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OPTIMIZATION OF FAN SPEED IN VAV AIR CONDITIONING USING ANN

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ABSTRACT

The Variable Air Volume (VAV) system is considered to be a promising air conditioning scheme in most of the heating, ventilation and air conditioning (HVAC) applications. It is designed to deliver variable airflow rate for varying thermal load conditions prevailing inside the conditioned space. This paper reports the application of artificial neural network to optimize the fan speed in a variable air volume system. Based on the polynomial model, for various supply voltage and airflow rate the fan performance curves were obtained. These curves show a deviation from the real curves. Experimental results were utilized for training the artificial neural network (ANN) model. The optimized ANN model curves show less deviation with that of the real curves. This optimization technique can be used to predict the thermal comfort to be maintained in the conditioned space.

Key words: Artificial neural network, Fan speed, Optimization, Thermal comfort, VAV.

INTRODUCTION

In modern building air conditioning applications the concept of variable air volume (VAV) system has a significant role in maintaining the thermal comfort inside the building envelope by delivering a varied quantity of supply air to satisfy the thermal load fluctuations persisting in the conditioned space. An interesting feature of VAV system utilizing a variable speed fan is that a substantial quantity of energy savings is possible. However, the fan performance is greatly influenced by the quantity of air delivered into the conditioned space.

Bennakhi et al.[1] Presented general regression neural networks (GRNNs) used to optimize air conditioning set back scheduling in public buildings. The objective was to

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predict the time of the need of thermostat setback (EoS) such that the design temperature inside the building was restored in time for the start of business hours. State of the art building simulation software, ESP-r, was used to generate a database that covered the past five years. The robustness of the trained neural network (NN) was tested by applying them to a "production" data set. The results showed that the neural control-scheme was a powerful instrument for optimizing air conditioning setback scheduling based on external temperature records. D. J. Swider et al.[2] presented the modeling of vapor compression liquid chillers. The generalized radial basis function networks have been successfully applied to two different chillers. The neural network predicted the compressor work input and the COP within ± 5% error for the single circulated chiller and the more complex twin circulated chiller. The developed general regression radial basis function chiller model was applied to chiller system and sufficient amount of measured steady state data were obtained.

D. J. Moschandreas and S. W. Choi[3] performed two series of experiments in an aluminum chamber under controlled conditions to investigate whether the variable-air-volume/bypass filtration system (VAV/BPFS) reduces indoor air pollutant concentrations relative to a conventional variable-air-volume (VAV) system. The particulate matter VAV/BPFS total effective removal rate was 50% higher than the corresponding VAV total effective removal rate. Also the VAV/BPFS total volatile organic compound total that the VAV/BPFS system is a promising alternative to the conventional VAV system because, under the conditions tested, it was capable of reducing and maintaining good indoor quality and decreasing outdoor supply air rate. Erick Jeannette[4] explained the significance of artificial neural networks for improved control of processes through predictive techniques. They introduced and showed that experimental results of a predictive neural network (PNN) controller applied to an unstable hot water system in an air-handling unit minimized the process fluctuations reasonably.

Haruro Uehara et al.[5] presented a neural network model to control an ammonia refrigerant evaporator. A dynamic synaptic unit (DSU) was proposed to enhance the information processing capacity of artificial neurons. The NN architecture has been compared with two other conventional architectures one with dynamic neural units (DNU'S) and other with non linear static functions as perceptron. The objective was to control evaporator heat flow rate and secondary fluid outlet temperature while keeping the degree of refrigerant superheat in the range of 4-7 K at the evaporator outlet by manipulating refrigerant and evaporator secondary fluid flow rates. The drawbacks of conventional approaches to this problem are discussed and how neural method can overcome them are presented.

