STUDY ON THE CONTROL ALGORITHM OF THE HEAT PUMP SYSTEM FOR LOAD CHANGE

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Abstract: The base study for the optimal control algorithm of the heat pump system was investigated. The research object is a heat pump system of the desiccant cooling and vapor compression hybrid system using solar thermal energy. The severe load change could be carried to the heat exchangers of the heat pump due to the complexity of this hybrid system. Therefore the rapid adaptation control of the heat pump is very important for the stable and reliable operation to the whole system. To study on the refrigeration cycle characteristics, the heat pump system which consists of the controllable components such as the EEV (electronic expansion valve) and the variable speed compressor was built. The ANN (artificial neural network) algorithm was used to relate between the control parameters and the measured data of the refrigeration cycle. According to the change of rotational frequency of compressor and the opening of expansion valve, the parameters such as temperatures and pressures of the refrigeration cycle is changed. In this study, the relation of the control parameters and the experimentally measured data was found to set the appropriate target value for the control the heat pump system.

Key Words: heat pumps, control algorithm, neural network

1 INTRODUCTION

The desiccant cooling-vapor compression hybrid heat pump using solar thermal energy is shown in Fig. 1. This system is composed of the vapor-compression heat pump system, the desiccant cooling system, and the solar thermal system. The solar thermal energy is collected and accumulated in the thermal storage tank, and then applied to regenerator in the desiccant system as a heat source in summer. In winter, this stored energy is used to as a heat source of evaporator in the heat pump system during heating operation. The thermal storage tank includes the two different types of thermal storage materials which are the high temperature material for the regeneration heat source and the low temperature material for the evaporator heat source. The dehumidifying system is liquid desiccant type. Figure 1 shows the cooling operation of this hybrid system. In the cooling operation, warm and humid air inflows to the dehumidifier and losses the latent load, and becomes an air of high temperature and low humidity. And then this air passes through the evaporator of heat pump system and becomes to an air of low temperature and low humidity for supplying to the cooling space. The liquid desiccant absorbed the moisture goes to the regenerator, and regenerated using the high-temperature solar thermal energy accumulated in the thermal storage tank. In addition, the released heat from condenser of the heat pump system is used to preheat the supply air of the regenerator. Consequently, the total cooling capacity is the cooling capacity summation of the liquid desiccant system and vapor compression system. In the heating mode, the solar thermal energy are applied to the evaporator of heat pump system, and the evaporate temperature is elevated and the heating efficiency of heat pump is raised. The dehumidification system is not used in the heating mode.

