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Intelligent system based on wavelet decomposition and neural network for predicting of fan speed for energy saving in HVAC system

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ABSTRACT

In this study, a heating, ventilating and air-conditioning (HVAC) system with different zones was designed and tested. Its fan motor speed and damper gap rates were controlled by two controllers (i.e. a PID controller and an intelligent controller) in real time to minimize its energy consumption. The desired temperatures were realized by variable flow-rate by considering the ambient temperature for each zone and evaporator. The PID parameters obtained in our previous theoretical work using fuzzy logic were utilized in this study. The experimental data used in this study was collected using a HVAC system built in a laboratory environment. The fan motor speed and damper gap rates were predicted using wavelet packet decomposition (WPD), entropy, and neural network (NN) techniques. WPD was used to reduce the input vector dimensions of the intelligent model. The suitable architecture of the NN model is determined after certain trial and error steps. According to test results, the developed model performance is at desirable level. Efficiency of the developed method was tested and a mean 95.62% recognition success was obtained. This model is an efficient and robust tool to predict damper gap rates and fan motor speed to minimize energy consumption of the HVAC system.

1. Introduction

In recent years, intelligent modeling studies related to HVAC system have become popular because of the rising concern about environment. The developments in intelligent methods make them possible to use in complex systems modeling. Intelligent modeling was firstly used to increase the robustness of existing models but now it is used to obtain new models. The comfort of the people in their living environment is partially dependent on the quality and temperature of air in their building. Three interrelated systems are used to provide the desired air temperature and quality. These are the ventilating system, the heating system and the air conditioning system. The purpose of a HVAC system is not only to provide thermal comfort, but also to maintain comfortable air quality. On the other hand, energy saving in this system is one of the most important issues because of its cost. Hence, it is necessary to understand the aspects of minimum energy consumption in order to design an effective HVAC system.

Many authors have employed for variable frequency drives method which is routinely used to vary pump and fan motor speed in heating, ventilating and air conditioning of buildings [1]. In these applications, speed control is used to regulate the flow of water or air because speed adjustment is an energy efficient method of flow control. The aim of this study is to present a thermodynamic model for an air-cooled centrifugal chiller which is developed specifically to analyze how the speed control of the condenser fans influences the chiller's COP under various operating conditions [2,3]. Moreover, the other study of the same authors investigates how the use of variable speed condenser fans enables air-cooled chillers to operate more efficiently [4]. Besides, variable fan speed control is increasingly used for chiller compressors to save power when chillers are operating at part load. The power saving comes from the improved efficiency of the motors when operating at a lower speed under part-load conditions [5,6].

In the last decade, many studies were performed in HVAC systems and buildings based on intelligent methods. These researches are related to modeling HVAC systems and thermal comfort for buildings such as predictions of HVAC system parameters, process control of HVAC systems, estimating HVAC systems output parameters characteristics and humidity and temperature control of buildings. The developments in intelligent methods make them possible to use in nonlinear analysis and control. In addition to PID control of HVAC systems, the various studies using intelligent methods were presented. Many NN models were developed to predict temperature, humidity, heat transfer, optimal time, pressure coefficients and energy consumption [7–13]. Soyguder and Alli studied about the estimation of humidity and temperature in a HVAC system [7]. Kalogirou et al. discuss about estimation of pres-

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Nomenclature

$\dot{m}_{ca}$	the mass flow-rate in fan channel (kg/h)
$\dot{m}_{z1a,in}$	the mass flow-rate entered to Zone-1 (kg/h)
$\dot{m}_{z2a,in}$	the mass flow-rate entered to Zone-2 (kg/h)
Q	convection and transmission heat (J)
$\dot{m}_{za,in} = \dot{m}_{za}$	the mass flow-rate entered to each zone (kg/h)
C_v	specific heat capacity of air at constant heat (kJ/kg K)
C_p	specific heat capacity of air at constant pressure (kJ/kg K)
T	inner temperature (°C)
T_n	instant temperature (°C)
T_{n-1}	vicious circle temperature (°C)
$T_{ca,in}$	canal temperature (°C)
O_i	output of ANFIS layer
A_i	linguistic label
w_i	firing strength of rules
$\psi_{i,j}(x)$	the wavelet expansion functions
$c_{i,j}$	expansion coefficients
$\phi(x)$	scaling function
ψ_m	the decomposition filter
P	entropy
$y_{pre,m}$	predicted value
$t_{mea,m}$	measured value

sure coefficients in a naturally ventilated test room using artificial neural networks [8]. Yang et al. performed energy prediction for a building using adaptive artificial neural networks [10]. Yang et al. used application of artificial neural network to predict the optimal start time for heating system in building and HVAC system [11]. Sablani et al. developed an ANN model for calculating thermal conductivity of a variety of bakery products under a wide range of conditions of moisture content, temperature in bakery story [12]. In another study, Ben-Nakhi and Mahmoud worked about general regression neural networks (GRNN) and designed the GRNN and trained to investigate the feasibility of using this technology to optimize HVAC thermal energy storage in public buildings as well as office buildings [14]. Consequently, many studies about artificial neural network and intelligent method can be mentioned [15–19].

In this study, based on the above literature the required fan motor speed to minimize energy consumption and the required damper gap rates for obtaining the desired temperatures of two different zones for each time step were found using intelligent control algorithm. The damper gap rate is also proportional with air flow rate. Besides, in this study, an intelligent system for fan motor speed and air flow control of HVAC system based on WPD-NN is presented. All simulations have shown that the proposed method is more effective and controls the systems quite well.

