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Performance Prediction of Refrigeration Systems by Artificial Neural Network

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ABSTRACT: Simulation has been widely used for performance prediction and optimum design of refrigeration systems. Existing literature consists of significant work on vapour compression system models; however, not as much exists on transient models of complete heat-pump systems and even less on chiller systems, which constitute a sizeable portion of the commercial refrigeration equipment in use. This report attempts to review the existing literature on dynamic models for vapour compression systems, components and controls and summarize, among other things, the methodologies adopted, and their applicability to chiller systems. The review includes papers with different approaches to transient modeling of individual components as well as complete systems.

KEYWORDS: compression systems, control, modeling, prediction, refrigeration, simulation.

I. INTRODUCTION

The output of refrigeration systems has been increasing rapidly in recent decades and refrigeration systems become more important for people's daily lives. For example, room air conditioners used in China increased by about 15% per year in the past 10 years, and nowadays the use of air conditioners consumes a lot of electricity, amounting up to 40% of the total electricity consumption in the summer in some cities like Shanghai. Therefore, it is important to make the design process of refrigeration systems more efficient and the product performance better. Computer simulation is one of the valuable means to accomplish this target.

The following conventional method is still used for designing refrigeration systems: to determine the required performance object of a product at first, then to estimate the working conditions, and to calculate the structural parameters at last. This process is very straightforward and quite easy to be understood. However, the actual performance of the product might obviously deviate from the required one because there is no accurate model used in the design process. In order to make the products have the desired performance, the processes of developing prototypes, testing their performance and modifying their structures have to be repeated many times, which will increase the cost and delay the design process.

The computer simulation method has been used for designing refrigeration systems and has shown its advantages over the conventional one. With the computer simulation method, the working conditions and the configuration parameters of the product are given at first, then the performance is predicted, and at last the configuration parameters of the product is evaluated based on the performance prediction. If the predicted performance does not meet the requirement, the configuration parameters should be adjusted, and simulation with the adjusted structural parameters will be done again. The process of modifying the parameters and simulating with modified parameters will be repeated for many times until a set of the most suitable parameters is obtained. Such a computation process can be implemented by adding some optimization subprograms or directly operated by users based on their experiences, and can be used for optimum design of refrigeration systems. The requirements for simulation at least include:

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(1) Stability
(2) Rapidness
(3) Accuracy

These three requirements may conflict with each other, and then a compromise has to be made. A lot of techniques to improve the stability, rapidness and accuracy have been presented, but the effects are still not good enough in many cases and more researches are necessary. The present paper will summarize the state of the art of the simulation techniques for vapour compression refrigeration systems and predict the possible development in the future.

II. REFRIGERATION AND ITS IMPORTANCE

Refrigeration is a process in which work is done to move heat from one location to another. The work of heat transport is traditionally driven by mechanical work, but can also be driven by heat, magnetism, electricity, laser, or other means. Refrigeration has many applications, including, but not limited to: household refrigerators, industrial freezers, cryogenics, and air conditioning. Heat pumps may use the heat output of the refrigeration process, and also may be designed to be reversible, but are otherwise similar to refrigeration units.

Refrigeration has had a large impact on industry, lifestyle, agriculture and settlement patterns. The idea of preserving food dates back to the ancient Roman and Chinese empires. However, refrigeration technology has rapidly evolved in the last century, from ice harvesting to temperature-controlled rail cars. The introduction of refrigerated rail cars contributed to the westward expansion of the United States, allowing settlement in areas that were not on main transport channels such as rivers, harbours, or valley trails.

Refrigerators are one of the most valuable equipments found in our home today. Almost every household in the world needs something to store their food to prevent them from spoiling. This magical equipment which is craftily made turns on every five minutes and keeps everything cold. Without it, there will be enormous amount of food that will go to be on the garbage every day. Surely, such invention is great that it affects almost every people on earth regarding whatever their walks of life are. Refrigeration is also widely used for the purposes of air conditioning in homes, public buildings and restaurants. It is also used for refrigeration of foodstuffs in restaurants and also in large storage warehouses.

Refrigeration is also used commercially and in manufacturing industries. It is used to liquefy gases including oxygen, nitrogen, propane, and methane. It is used to compress and condense water vapor in compressed air purification. This process is aimed at reducing the moisture content of compressed air. In industries like petrochemical, refineries and chemical plants, refrigeration is important as it is used for the maintenance of certain chemical processes and reactions at low temperatures. An example is in the production of high octane gasoline component where the alkylation's of butanes and butane is done at low temperatures.

