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Neural modeling of vapor compression refrigeration cycle with extreme learning machine

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ABSTRACT

In this paper, a single-hidden layer feed-forward neural network (SLFN) is used to model the dynamics of the vapor compression cycle in refrigeration and air-conditioning systems, based on the extreme learning machine (ELM). It is shown that the assignment of the random input weights of the SLFN can greatly reduce the training time, and the regularization based optimization of the output weights of the SLFN ensures the high accuracy of the modeling of the dynamics of vapor compression cycle and the robustness of the SLFN against high frequency disturbances. The new SLFN model is tested with the real experimental data and compared with the ones trained with the back propagation (BP), the support vector regression (SVR) and the radial basis function neural network (RBF), respectively, with the results that the high degree of prediction accuracy and strongest robustness against the input disturbances are achieved.

1. Introduction

It is well known that the function of refrigeration and air-conditioning systems is to remove heat from one physical location to another. And it is essential in modern way of life to use these refrigeration equipments for the preservation of food, human comfort, the cooling of chemical and industry processes and so on [1]. In recent years, many engineering techniques have been employed for modeling vapor compression cycle (VCC) systems. Neural networks [2,3], due to their excellent performance in approximating complex nonlinear functions, have been introduced for modeling and optimizing air conditioning systems. Hosoz and Ertunc [4] developed a neural network model with five neurons in input layer for the system states and performance of a refrigeration system with an evaporative condenser. Yilmaz and Atik [5] proposed a feed-forward neural network with condenser water flow rate as the input to predict the performance of a variable cooling capacity mechanical cooling system. Navarro et al. [6] developed a radiant based function neural network model for predicting the performance parameters (such as cooling capacity, power consumption and chiller water outlet temperature) of a variable speed compression based refrigeration systems.

Recently, a novel learning algorithm for single-hidden-layer feedforward neural networks (SLFN), called extreme learning machine (ELM), has been developed in [7–12] by Huang et al. The main characteristics of the ELM are that both the input-weights and hidden biases are randomly chosen, and the output weights are analytically determined by using the Moore–Penrose (MP) generalized inverse [13]. It has been further shown in [14] that ELM achieves the better generalization performance for equality constrained optimization problems, the extremely fast speed of convergence, and the easy conversion of complex learning into simple linear fitting. Most importantly, the ELM avoids many difficulties brought by gradient-based learning methods such as choosing stopping criteria, learning rate, learning epochs, local minima, and the over-tuned problems. ELM has been widely used in various fields due to its excellent speed and high accuracy. Nizar et al. [15] employed both ELM and online ELM to analyze the nontechnical loss and extracted customer behavior patterns with ELM as data mining techniques. Zhan et al. [16] applied ELM to investigate the relationship between sales amount and some significant factors which affect demand. The experiment results show that ELM outperforms back propagation in accuracy and speed. Kim et al. [17] proposed to use morphology filter and principle component analysis for feature extraction, and then used ELM to classify the ECG signal into six beat types, experiment results prove that its performance is better than that of BP, RBF and SVM.

In this paper, we will use an SLFN to model the dynamics of a vapor compression cycle. It will be shown that, with the ELM, the

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Nomenclatures

A	opening percentage
F	frequency
H	enthalpy
P	pressure
Q	heat transfer rate
SH	superheat
SC	subcool
T	temperature
$\dot{W}$	power consumption
$\dot{m}$	mass flow rate
ω	compressor rotation speed

Subscripts

c	condenser
ca	condenser fan
e	evaporator
ea	evaporator fan
ev	expansion valve
i	inlet/*i*th group
in	indoor
o	outlet/outside
req	requirement
t	total

input weights are randomly assigned and the output weights are globally trained with the batch learning type least squares. In addition to the standard constraint used in the ELM, the constraint that satisfies the cooling load requirement in a vapor compression system is included in the global optimization for deriving the optimal output weights of the SLFN. In the experimental section, all training data pairs are obtained from the experiments, and the SLFN model is tested and compared with the ones trained with the BP, the SVR and the RBF, with the results that the developed SLFN model behaves with excellent robustness against high frequency noises involved in the testing data and provides the high accuracy for the prediction of the system states in the vapor compression cycle.