Jin Wen and Theodore F.Smith[6] presented the energy consumption by heating, ventilating and air conditioning (HVAC) systems has evoked increasing attention to promote energy efficient control operation of HVAC systems. In this paper, online models with parameter estimation for a building zone with a variable air volume system were developed and validated using experimental data. Kevin S. Maki[7] investigated outside air delivery and thermal comfort in a normally operating variable-air-volume (VAV) system. The scope of this paper was to cover some of the practical findings obtained regarding airflow measurements in a VAV system. It was concluded that unless a VAV system was well understood or continuously monitored the likelihood of unexpected system behavior that cane be impact the outside air delivery and thermal comfort was high.

M.Hosoz[8] dealt the applicability of artificial neural networks (ANNs) to predict the performance of automotive air conditioning (ACC) systems using HFC134a as the refrigerant. They developed an experimental plant comprising of original components from the air conditioning system of a compact size passenger vehicle. Experimental data were used to train the ANN model of the system based on the standard back propagation algorithm. The ANN predictions were agreed well with the experimental values. Mehmet Azmi Aktacir et al.[9] presented a life cycle cost analysis using detailed load profiles and initial and operating costs to evaluate the economic feasibilities of constant air volume (CAV) and variable-air-volume (VAV) air-conditioning systems. It was found that the present worth cost of the VAV system was always lower than that of the CAV system at the end of the lifetime for all the cases considered.

Osman Ahmed[10] presented feed forward controllers having the unique aspects of achieving energy savings with the variable-air-volume (VAV) system. The combined feedforward-feedback approach was found to outperform the conventional feedback controller. The combined approach uses a general regression neural network (GRNN) to identify the parameter of the component characteristics and control. The combined approach showed good results in terms of providing stable and accurate pressure control over a wide operating range and with different damper characteristics. Shimming Deng and Wu Chen[11] reported the development of a representative and complete dynamic mathematical model for the DX VAV A/C system having a variable speed compressor and pressure independent VAV terminals. The model was component based and takes into account the dynamic behaviors of both the DX refrigeration plant and the VAV air distribution subsystem simultaneously. Experimental work has been conducted to obtain the system responses to the step change of compressor speed. The dynamic model developed was then validated using the experimental data obtained. Steady state and transient responses for operating parameters obtained from both the model and the experiment were compared and found to be satisfactory.

Soteris A. Kalogiru[12] presented paper in various applications of neural networks in energy problems in a thematic manner rather then chronological or any other order. It included the use of artificial neural networks in heating, ventilating and air conditioning system modeling and control of power generation systems, load forecasting and prediction and refrigeration. The algorithm employed for the estimation of the flow of energy and performances of systems were complicated having solution of complex differential equations. Instead of complex rules and mathematical routines, artificial neural networks were able to learn the key information pattern with in a multidimensional information domain. Neural network tool predicts energy prediction and modeling.

Tuncay Tanyolu[13] represented a method that generalized various conditions in the plate finned-tube finned tube cooling and heating coils. An artificial neural network (ANN) with principal component analysis (PCA) has been used as an inverse plant identifier. Correlation among input and output temperatures of dry and wet air and water temperatures through the plate finned-tube coils has been modeled using ANN. A self-organized principal component analysis network (SOPCAN) was used as a processing technique. Eight percent of the data were evaluated for the training and the remaining for the test using multilayer perceptron network (MLPN) with back-propagation algorithm. Principal component that had small variance were discarded, and the reduced number of uncorrelated variables were applied to the MLPN.The effects of discarding these components on the convergence of the algorithm were investigated.

Artificial neural network

Artificial neural network models are used as alternative methods in engineering analysis and predictions. ANN is capable of handing tasks involving incomplete data sets, complex and ill-defined problems and non-linear problems. The artificial neural network consists of many nodes which are called as processing units analogous to neurons present in the human brain. Each node has a node function associated with it which along with a set of local parameters determines the output of the node, given an input. Modifying the local parameter may alter the node function. Artificial neural networks are an information processing system. In information processing system, the elements called neurons, process the information. The signals are transmitted by means of connection links. The links posses an associated weight, which is multiplied along with incoming signal net input for any typical neural net. The output signal is obtained by applying activations to the net input.