III. CONTROL STRATEGIES IN REFRIGERATION

Refrigeration System Controls are defined as equipment that controls and optimizes the temperatures and pressures in a refrigeration system, and automatically adjusts the refrigeration system's operation to minimize its energy consumption, while maintaining within predefined temperature limits the spaces, processes or equipment being refrigerated, and reflecting changes in load, weather conditions and operating requirements.

Refrigeration System Controls equipment is considered to include the following:

System management package consisting of one or more control units or modules that are designed to optimize an entire refrigeration system, including the operation of refrigeration compressor, evaporator and condenser Add-on controllers that are designed to be used in conjunction with a specific system management unit or package, and enable the operation of additional refrigeration compressors, evaporators and condensers to be optimized.

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Table 1-5 gives the control strategies applied for each unit in the refrigerator.

Table 1 Conditions for System Management Package

S.No	CONDITIONS
1.	Must automatically adjust the system operating set points in a manner that minimises the refrigeration system's energy consumption under different operating loads, weather conditions and surrounding air temperatures.
2.	Monitor temperatures and/or pressures around the refrigeration system, and automatically initiate defrost cycles, or inhibit (or delay) scheduled defrost cycles, within individual parts of the refrigeration system, as required, to optimize the overall performance of the refrigeration system.
3.	Must provide facilities that enable system managers to define the default set points, and alarm limits, for each item of refrigeration equipment controlled.

Table 2 Conditions for Add-on Controllers

S.No	CONDITIONS
1.	Must automatically accept instructions from the system manager to change its operating set points or alarm limits, or to initiate or inhibit a defrost cycle.
2.	Must automatically transmit data on operating temperatures, pressures, or flow rates to the system manager at specific intervals.

Table 3 Conditions for Control of Evaporators

S.No	CONDITIONS
1.	To directly measure evaporator pressure or temperature by means of a sensor, and automatically adjust the flow of refrigerant through the evaporator to maintain the refrigerated space within pre-defined operating limits.
2.	Automatically terminate its defrost cycle when: (1) The temperature of the evaporator or refrigerated space exceeds a preset value. (2) A maximum defrost time consistent with sensor failure has been exceeded.

Table 4 Conditions for Control of Condensers

S.No	CONDITIONS
1.	To directly measure condenser pressure or temperature by means of a sensor, and automatically adjust the air flow across the condenser(s) in a manner that maintains condensation at the rate required to maintain the thermal balance of the refrigeration system under different operating loads and weather conditions.
2.	Allow the compressor discharge (head) pressure to 'float' with ambient temperature down to the minimum safe level for the particular refrigeration system for maximum system efficiency.

Table 5 Conditions for Control of Compressors

S.No	CONDITIONS
1.	Be able to control the operation of at least two refrigeration compressors.
2.	Incorporate automatic control algorithms that monitor rate of change in system suction pressure or refrigerant temperature to prevent compressors from unnecessarily being controlled to load or unload in response to small fluctuations in cooling demand.

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IV. MODELING OF REFRIGERATOR

The complete operation cycle of a refrigeration system can be characterized by two major time-regimes, namely transient and steady state. In the latter, the system input/output parameters are constant over time; transient operation is then, by default, the non-steady state. Typically, this is the case when the system is started-up and is approaching steady state, or when it is shutdown from a steady state, or when it is disturbed from its steady state. This disturbance could be caused by either external changes in conditions (such as load, ambient temperatures etc.) or by feedback control. In either case, the system attempts to move from one equilibrium state to another. Transient modeling is the predictive analysis of the system's operation during such conditions. In practice, however, there exists a third time-regime in between the true steady state and transient perspectives, termed the 'quasi-steady state', in which the systems transient responses are much faster than the transients of the inputs. This representation is useful when the time constants of the inputs and of the system differ by orders of magnitude. For such cases, steady-state modeling could be used to study transient behaviour.

During transient operation, all the components experience phenomena absent in steady state operation, due to the non-uniformity of conditions within them. The refrigerant mass flow rate, in general, is continuously changing, causing changes in refrigerant distribution in the system components, inlet/outlet conditions of the compressor and the operating point of the expansion device. Of the four major components in the vapor compression system, the transients in the heat exchangers are usually the slowest and have the largest impact on transient performance. It is necessary to consider mass distribution within the heat exchangers as a function of time and space and this requires transient mass balances to allow for local storage.

