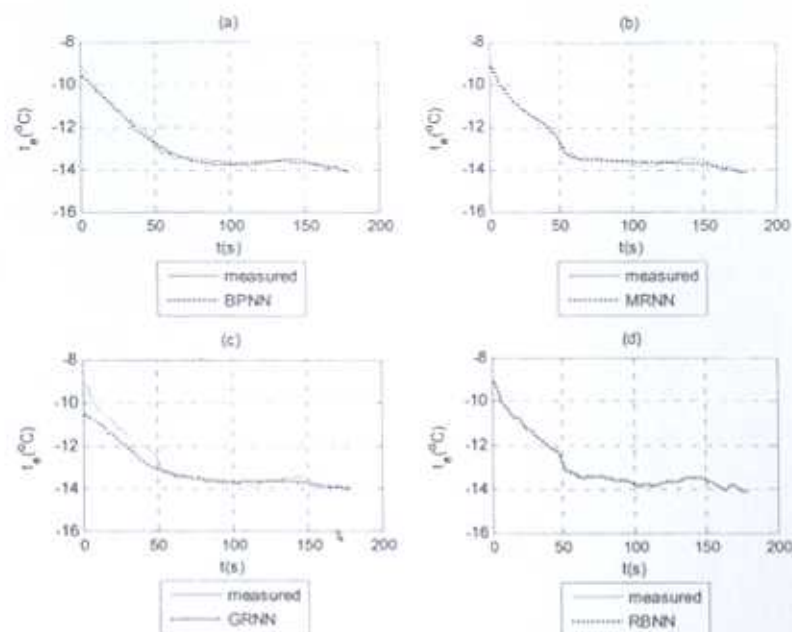


Figure 5. The result of variation of external temperature using neural network predictors ($t(s)$ = collected samples in 3 hours)

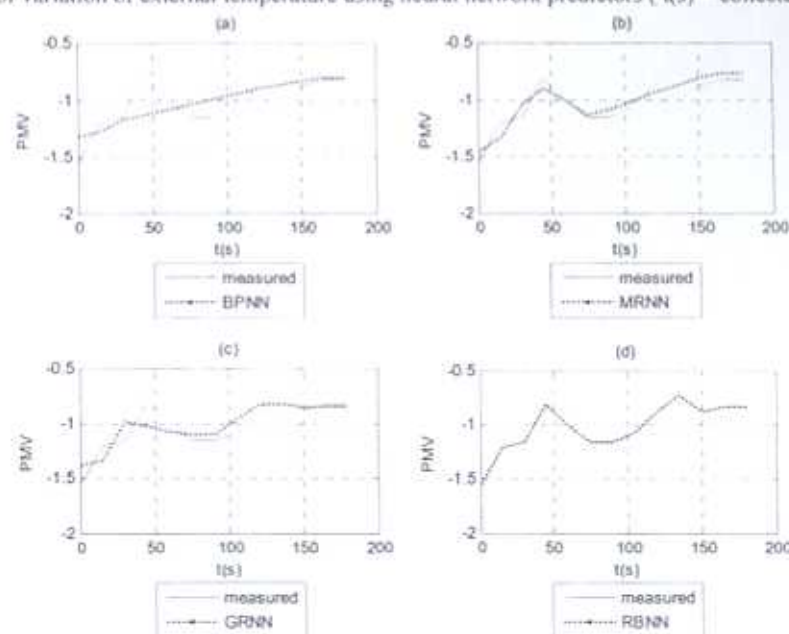


Figure 6. The result of mean PMV values using neural network predictors ($t(s)$ = collected samples in 3 hours)

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