The multilayered neural network is represented in Fig. 1. The knowledge of the network is stored as a set of connection weights. Training is the process of modifying the connection weights in some orderly fashion using a suitable learning method. In this type of network a layer of input units is connected to a layer of hidden units, which is connected to a layer of output units. The activity of neurons in the input layer represents the raw information that is fed in to the network. The activity of neurons in the hidden layer is determined by the activities of the input neurons and the connecting weights between the input and hidden units. The behavior of the output units depend on the activity of the neurons in the hidden layer and the connecting weights between the hidden and the outputs layers. In this context, X1, X2, X3 are the input neurons, Y1, Y2, Y3 are the output neurons and b is the bias of the neuron.

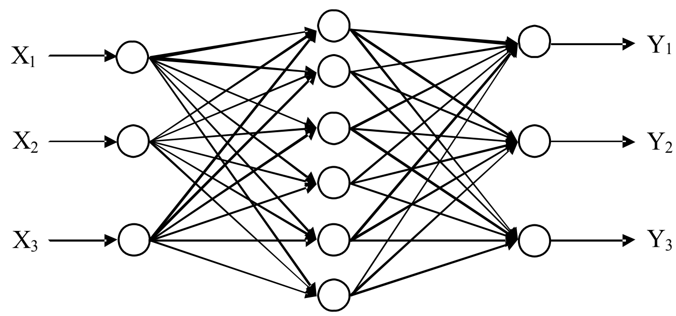

Fig. 1: Multi layered neural network

ANN model of fan

Neural networks are able to approximate many continuous non-linear functions to a pre-specified accuracy and are used to express the unknown non-linear function.