The outline of the present paper is as follows. In Section 2, the model of the HVAC system is presented. The design of the considered real-time HVAC system is given Section 3. Section 4 briefly describes the wavelet transform (WT), WPD and NN. In Section 5, model procedure was designed about the wavelet packet and NN structure for intelligent modeling. Then, in Section 6, the experimental and modeling results are presented. In the experiment, the fan motor speed and the damper gap rate being proportional with air flow rate have been controlled using WPD-NN. In Section 7 was discussed the strengths and weaknesses of the present study. Finally, conclusions are given in Section 8.

2. The model of the HVAC system

The mathematical model of the system obtained according to the thermodynamic laws. However, obtaining of the mathematical model of the cooled zone by considering all parameters is quite difficult. For this reason, we consider some assumptions. More information about the assumptions can be seen in the author's other work [7]. Every testing laboratory has its own HVAC system including cooling unit, electric heater (resistance), fan, damper motors, thermocouples and evaporator of refrigeration plant to maintain the temperature of the Zone-1 and Zone-2 space.

In this study differs from previous work [7], the mass flow-rate ($\dot{m}_{ca}$) absorbed from the cooling unit does change because the supply fan speed is controlled for energy saving. At the same time, the mass flow-rate of the air entering to the zones changes depending on the temperatures of the zones. The continuously variations of the input mass flow-rate ($\dot{m}_{z1a,in}$) Zone-1 and ($\dot{m}_{z2a,in}$) Zone-2 are realized by regulating the gap rates of dampers into the entrances of zone-channels, depending on the control output signals. The continuity equation of the controlled system can be formed as:

$$\dot{m}_{ca} = \dot{m}_{z1a,in} + \dot{m}_{z2a,in} + \dot{m}_{sva,out} \tag{1}$$

The mass flow-rate ($\dot{m}_{sva,out}$) in Eq. (1) belongs to the safety valve discharging the excessive air coming from the zones.

Fig. 1 shows the schematic diagram of the modeled system in this study. The heat transfer from the outside to the system can be stated as:

$$\frac{dT}{dt} = \frac{Q + \dot{m}_{za}.C_p(T_{ca,in} - T_n)}{m_{za}.C_v} \tag{2}$$

More information about HVAC system model can be seen in the author's other work [7].

3. The design of the considered real-time HVAC system

In this experimental study, the cooling process was performed for the two zones having the different properties as shown in Fig. 2(a and b). The volume of the each zone has 0.5 m^3. The all surface areas of Zone-1 were isolated with the isolation materials (strafor) while those of Zone-2 were not. The aim of this choice is to clearly see the steady-state differences of reference temperatures. The cooled air transfer has been realized from the main channel having the supply fan to the region of Zone-1 and Zone-2 as seen in Fig. 2(a and b). The channel flow cross-section area is 0.02 m^2. The 0° position of the damper (opening angle (θ)) is the full open position and the system has the maximum air mass flow-rate. Maximum air mass flow rate is 50 kg/h for the 0° position of the damper (opening angle (θ)). Air mass flow rate changes as direct proportional of opening angles (θ) between the 0° position of the damper and the 90° position of the damper. At the same time, air mass flow rate changes as direct proportional of fan motor speed. Furthermore, fan motor speed is dependent on evaporator temperature, as seen from the block diagram in Fig. 3. The 90° position of the damper is the closed position of the damper and the cooled air cannot pass through the zones. Air mass flow rate is controlled by a stepper-driven throttle damper-valve. More information about the design of the considered real-time HVAC system can be seen in the author's other work [7].

In testing real-time HVAC system, the air compressor and the evaporator were used for cooling the system and the required air flow was supplied by controlled of the dampers placed on the entrance ducts of each zone. There are the damper motors in the entrances of the each zone, controlled by intelligent control algorithm, as seen from the block diagram in Fig. 3. The air supply fan first absorbs 5 °C air from the evaporator, then sends to the zones. In this study, the fan motor speed is also controlled by intelligent

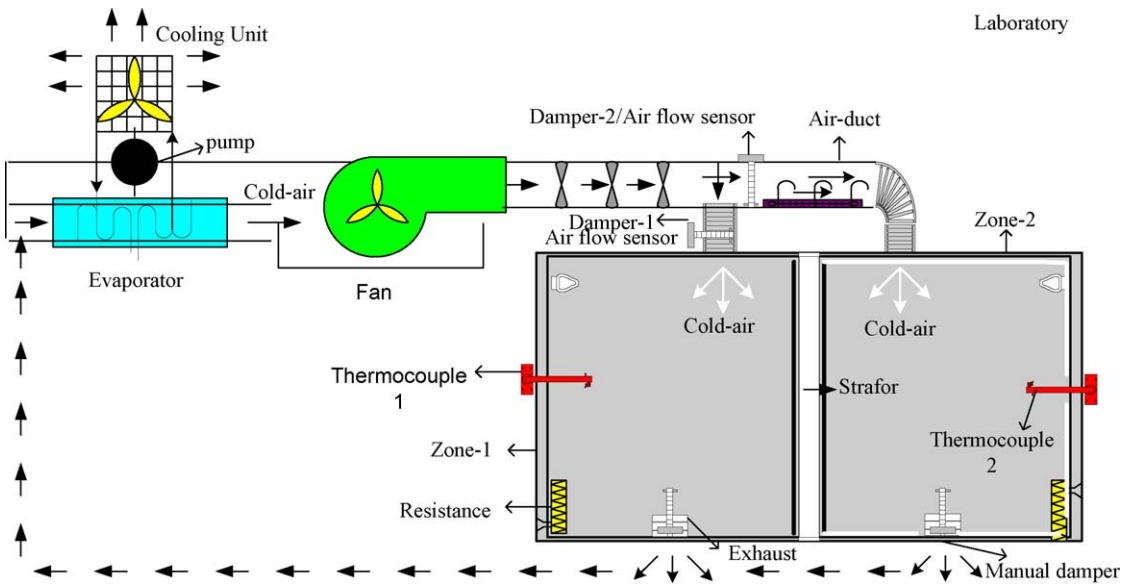

Fig. 1. The schematic view of the HVAC system having two zones.

control algorithm to minimize energy consumption, as seen from the block diagram in Fig. 3.