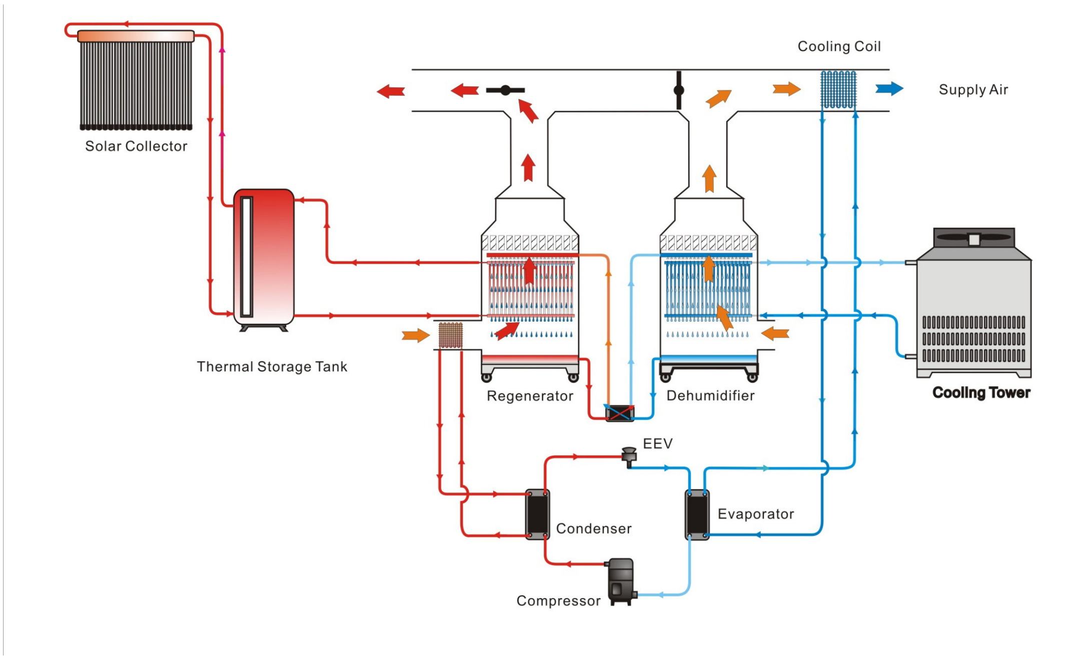


Figure 1: The schematic diagram of the desiccant cooling and vapor compression hybrid system using solar thermal energy

The object of this study is to build the control strategy of the heat pump which is the vapor-compression side of this system. This heat pump needs a proper control algorithm due to the complexity of this desiccant cooling-vapor compression hybrid system. The relation of the control parameters such as the opening of EEV (electronic expansion valve) or the rotational frequency of variable speed compressor and the refrigeration cycle parameters such as saturation pressures or superheat has to be identified to set the appropriate target values of the control parameters. The ANN (artificial neural network) algorithm is applied to relate between the control parameters and the measured data of the refrigeration cycle in this study.

2 THE CONTROL ALGORITHM OF THE HEAT PUMP

2.1 Control Strategy for the Heat Pump

The object of the control for the heat pump is the stabilization of the refrigeration cycle. If the saturation temperature in the evaporator (T_{eva}), the saturation temperature in the condenser (T_{cond}), the superheat (T_{sup}), and the subcooling (T_{sub}) are controlled as intended, the heat pump cycle can be stabilized. In this study, there are only two controllable components which are variable capacity compressor and electronic expansion valve (EEV). The rotational frequency of the compressor and the opening of the EEV can be changed. To find the appropriate setting value of the compressor speed and the opening of the EEV according to the load change, the relationship between these control parameters and the cycle parameters (T_{eva}, T_{cond}, T_{sup}, and T_{sub}) was investigated in this study.

2.2 Artificial Neural Network (ANN) Algorithm

The relationship of the cycle parameters and the control parameters is learned by an artificial neural network using a back propagation algorithm (Hassoun, 1995). Figure 2 shows the structure of the ANN used in this study. It has three input variables (P_{eva}, P_{cond}, and T_{sup}) and one output. To represent the refrigeration cycle state, measured saturation pressure values were used on the behalf of the temperature values. An artificial neural network (ANN) model was developed for the two control parameters. Two features are the opening of electronic expansion valve and the rotational frequency of the compressor. This neural network has three layers consisting of an input, hidden, and output layer with the hidden layer having three nodes. The sigmoid function is used as the activation function of the hidden layer. The weight coefficients and offsets are learned using a momentum back propagation algorithm. The various arrows between the input layer and the hidden layer indicate weights, or multipliers, applied to each input variable before passing to the sigmoid function within each hidden layer node. Equation 1 illustrates the output of a neuron, *f(s)*, and how the sigmoid function, *s*, is applied within the layers. Sigmoid function includes weighting coefficients, *w*, and offset coefficients, *c*.

$$f(s)=\frac{1}{2}\left(1+\tanh(2s)\right) \qquad s=\left(\sum_{k=1}^{3} x_k w_k\right)+c \tag{1}$$

The predicted value (F_{pred}) using the neural network is compared to the measured value (F_{meas}) to produce an error. The back propagation algorithm is then used to adjust the weights and offsets to minimize the error.