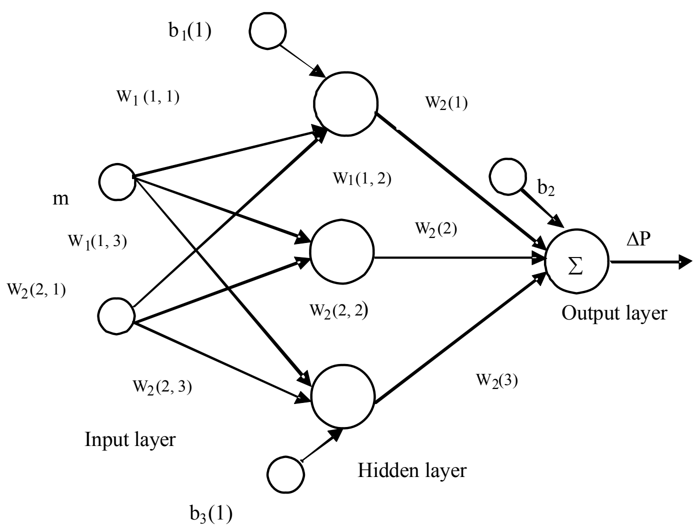

Fig. 2: ANN model of fan

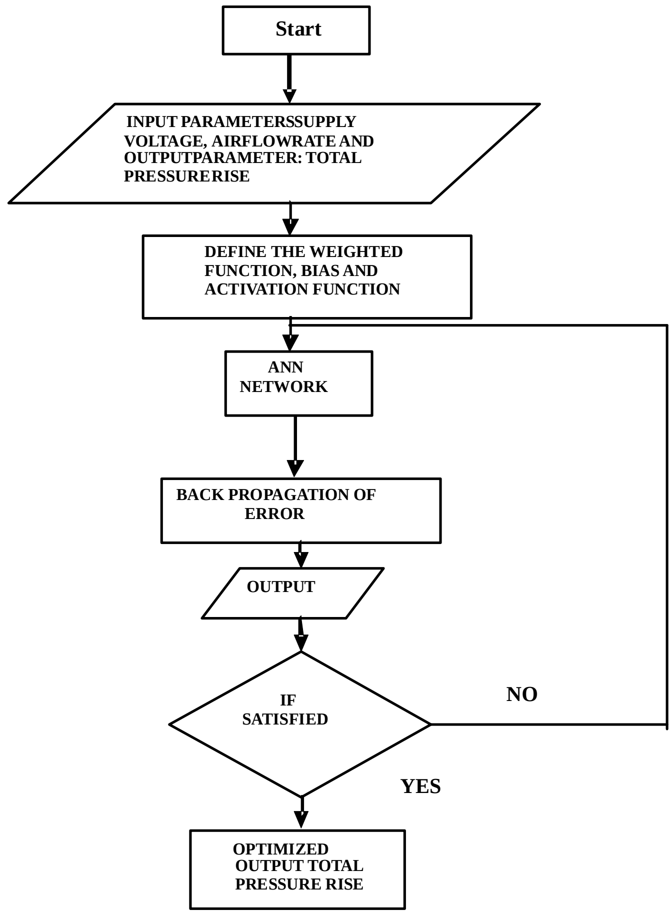

Fig. 3: Flow chart for neuron model of fan

The model is estimated by using a widely applied multilayer perceptron (MLP) neural network. The main purpose of this estimation is to use the data obtained from the real characteristics curves to train the neural network. Trained ANN algorithm helps produce the optimized value. The ANN fan model is depicted in Fig. 2. The input parameters considered were supply voltage and air flow rate and the output parameter was total pressure rise. Fig. 3 show the flow diagram for the neuron model of fan.

Experimental methodology

A single zone VAV air handling system was considered for analysis. The schematic representation of the system is shown in Fig. 4. The system comprises of an air handling unit equipped with refrigeration circuit, variable speed fan, return air fan, air distribution system, building scale model and sensors. The system was made to operate on cooling mode. Only

20% of fresh air is drawn into the system and it get mixed with 80% of recirculated air in the mixing plenum and the cold air depending on the load fluctuation was delivered into the conditioned space by variable speed fan through supply air duct.

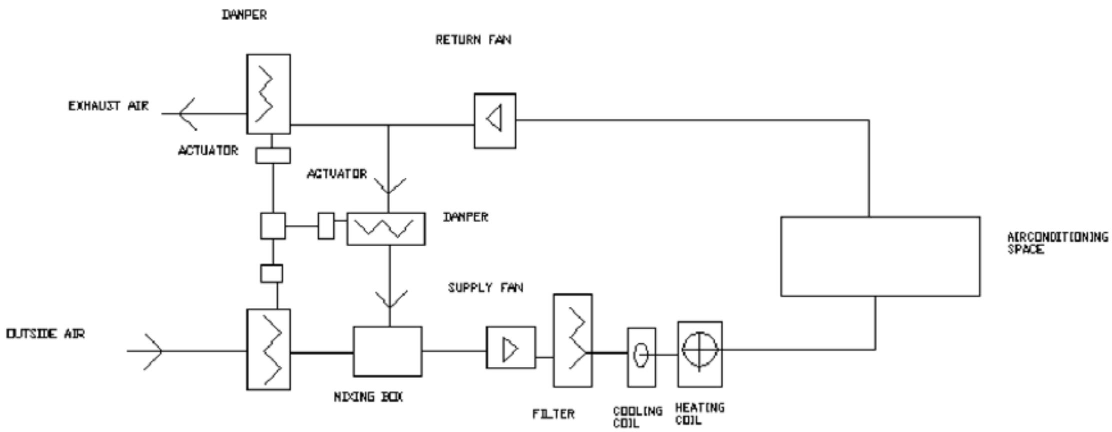

Fig. 4: Schematic representation of single zone VAV system

Artificial neural network optimization technique was used to control the fan speed. The temperature in the zone and static pressure in the supply air duct were the parameters considered to maintain the thermal comfort in the zone. The occupancy load pattern obtained for the software laboratory located in Anna University on a summer design day is shown in Fig. 5. A scale model of the software laboratory was built and experiment was conducted. The total pressure rise between the entry and the exit of the supply fan was measured.