4. Preliminaries

In this section, the theoretical foundations for the intelligent modeling used in the presented study are given in the following subsections.

4.1. Wavelet transform

Wavelet transforms are finding inverse use in fields as diverse as telecommunications and biology. Because of their suitability for analyzing non-stationary signals, they have become a powerful alternative to Fourier methods in many medical applications, where such signals abound [20]. The main advantages of wavelets are that they have a varying window size, being wide for slow fre-

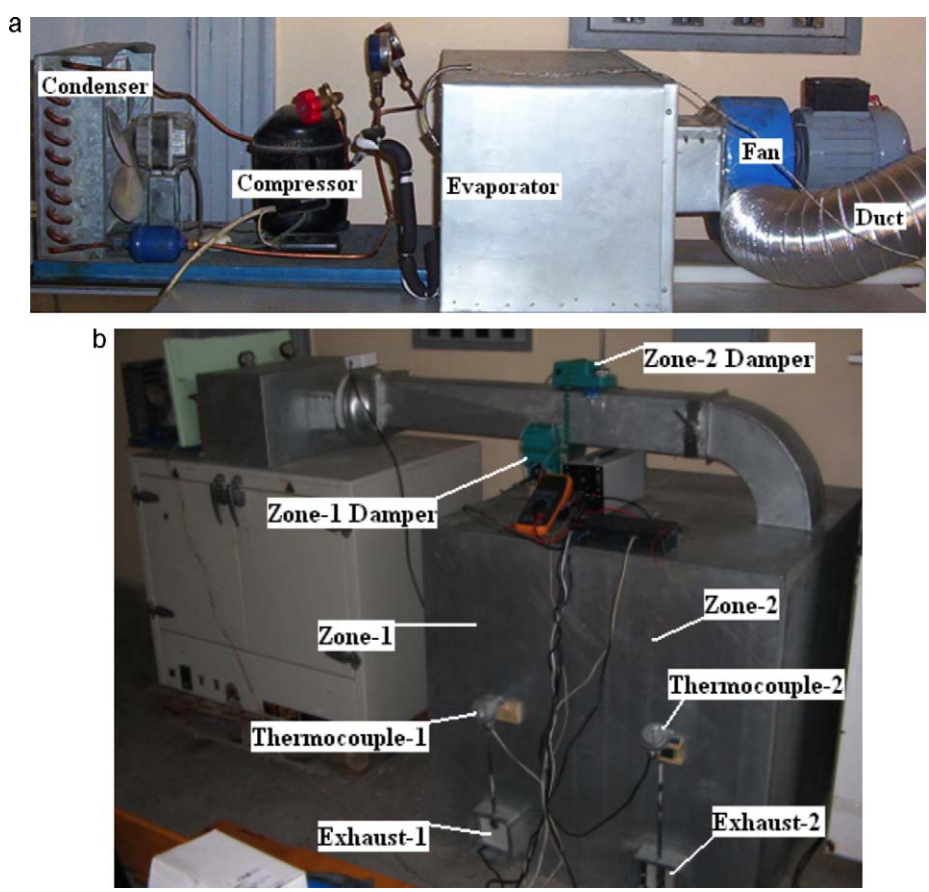

Fig. 2. (a and b) A prototype of the real-time HVAC system experimental setup.

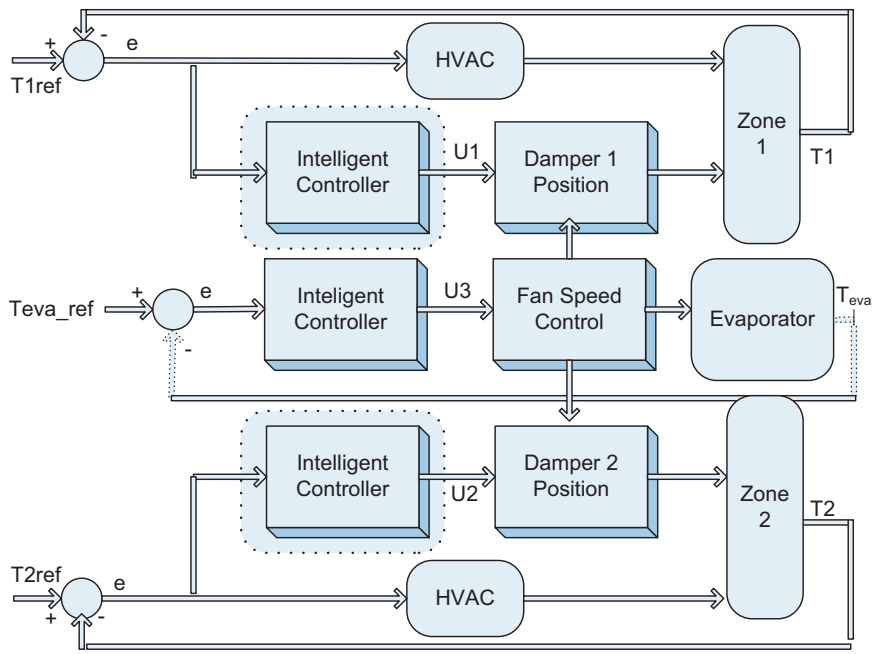

Fig. 3. The block diagram of the considered system.

quencies and narrow for the fast ones, thus leading to an optimal time-frequency resolution in all the frequency ranges. Furthermore, owing to the fact that windows are adapted to the transients of each scale, wavelets lack the requirement of stationary.