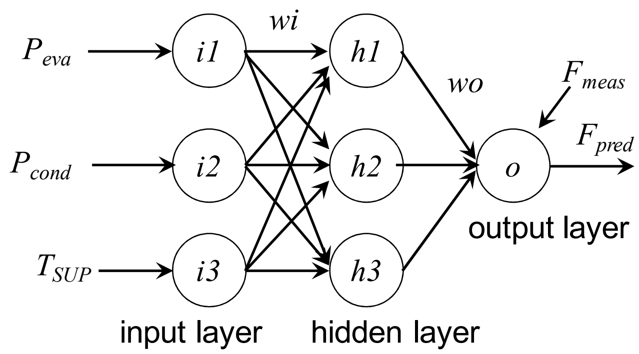


Figure 2: The artificial neural network structure

3 EXPERIMENTAL SETUP FOR HEAT PUMP SYSTEM

An experimental setup for heat pump performance test was constructed. Figure 3 shows a schematic diagram of the refrigeration part composed of a compressor, a condenser, an electronic expansion valve, an evaporator, and other accessories. Open type reciprocating compressor designed for R134a was installed. The compressor is driven by 3-phase induction motor. The compressor work is measured by torque transducer and the compressor speed was controlled by an inverter, which modulates output electronic frequency to a desired value. The mass flow rate of refrigerant was measured by the coriolis mass flow meter. Both the condenser and the evaporator were aluminum brazed plate type heat exchanger. R134a was used as a refrigerant and water was used in the condenser and the evaporator as a secondary fluid. Secondary fluids are circulated by the pumps and the flow rates were measured. Temperatures and pressures were measured using T-type thermocouple probes and pressure transducers, respectively. The expansion device in this experiment was EEV, which can finely control its opening with the electric signal. All the measured data were saved in the PC as digital data.