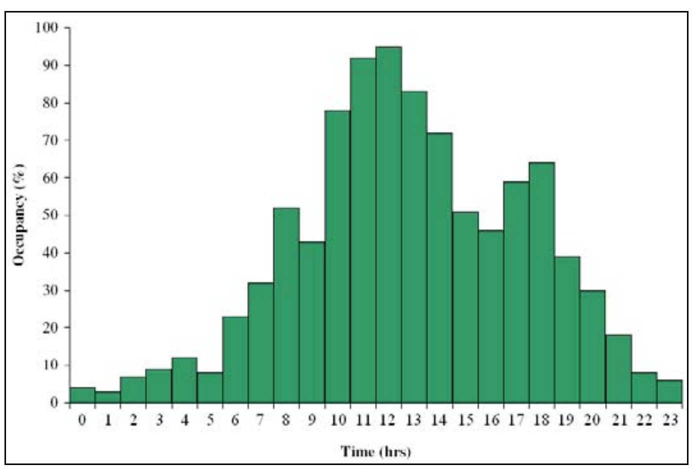

Fig. 5: Occupancy load pattern

Fig. 6: Photographic view of VAV Air system conditioning

Fig. 7: View of supply and return duct system

The static pressure and the supply air velocity values were noted. By taking 100 set of experiment readings, the artificial neural network (ANN) was trained for the input parameters and after subsequent training process the optimized fan speed was obtained.

Mathematical model

Polynomial model

The following form defines the model of the fan:

$$\Delta P = n^2 P_0 + k_1 m + k_2 m^2 \qquad \ldots(1)$$

where, ΔP – Pressure rise of the fan (Pa).

n – Normalized rotational speed.

P_0 – Total pressure rise of the fan when the air flow rate equals zero.

m – The air flow rate, and

k_1, k_2 – Constants.

Based on the characteristic curves of the fan, the speed of the fan is a non- linear function of the supply voltage of the motor. The following higher order polynomial is used to express this non-linear function:

$$n^2 = f(v) = b_0 + b_1 v + \cdots + b_n v^n = B^T V \qquad \ldots(2)$$

where, $v = V/V_{max}$ is the normalized value of the supply voltage.

b_0, b_1,…… and b_n are the coefficients.

$B^T = [b_0\ b_{1 \ldots\ldots}\ b_n]$.

$V\ = [1\ v\ v^2\ \ldots\ldots\ v^n]^T$.

The characteristic curves of the fan are represented by a polynomial with the estimated coefficients. By substituting Eq. (1) to Eq. (2), the following form is expressed as:

$$\Delta P = P_0 \left(\sum_{i=1}^{n} {}_{biv}{}^{i} \right) k_1\, m + k_2\, m^2 \qquad \ldots(3)$$

The unknown coefficients are linear with respect to the measured variables of v and m. using the performance data provided by manufacturer.

RESULTS AND DISCUSSION

To optimize the fan speed the mathematical model for the corresponding fan is solved and the fan performance curves are estimated. For various supply voltage and the corresponding air flow rate the total pressure rise of the fan is obtained. Based on the Fig. 8 it is inferred that at lower airflow rates the airflow rate corresponding to total pressure rise obtained from ANN model is similar to real performance curves. However at higher flow rates, the real curves deviate much from the polynomial model curves.