A wavelet expansion is Fourier series expansion, but is defined by a two-parameter family of functions. It can be defined as follows:

$$f(x) = \sum_{i,j} c_{i,j}\psi_{i,j}(x) \tag{3}$$

where i and j are integers, the functions $\psi_{i,j}(x)$ are the wavelet expansion functions and the two-parameter expansion coefficients $c_{i,j}$ are called the discrete wavelet transform (DWT) coefficients of $f(x)$. The coefficients are given by;

$$c_{i,j} = \int_{-\infty}^{+\infty} f(x)\psi_{i,j}(x) \tag{4}$$

The wavelet basis functions can be computed from a function $\psi(x)$ called the generating or mother wavelet through translation and dilation;

$$\psi_{i,j}(x) = 2^{-i/2}\psi(2^{-i}x - j) \tag{5}$$

where j is the translation and i the dilation parameter. Mother wavelet function is not unique, but it must satisfy a small set of conditions. One of them is multi-resolution condition and related to the two-scale difference equation;

$$\phi(x) = \sqrt{2}\sum_k h(k)\phi(2x - k) \tag{6}$$

where $\phi(x)$ is scaling function and $h(k)$ must satisfy several conditions to make basis wavelet functions unique, orthonormal and have a certain degree of regularity. The mother wavelet is related to the scaling function as follows:

$$\psi(x) = \sqrt{2}\sum_k g(k)\phi(2x - k) \tag{7}$$

where $g(k) = (-1)^k h(1-k)$. At this point, if valid $h(x)$ is available, one can obtain $g(x)$. Note that h and g can be viewed as filter coefficients of half band low pass and high pass filters, respectively. J-level wavelet decomposition can be computed with Eq. (8) as follows:

$$f_0(x) = \sum_k c_{0,k}\phi_{0,k}(k) = \sum_k (c_{J+1,k}\phi_{J+1,k}(x) + \sum_{j=0}^{J} d_{j+1,k}\psi_{j+1,k}(x)) \tag{8}$$

where coefficient $c_{0,k}$ are given and coefficients and coefficient $c_{J+1,n}$ and $d_{j+1,n}$ at scale $j+1$ and they can be obtained if coefficient at scale j is available;

$$\begin{aligned} c_{j+1,n} &= \sum_k c_{j,k}h(k-2n) \\ d_{j+1,n} &= \sum_k c_{j,k}g(k-2n) \end{aligned} \tag{9}$$

4.2. Wavelet packet decomposition

As an extension of the standard wavelets, wavelet packet represent a generalization of multi-resolution analysis and use the entire family of sub band decomposition to generate an over complete representation of signals [21]. Wavelet decomposition uses the fact that it is possible to resolve high frequency components within a small time window, while only low frequency components need large time windows. This is because a low frequency component completes a cycle in a large time interval whereas a high frequency component completes a cycle in a much shorter interval. Therefore, slow varying components can only be identified over long time intervals but fast varying components can be identified over short time intervals. Wavelet decomposition can be regarded as a continuous time wavelet decomposition sampled at different frequencies at every level or scale. The wavelet decomposition functions at level m and time location tm can be expressed as:

$$d_m(t_m) = x(t)\Psi_m\left(\frac{t - t_m}{2^m}\right) \tag{10}$$

where ψ_m is the decomposition filter at frequency level m. The effect of the decomposition filter is scaled by the factor $2m$ at stage m, but otherwise the shape is the same at all scales [22]. Wavelet

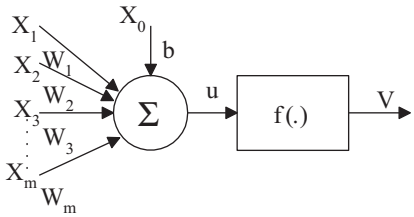

Fig. 4. Artificial neuron model.

packet analysis is an extension of the discrete wavelet transform (DWT) [23] and it turns out that the DWT is only one of the much possible decomposition that could be performed on the signal. Instead of just decomposing the low frequency component, it is therefore possible to subdivide the whole time-frequency plane into different time-frequency pieces. The advantage of wavelet packet analysis is that it is possible to combine the different levels of decomposition in order to achieve the optimum time-frequency representation of the original [24].

4.3. Neural networks

Neural networks (NNs) are biologically inspired and mimic the human brain. They are consisting of a large number of simple processing elements called as neurons. A schematic diagram for an artificial neuron model is shown in Fig. 4. Let $X = (X_1, X_2 \ldots X_m)$ represent the m input applied to the neuron. Where W_i represents the weight for input Xi and b is a bias then the output of the neuron is given by Eq. (11). These neurons are connected with connection link. Each link has a weight that multiplied with transmitted signal in network. Each neuron has an activation function to determine the output. There are many kind of activation function. Usually nonlinear activation functions such as sigmoid, step are used. NNs are trained by experience, when applied an unknown input to the network it can generalize from past experiences and product a new result [25].

$$u = \sum_{i=0}^{m} x_i w_i - b, \text{ and } V = f(u) \tag{11}$$

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. They represent the promising new generation of information processing systems. Neural Networks are good at tasks such as pattern matching and classification, function approximation, optimization and data clustering [26].