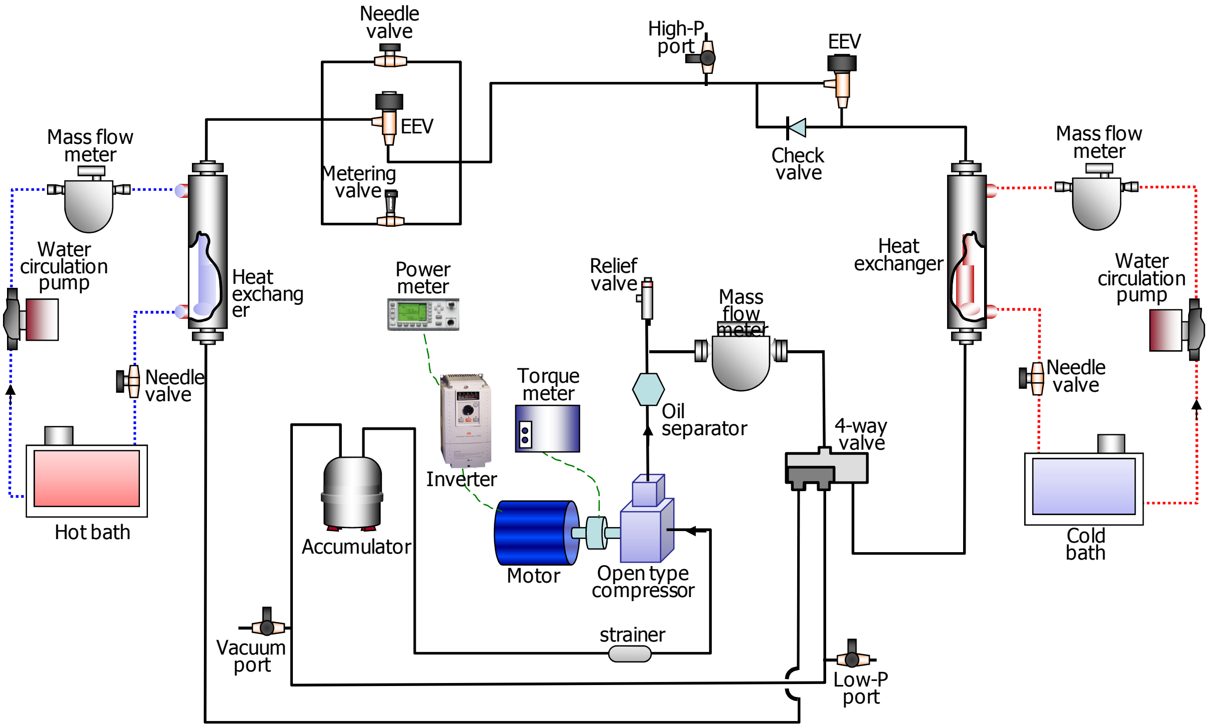


Figure 3: Schematic diagram of experimental apparatus

4 RESULTS

4.1 EXPERIMENTAL RESULTS

To get an experimental data for training the neural network, the evaporator and condenser inlet temperature and flow rate of the secondary fluid was fixed. The water inlet temperature of evaporator is 20°C and flow rate is 20 l/min, and the water inlet temperature of condenser is 30°C and flow rate is 20 l/min, respectively. The rpm of the compressor and the opening of EEV were changed step by step. The frequency of inverter varies from 19 to 25 Hz and the opening pulse of EEV varies from 130 to 290 (maximum pulse is 500). More than 2,800 points was acquired and used to learn the neural network. The cycle diagram derived from the measured data on the P-h diagram is shown in Fig. 4. This figure shows the cycle characteristics according to the rpm of compressor at the fixed EEV opening. As a frequency was raised, the discharge pressure and the saturation pressure of the condenser were increased. If the conventional method for mapping is used, tests more than ten times have to be conducted according to the resolution of the opening of EEV. The neural network method enables to reduce the experimental cases. The more accurate a learning process of ANN is, the fewer test cases can be conducted.

4.2 TRAINING NEURAL NETWORK

If the setting value of the pressure at evaporator and condenser is confirmed, the appropriate the rotational frequency of compressor and the opening pulse of EEV have to be determined. The proper target value for control the system can be predicted after the artificial neural network is trained by the experimental data. First, clustering technique was used to group data for reducing the measurement noise and system disturbances. One data represents the group of data inner bound of clustering radius. In this study, 2,824 data points was taken and there were 58 clusters after it was clustered. To learn the neural network, the measured input

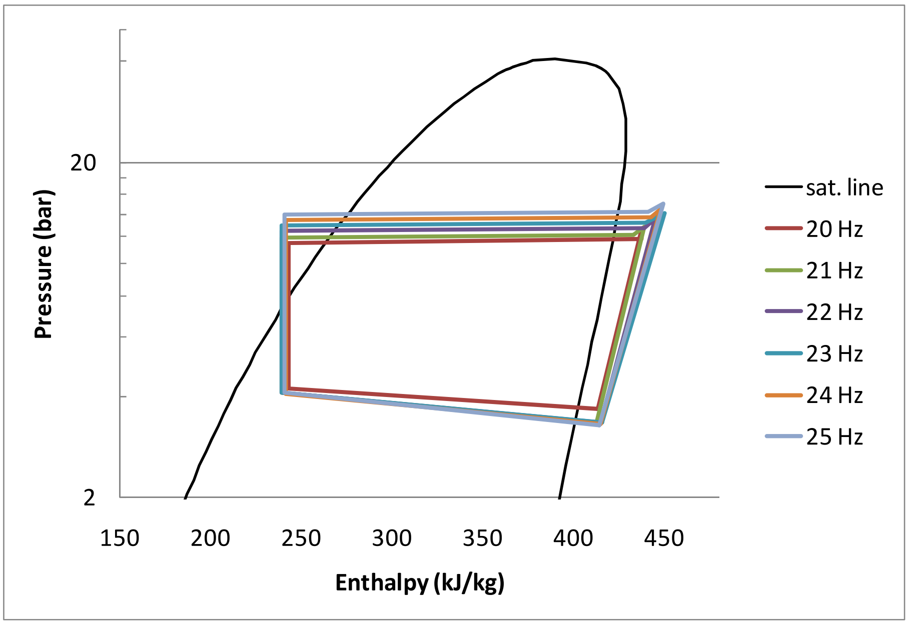
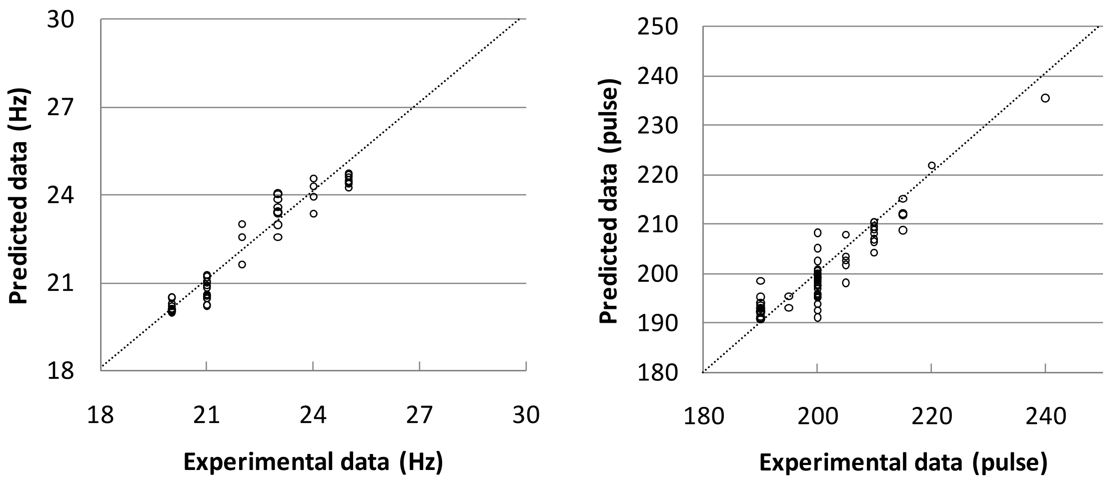