Thermal capacitances of the heat exchanger bodies and the refrigerant have to be considered to account for local energy storage. When the secondary fluid is a liquid such as brine or water, the thermal inertia of this fluid also becomes a significant factor. To determine spatial and time variations of pressure within the heat exchangers, which is the driving potential for mass flow, the transient form of the momentum balance has to be used in some form. Some of the common assumptions found to be made (though not all simultaneously) in the models studied in the literature survey were-

(1) Flow in the heat exchangers is one dimensional and homogenous.
(2) Axial conduction in the refrigerant is negligible.
(3) Liquid and vapor refrigerant in the heat exchangers are in thermal equilibrium.
(4) Expansion is isenthalpic.
(5) Compression is isentropic or polytrophic.
(6) Thermal resistances of metallic elements in the system are negligible in comparison with their capacitances.

V. MODELING BY ARTIFICIAL NEURAL NETWORK

The use of Artificial Neural Networks (ANNs) for modeling and performance prediction is becoming increasingly popular in the last two decades. This is mainly due to the fact that ANNs have very good approximation capabilities and offer additional advantages such as short development and fast processing time.

Artificial neural networks are one of the most powerful computer modeling techniques based on statistical approach, currently being used in many fields of engineering for modeling complex relationships, which are difficult to describe with physical models. There has been continual increase in research interest in the applications of ANNs in the refrigeration system modeling. Numerous applications of neural network related to refrigeration system can be found in the open literature.

Neural networks consist of simple processors, which are called neurons, linked by weighted connections. The neuron forms the basis for designing neural networks. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons as input signals via interconnections. Since the capability of a single neuron is limited complex functions can be realized by connecting many processing elements. Network structure, representation of data, normalization of inputs and

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outputs and appropriate selection of activation functions etc. are the factors that have strong influence on the performance of the network.

VI. BACKPROPAGATION NETWORK

The back-propagation network is composed of many interconnected artificial neurons that are often grouped into input, hidden and output layers. The artificial neuron evaluates the inputs and determines the strength of each one through its weighting factor. The weighted inputs are summed to determine the output of the neuron using a transfer function. The output of the neuron is then transmitted along the weighted outgoing connections to serve as an input to subsequent neurons. To properly modify the connection weights, a supervised learning algorithm is employed. The supervised learning algorithm involves two phases. First one is the forward phase and the other is a backward phase. In the forward phase, an input vector is applied to the sensory nodes of the networks, and their effect propagates through the network, layer by layer. Finally a set of outputs is produced as the actual response of the networks. During the forward pass, the synaptic weights of the networks are all fixed, while during the backward pass, the weights are adjusted in accordance with the error correction rule. To minimize the error between the desired output and actual output as rapidly as possible, the gradient-descent method is used. The synaptic weights are adjusted so as to make the actual response of the network closer to the desired response. The forward process, backward process and adjustment of weights are iterated until the error of the output is satisfied. After the learning process, the network memorizes the relationships between input and output variables through the connection weights.

The arrangement of neurons into layers and the connection pattern within and between the layers is called as network architecture. The neural network has three layers or subgroups of processing elements as input layer, which accepts the input and distributes it to the neurons in the hidden layer. The hidden layer receives the signal from the input layer and it is useful in performing intermediary computations before directing the input signals to the output layer. The output layer receives the signal from the hidden layer and does computations to give the output signal, which represents the response of the neural network for the particular input vector**.** The BP algorithm is based on the error correction-learning rule, and it has been successful to solve difficult and diverse problems.

An attempt is made to predict the cooling effect, compressor input power and coefficient of performance. The architecture of neural network for the selection of vapour compression refrigeration system parameters consisted of four parts as shown in Fig. 6.1. The first part is the specification of input conditions viz., compressor speed, air temperature at evaporator inlet, air temperature at condenser inlet and air velocity at evaporator inlet and the second one is the hidden layer and the last is the output layer for obtaining the output responses.

The objective of training the network is to adjust the weights so that application of a set of inputs produces the desired set of outputs. Training assumes that each input vector is paired with a target vector representing the desired output and these together are called a training pair. Usually, a network is trained over a number of training pairs. The convergence of the network to the result is enhanced by a large number of training data. The flow chart for the back propagation algorithm is shown in Fig.1.