When designing a NN model, a number of considerations must be taken into account. First of all the suitable structure of the NN model must be chosen, after this the activation function and the activation values need to be determined. The number of layers and the number of units in each layer must be chosen. Generally desired model consist of a number of layers. The most general model assumes complete interconnections between all units. These connections can be bidirectional or unidirectional. We can sort the advantages of NN as follows:

- They can be implemented electrically, optically, or can be modeled on general purpose computer
- They are fault tolerant and robust
- They work in parallel and special hardware devices are being designed and manufactured which take advantage of this capability
- Many learning paradigm or algorithms are available in practice

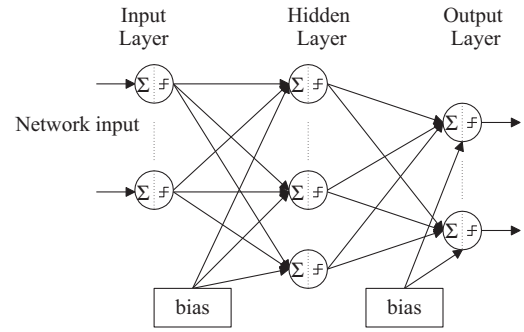

Fig. 5. Multilayer feed forward neural network structure.

- An ability to learn how to do tasks based on the data given for training or initial experience.

NN can create its own organization or representation of the information it receives during learning time.

There are many kind of NN structure. One of these is multilayer feed forward NN and is shown in Fig. 5.

5. Model procedure

The realization steps are as follows:

Step 1: first of all, parameters database is formed. The parameters data which have missing value are ignored. The data are normalized by Eq. (12).

$$s(i) = \frac{s(i) - \min(s)}{\max(s) - \min(s)} \tag{12}$$

Step 2: this step is related to feature extracting and classification. Fig. 6 shows the wavelet packet and NN structure for intelligent modeling. Feature extraction is the key process for intelligent methods. So that it is arguably the most important component of modeling based on intelligent. A feature extractor should reduce the input vector (i.e. the original waveform) to a lower dimension, which contains most of the useful information from the original vector. The goal of the feature extraction is to extract features from these data for reliable intelligent modeling. For feature extraction, the Wavelet packet and NN structure was used.

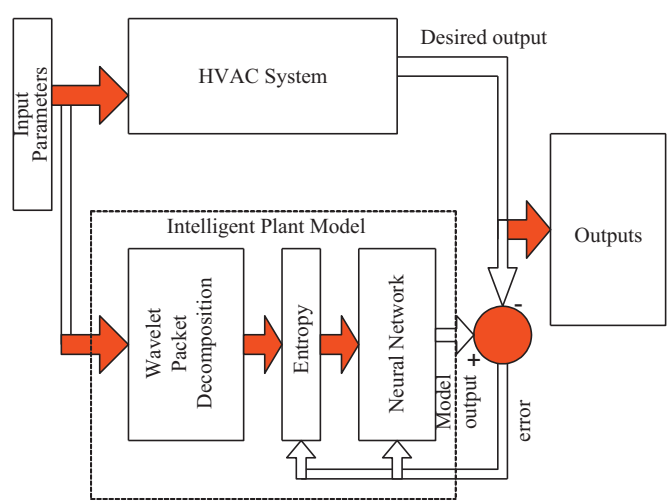

Fig. 6. The structure of intelligent modeling.

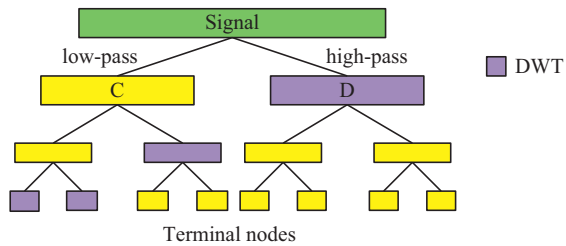

Fig. 7. Total decomposition tree of wavelet packet analysis.

The wavelet packet and NN structure is composed of two layers. These are wavelet packet layer and multilayer perceptions layer, respectively.

Wavelet packet layer: this layer is responsible for feature extraction from input data. The feature extraction process has two stages:

Stage 1 – wavelet packet decomposition: for wavelet packet decomposition of the input data, the decomposition structure at level 3 was realized and shown in Fig. 7. Wavelet packet decomposition was applied to the input data using the Symlet-1 wavelet decomposition filters, ψ.

Stage 2 – wavelet entropy: an entropy-based criterion describes information-related properties for an accurate representation of a given signal. Entropy is a common concept in many fields, mainly in signal processing [27]. A method for measuring the entropy appears as an ideal tool for quantifying the ordering of non-stationary signals. We next calculated the sure entropy of the wavelet packet coefficients as defined in Eq. (13).

$$E(s) = \sum_i \min(s_i^2, p^2) \quad |s_i| \le p \tag{13}$$

where, the wavelet entropy E is a real number, s is the terminal node signal and (s_i) is i the waveform of terminal node signals. In sure entropy, P is the threshold and must be a positive number. At the WPD-NN training process, while the P parameter is updated by 0.1 increasing steps, the weights of the NN is updated randomly. Thus, feature vectors which have the length of 4 are obtained.