2. Introduction to vapor compression cycle

The vapor compression cycle system consists of the four main components: evaporator, compressor, condenser, and expansion valve, as shown in Fig. 1.

It is seen that these components are connected in a closed loop so that the working fluid can be continuously circulated in the system. The working principle of the vapor compression cycle is briefly described as follows [18]:

i. Initial temperature T of the liquid refrigerant inside the evaporator is lower than the temperature $T_{e,air,i}$ of the cold reservoir, and such a temperature difference makes the heat transfer from the reservoir to the refrigerant. The refrigerant will then evaporate after absorbing enough heat.

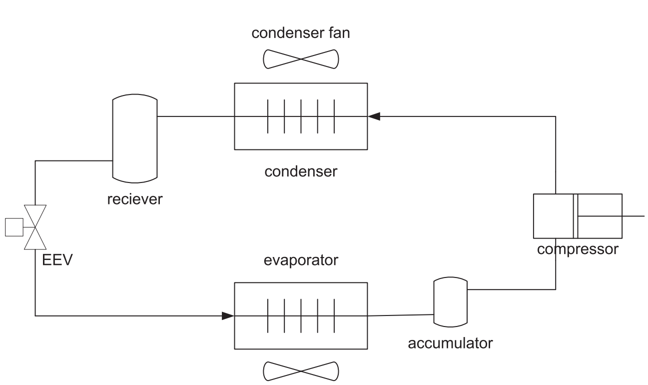

Fig. 1. Vapor compression refrigeration cycle.

ii. After entering the compressor, the refrigerant vapor is compressed with high pressure, and such a process has also raised the refrigerant vapor's temperature.

iii. In the condenser, the heat of the refrigerant vapor is removed and the refrigerant vapor is condensed to liquid with the lower temperature.

iv. As soon as passing through the expansion valve, part of the refrigerant liquid evaporates, as its pressure is immediately reduced from the condensing pressure P_c to the evaporating pressure P_e, the heat absorption in evaporation process results in steep temperature decrease. Then the refrigerant enters the evaporator for the next cycle.

3. Introduction to ELM

Consider N distinct sample data vector pairs (X_i, t_i) that are the collected measurements from a vapor compression cycle. The ith input pattern vector and the desired ith output vector are respectively defined as $X_i = \begin{bmatrix} x_{i1} & x_{i2} & \dots & x_{in} \end{bmatrix}^T$ and $t_i = \begin{bmatrix} t_{i1} & t_{i2} & \dots & t_{im} \end{bmatrix}^T$, for $i = 1, 2, \dots N$. The structure of SLFN to be used to learn the given input and output pairs is shown in Fig. 2 where the nodes in the input and output layer are linear, and the nodes in hidden layer are with the nonlinear activation functions, described by

$$y_{ki} = \varphi(W_k^T x_i) \tag{1}$$

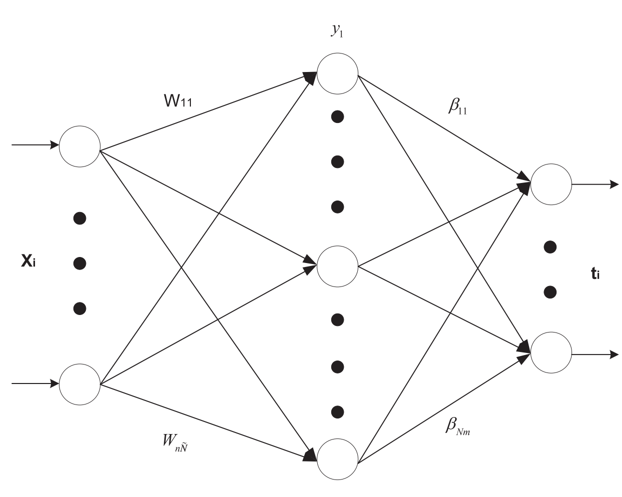

Fig. 2. Single hidden layer feed-forward neural network.