VII. CHOICE OF INITIAL WEIGHTS

The values of initial weights must not be too large, or the initial input signals to each hidden or output unit will be likely to fall in the region where the derivative of the sigmoid function has a very small value. On the other hand, if initial weights are too small the net input to the hidden or output unit will be close to zero, which also causes extremely slow learning. A common procedure is to initialize the weights to random values between = - 0.5 to +0.5. The generalization capability of the neural network essentially depends on the selection of appropriate input, output parameters of the process, the distribution of the data and the format of presentation of the data to the network. In order to balance the importance of each parameter during training process, the data should be normalized. Also neural networks works better in the range of 0 to 1. Hence the input and output vector values are converted in the range of 0 to 1 using the following equation.

$$X_n = (X - X_{min}) / (X_{max} - X_{min})$$

where X **-** actual input (or output) value.

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X_n - normalized input (or output) value.
X_{max} - maximum value of the inputs (or outputs).
X_{min} - minimum value of the inputs (or outputs).

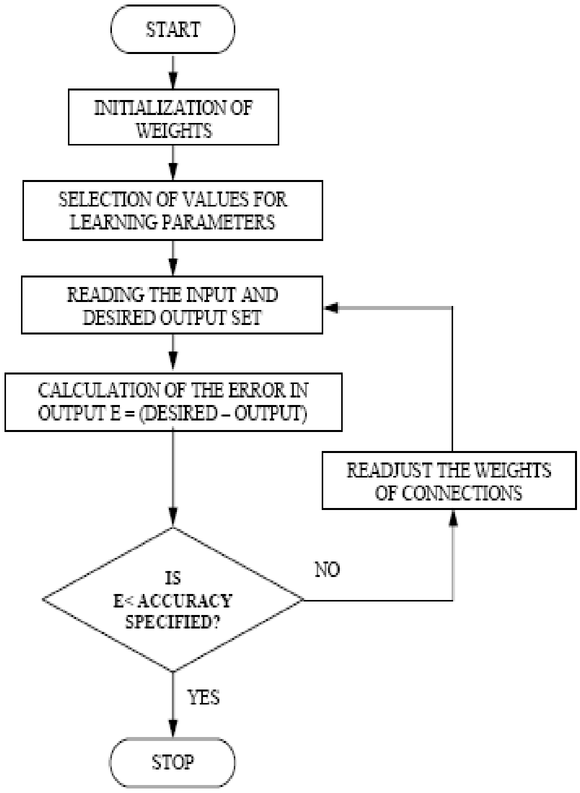

Fig. 1 Flowchart for Back Propagation Neural Network

VIII. EFFECT OF VARYING LEARNING RATE

Learning rate co-efficient determines the size of the weight adjustments made at each iteration and hence influences the rate of convergence. Poor choice of the co-efficient can result in a poor convergence. The co-efficient should be kept constant for all iterations for best results. If the co- efficient is too large then the search path will oscillate and converges more slowly. If the co- efficient is too small then the descent progress in small steps significantly increases the time to converge. The learning rate is taken as 0.9 which seems to be optimistic.

IX. PREDICTING THE PERFORMANCE USING THE TRAINED NETWORK

The set of measured values of the refrigeration system using the selected refrigerants were used as target data for back propagation neural network training. Each training data set consisted of four input nodes and three output nodes. The performance of the neural network depends on the number of hidden layers and the number of nodes in the hidden layer. The structure of the network applied for predicting the performance was chosen by trial and error method. Training was done based on the back propagation algorithm coding. The input data fixed by trial and error for training the network are presented in Table 7.1. The architecture of the proposed five layer network is given in Fig. 2.

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Table 6 Data Input for Training the Network

S.No	COMPUTER QUERY	INPUT SAMPLE DATA	REMARK
1.	Training Testing	1	Mode of operation –Training.
2.	Values of error tolerance and learning rate parameter	0.001 0.9	Error tolerance – 0.001 Learning parameter = 0.9
3.	Maximum number of Cycles	4000	By trial and error.
4.	Number of layers	5	Five implies one input and output with three hidden layers.
5.	Size of each layer	4-5-5-5-3	Number of nodes from input to output layer..

The Block diagram of the proposed neural network is shown in Fig.4.