Multi-layer perception (MLP) layer: this layer is realized the classification using features from wavelet packet layer. The training parameters and the structure of the MLP are shown for each zone in Table 1. These were selected for the best performance after several trial and error stages, such as the number of hidden layers, the size of the hidden layers, value of the moment constant and learning rate, and type of the activation functions. WPD-NN training performance is shown in Figs. 12, 14 and 16.

Table 1
MLP architecture and training parameters for Zone-1, Zone-2 and evaporator.

Architecture	
The number of layers	3
The number of neuron on the layers	Input: 3 Hidden: 15 Output: 1
The initial weights and biases	Random
Activation functions	Tangent-sigmoid Tangent-sigmoid Linear
Training parameters	
Learning rule	Levenberg–Marquardt Back-propagation
Sum-squared error	0.01

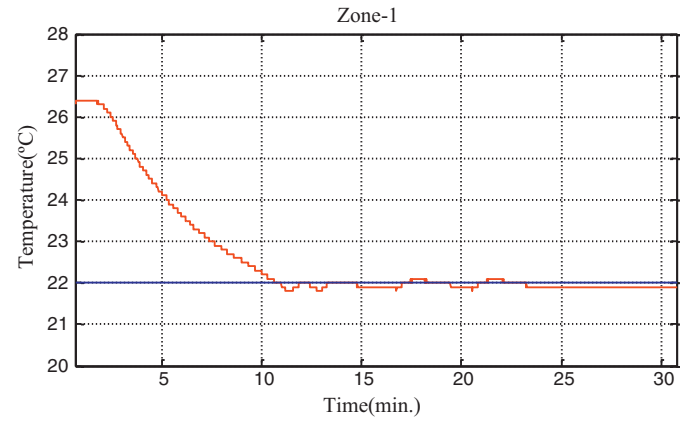

Fig. 8. The set temperature values of Zone-1 [°C].

6. Experimental and modeling results

In the experiment, air mass flow rate has been controlled by fan motor speed and dampers using PID and intelligent controllers. The ambience temperature was approximately 26.4 °C for each application. The set temperature values of Zone-1 and Zone-2 have been adjusted as 22.0 °C and 23.0 °C, respectively. Besides, the required set temperature values of evaporator have been adjusted as 5 °C. The set temperature of evaporator (5 °C) is theoretically taken in thermodynamic applications. The most important duration in HVAC systems is steady-state time which approximately contains three quarters of all day (i.e. the HVAC system may be turned off for approximately 6 h a day). The obtained results are presented in graphical form as seen in Figs. 8–10.

The realized HVAC system's data were used in this study to train and test the WPD-NN models. All program codes were written using MATLAB programme. Three WPD-NN models were performed. The first one of them is for Zone-1, the second one is for Zone-2 and the third one is for the evaporator. Half of the each zone data were used to training stages and the other parts were used to test stages. The set temperature of zone, the difference between the set temperature of zone and the ambient temperature and the first derivation of the difference between the set temperature of zone and the ambient temperature were used as input to the WD-NN model of zones and damper gap rate was used as WPD-NN model output. Besides, the set temperature of evaporator, the difference between the set temperature of evaporator and the evaporator temperature and the first derivation of the difference between the set temperature of evaporator and the evaporator temperature were used as input to the NN model of evaporator and fan motor speed was used as WPD-

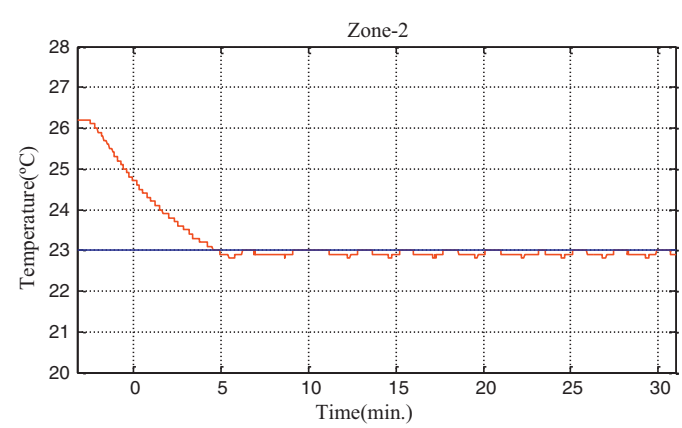

Fig. 9. The set temperature values of Zone-2 [°C].

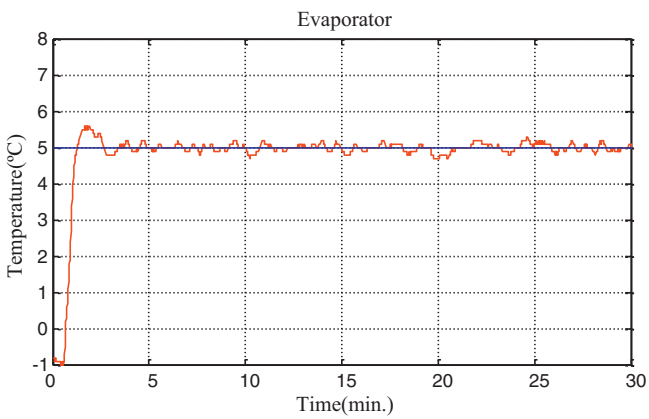

Fig. 10. The set temperature values of evaporator [°C].

NN model output. So each WPD-NN model has three inputs and one output.