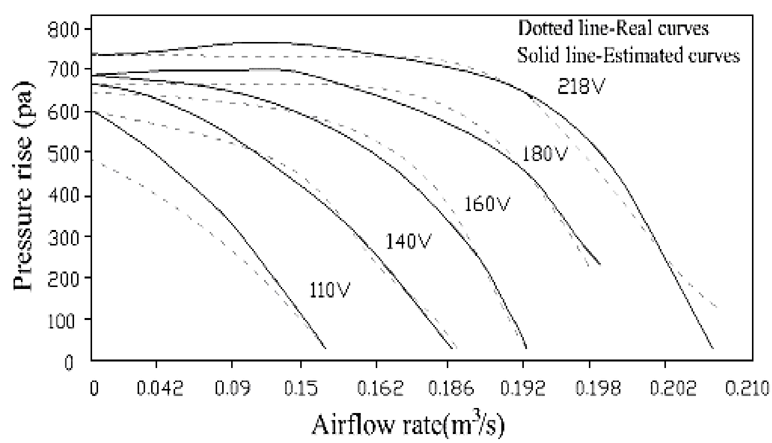

Fig. 8: Estimated fan performance curves for polynomial model

Fig. 9 illustrates influence of airflow rate corresponding to the total pressure rise is represented based on neural network analysis. From Fig. 9 it is observed that, the deviation occurred between the real curves and ANN model curves are substantially less which can be used to predict the thermal comfort required inside the conditioned space.

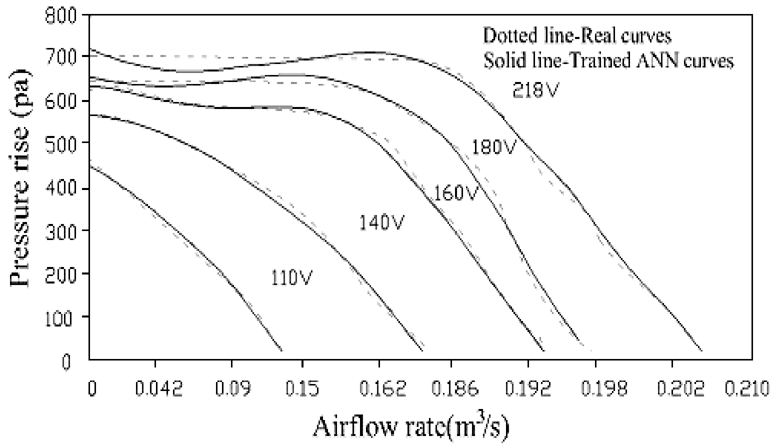

Fig. 9: Estimated fan performance curves using neural network model

By training the input data in the neural network the performance curves are observed to be very close to real curves. This yields the optimized fan speed.

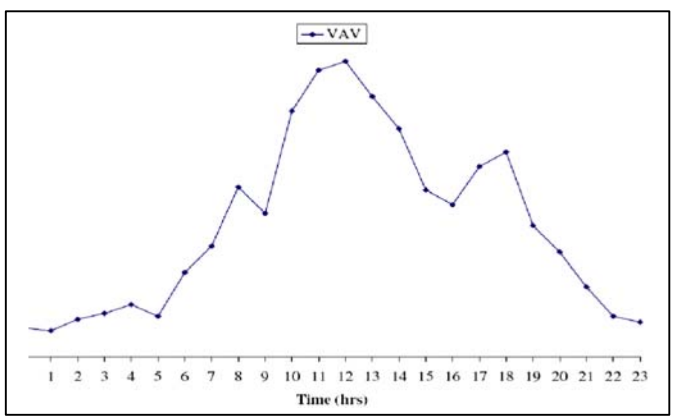

Fig. 10: Variation of supply airflow rate

Fig. 10 represents that with the use of variable speed fan optimized by ANN the supply airflow rate is varied for the corresponding load fluctuation persisting in the conditioned space. This infers that a substantial quantity of fan energy can be saved since the fan is operated at its optimized speed.

CONCLUSION

The fan speed was optimized using artificial neural network with input parameters of supply voltage and airflow rate. An experimental analysis was performed to validate the results obtained from ANN model curves to correlate with the real curves of supply air fan. From the results it was evident that controlling the fan speed in accordance with the load fluctuations well satisfies the thermal comfort required in the conditioned space of the building envelope. Implementation of artificial neural network leads to quick and precise optimization results.

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