Figure 4: Refrigeration cycle on the P-h diagram according to the rotational frequency of compressor (The EEV pulse=200)

parameters (P_{eva}, P_{cond}, T_{sup}) for the rotational frequency of compressor were used after normalization. Figure 5(a) shows the comparison between the experimental data and the predicted value of the rotational frequency of the compressor by neural network at the same condition. The ANN algorithm performed more than 10,000 times iteration for learning process and the standard deviation is 0.441. For the opening pulse of EEV, three parameters (P_{eva}, T_{sup}, Hz) were used to learn after normalization as input parameters. Figure 5(b) shows the comparison between the experimental data and the predicted value of the opening pulse of EEV by neural network at the same condition. The ANN algorithm also performed more than 10,000 times iteration for learning process and the standard deviation is 3.395. Because the rotational frequency of compressor and the opening pulse of EEV are coupled, the rotational frequency of compressor was used to predict the opening pulse of EEV as an input parameter of ANN.



(a) The rotational frequency of the compressor **(b) The opening pulse of EEV**

Figure 5: The comparison between the experimental data and the data predicted by ANN

To make a complete look-up table of this test, 1,127 test cases (7 Hz steps by 161 EEV steps) is needed in this test condition. However, ANN method acquired accurate correlations using only 58 data points. These results show that the ANN method could correlate the control parameters with the cycle parameters well by using smaller data set than that of conventional ways.

5 CONCLUSION

The base investigation of the optimal control algorithm for the heat pump system was conducted in this study. To study on the refrigeration cycle characteristics, the water heat sourced heat pump test system which consists of the controllable components which are the EEV and the variable speed compressor was constructed. The artificial neural network algorithm was used to relate between the control parameters and the measured data of the refrigeration cycle. To get an experimental data for training the neural network, test was performed as the rotational frequency of the compressor and the opening of EEV were changed when the secondary fluid inlet condition was fixed. Through the learning process of the neural network, the relationship between the control parameters and the cycle parameters such as saturation pressure or superheat was acquired. The rotational frequency of the compressor was predicted in the standard deviation of 0.441 and the opening of EEV was predicted in the standard deviation of 3.395. The feasibility for the applying method of the neural network algorithm to control the heat pump system by relating the control and cycle parameters was investigated in this study. It was shown that the artificial neural network method could predict the control parameters well by using smaller data set of the measured cycle parameters than that of conventional method.

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