To determine the model validation, the wavelet and neural network model performance and actual HVAC system model performance are compared graphically as shown in Figs. 11, 13 and 15. It clearly indicates that the nonlinear dynamics of HVAC have been modeled accurately. Some statistical methods, such as the root-mean squared (RMS), the coefficient of multiple determinations R^2 are used to compare the predicted and actual values for model validation. The RMS and R^2 can be evaluated by Eqs. (14) and (15), respectively.

$$\mathrm{RMS} = \sqrt{\frac{\sum_{m=1}^{n}(y_{pre,m} - t_{mea,m})_2}{n}} \tag{14}$$

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(y_{pre,m} - t_{mea,m})^2}{\sum_{m=1}^{n}(t_{mea,m})^2} \tag{15}$$

where n is the number of data patterns in the independent data set, $y_{pre,m}$ indicates the predicted, $t_{mea,m}$ is the measured value of one data point m, and is the mean value of all measured data points. Some statistical values for HVAC system performance are shown in Table 2.

For modeling evaporator; the formed WPD-NN model was trained for 1000 epochs and the structure of WPD-NN model is presented in Table 1. The predicting performance is shown in Fig. 11. WPD-NN training performance is shown in Fig. 12.

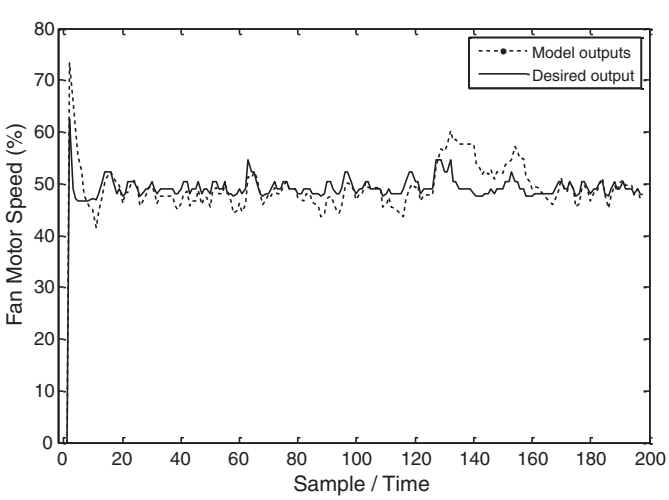

Fig. 11. Predicted and actual fan motor speed (%) for evaporator.

Table 2
Some statistical results for HVAC system performance.

HVAC system	R^2 (%)	RMS	Epochs
Fan motor speed for evaporator	99.53	3.40	1000
Damper gap rate for Zone-1	93.24	16.76	1000
Damper gap rate for Zone-2	94.09	17.70	1000

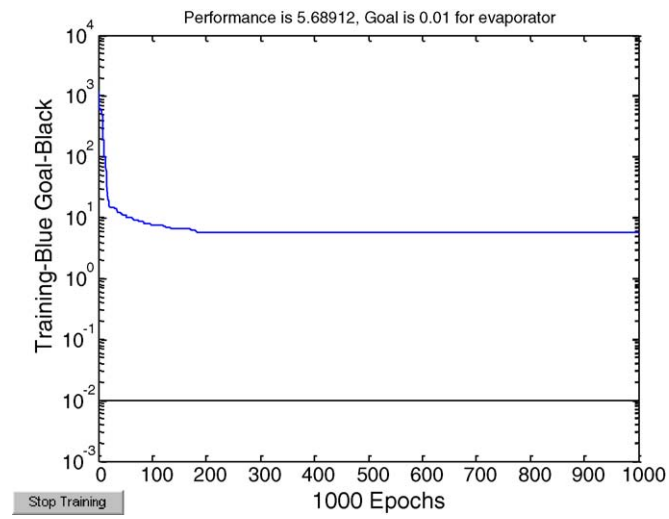

Fig. 12. Training performance of ANFIS model for evaporator.

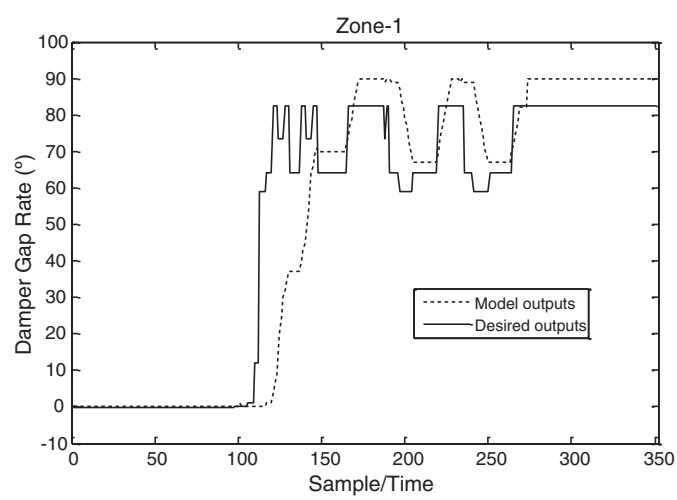

Fig. 13. Predicted and actual gap rate for Zone-1.

For modeling Zone-1; the formed WPD-NN model was trained for 1000 epochs and the structure of WPD-NN model is presented in Table 1. The predicting performance is shown in Fig. 13. WPD-NN training performance is shown in Fig. 14.

For modeling Zone-2; the formed WPD-NN model was trained for 1000 epochs and the structure of WPD-NN model is presented in Table 1. The predicting performance is shown in Fig. 15. WPD-NN training performance is shown in Fig. 16.