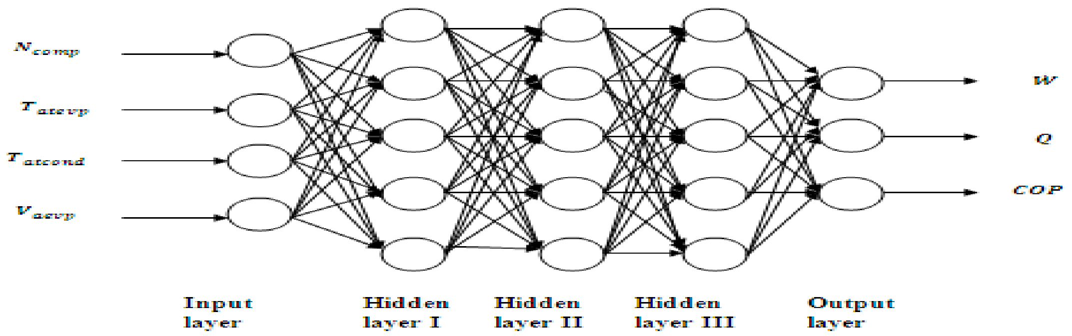

Fig. 2 Architecture of Proposed Network

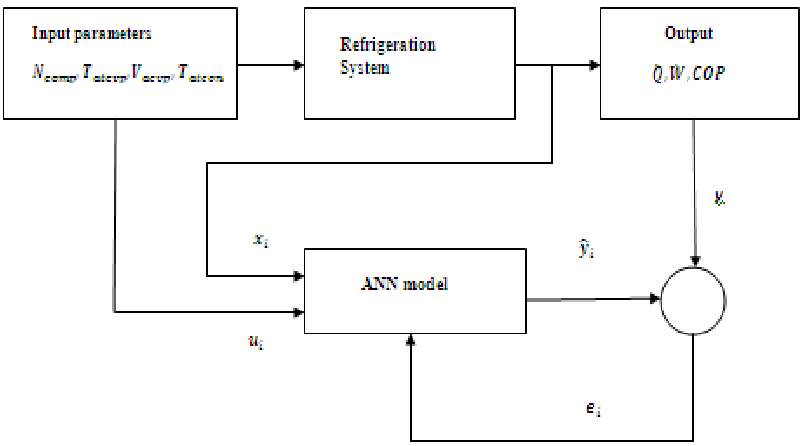

Fig. 3 Block diagram representation with ANN Model

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X. COMPARISON RESULTS

Table 7 Comparison of error (%)

S.No	TYPE	METHODOLOGY	ERROR (%)
1.	Cascade vapour compression refrigeration system	Back propagation algorithm	0.2-0.6
2.	Vapour compression refrigeration (shell & tube)	Back propagation algorithm	Less than 5
3.	Vapour compression refrigeration system	Recurrent multilayer perceptron algorithm	1-3
4.	Vapour absorption refrigeration system	Feed forward back propagation algorithm	0.99961
5.	Vapour absorption refrigeration system	Back propagation algorithm	0.33-0.95
6.	Vapour compression refrigeration (evaporative type)	Back propagation algorithm	1.90-4.18

XI. CONCLUSION

Simulation has become a useful method in design of vapour-compression refrigeration systems. A practical simulation method must be stable, rapid and accurate. The requirements on stability, rapidness and accuracy may conflict with each other, and then a compromise has to be made according to the specific simulation objective. For different simulation purpose, the suitable model and algorithm may be different. For the simulation of a refrigeration system consisting of several components, the component models should be simpler than that for the simulation of a single component. The dynamic model of compressor for simulation of refrigeration systems can be divided into two parts: the steady state part for the mass-flow rate calculation and the dynamic part for the calculation of heat exchange process. The approximate analytic model for capillary tubes, and the zone and long-term dynamic model for heat exchangers are recommended for dynamic simulation of refrigeration systems.

From the literature reviewed, it has been seen that artificial neural network based simulation techniques are implemented for the performance prediction of refrigeration systems. The percentages (%) of error obtained by different approaches are varying. The advantage of using evaporative condenser is that it offers condensing temperatures limited by ambient wet bulb temperature, which is almost always lower than ambient dry bulb temperature, refrigeration systems employing it can work with lower condensing temperatures. Therefore, these systems are usually more energy-efficient compared to ones using air-cooled condensers. Furthermore, initial cost of the evaporative condenser is lower than that of the water-cooled condenser due to the reduced space and number of the components. By using an evaporative condenser for the refrigeration systems and simulating the model by Artificial Neural Network Model Predictive Control, the performance of the refrigeration systems can be further increased thus minimizing the error.

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