7. Discussions

This study used a HAVC system that was designed and built in our research laboratory. Although this system is smaller than a typical HVAC system used in daily life, the developed modal, method and experimental results are very promising (with recognition rate of 95.62%) that this system should be applicable for a typical HVAC

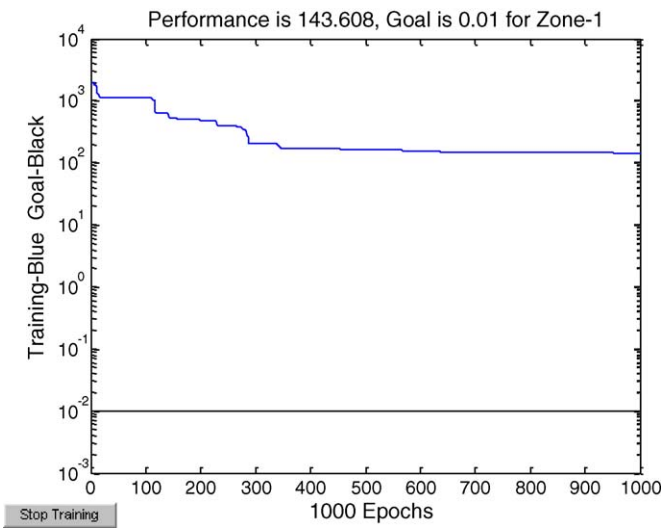

Fig. 14. Training performance of WPD-NN model for Zone-1.

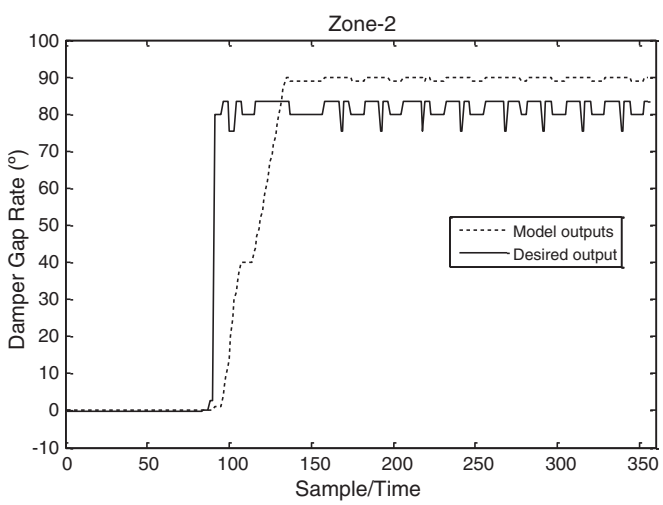

Fig. 15. Predicted and actual gap rate for Zone-2.

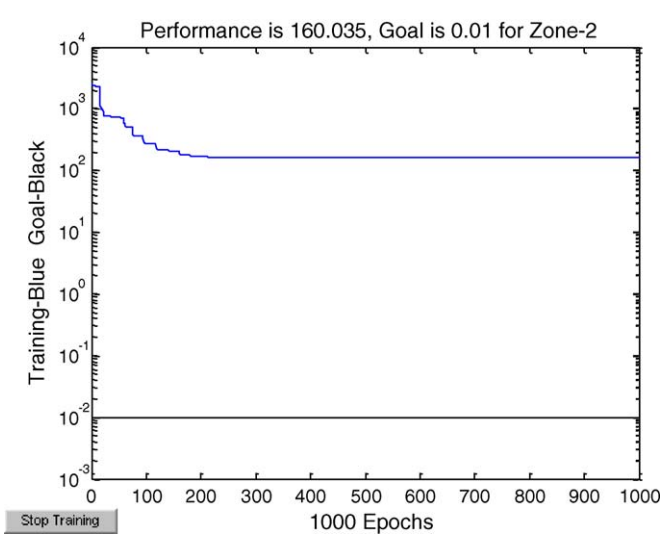

Fig. 16. Training performance of WPD-NN model for Zone-2.

system. In this study, the statistical values have been obtained for the WPD-NN model that the RMS value is 3.40 and the R^2 value is 0.9953 (%) for the fan used for controlling fan motor speed to minimize energy consumption of the HVAC system. In the best of author's knowledge both fan speed control to minimize energy consumption and temperature control with WPD-NN is the first study in the literature. The excellent improvements of this system in terms of steady-state errors were obtained. It is well known that modeling such a complex system is not a trivial task, however, the intelligent control techniques (i.e. NN, WPD, and fuzzy logic) employed in this study made the modeling easier. At the same time, the practical applications of the developed modals and methods will be considered in the future study.

8. Conclusions

In this study, the cooling process of the system was realized by being cooled the two different zones from the ambient temperature 26.4 °C to the desired temperatures. The required fan motor speed to minimize energy consumption and the required damper gap rates for obtaining the desired temperatures of two different zones for each time step were found using intelligent control algorithm. The fan motor speed was controlled using the required temperature for the evaporator while the dampers were controlled using the required temperatures for the Zone-1 and Zone-2. In this work, the fan motor speed to minimize energy consumption and the damper gap rates of a HVAC system with two zones were predicted using WPD-NN method. This work indicates the use of wavelet packet decomposition and NN for feature extracting and classification in intelligent modeling. The most important aspect of the intelligent model is the ability of self-organization of the WPD-NN without requirements of programming and the immediate response of a trained net during real-time applications. These features make the intelligent model suitable for complex systems. These results point out the ability of design of a new intelligence model. This means that with this method, new information can be accessed with an approach different from the traditional analysis methods. In addition, this paper shows that the values predicted with the WPD-NN can be used to predict fan motor speed and damper gap rate of HVAC system quite accurately. Therefore, the test results of the realized model are showed the advantages of intelligent modeling; it is rapid, easy to operate, non-invasive, and not expensive.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.enbuild.2010.12.001.

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