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Hybrid Artificial Neural Network−Genetic Algorithm Technique for Condensing Temperature Control of Air-Cooled Chillers

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Abstract

Air-cooled chillers are commonly used in commercial buildings in the subtropical climate, which are considered inefficient due to operating under traditional head pressure control. This study presents a hybrid intelligent control technique, including neural networks and genetic algorithms, for the optimal control of the set points of the condensing temperature to improve the coefficient of performance (COP) of air-cooled chillers under various operating conditions. The neural network is used to model the air-cooled chillers, and genetic algorithm is adopted in searching optimal set points of condensing temperature based on the predicted fitness values. Results show that this control technique allows optimal set point of the condensing temperature to be successfully determined, and the chiller performance can be improved considerably.

Keywords: Air-Cooled Chiller; Condensing Temperature Control; Artificial Neural Network; Genetic Algorithm

1. Introduction

Air conditioning system is intensively used in commercial buildings in the tropical and subtropical climate area, and air-cooled chillers are commonly used to provide cooling energy but with considerable electricity consumption. Low operational efficiency especially under partial load conditions and poor control are part of reasons for such

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huge energy consumption. The deficient performance of air-cooled chillers is mainly due to head pressure control (HPC). HPC means that the number of staged condenser fans is kept minimal in most operating conditions in order to allow the condensing temperature to hover around its high set point of 50 °C. Some researchers have stated the opportunity to implement variable condensing temperature control (CTC) to save compressor power to improve the chiller efficiency [1,2]. The condenser fans under CTC are staged as many as possible in most operating conditions to enhance the heat rejection airflow to decrease the condensing temperature. This causes an increase in the fan power, but the condensing temperature can hover closely above the outdoor temperature to minimize the compressor power and hence to maximize the chiller COP. To implement CTC, the set point of condensing temperature should be adjusted in response to variations of outdoor temperature, chiller part load ratios and some other parameters.

Availability of a process model is a prerequisite to process optimization. Conventionally, two approaches based on physical models and empirical models are employed for building energy systems. Physical models represent physical phenomenon underlying the process explicitly. However, most physical models are rather complicated, and the iteration process is always required in most of these models, which may result in instability and divergence as well as high computational cost and time consuming. These characteristics may seriously prevent their applications on online control.

Modeling using artificial neural networks (ANNs) is an alternative, which are a nonlinear regression technique that can be used to model complex relationships between inputs and outputs. The main advantages of ANNs are their abilities to map nonlinear functions, to learn and generalize by experience, as well as to handle multivariable problems. These desirable properties make ANNs feasible for modeling and control applications [3,4]. GAs are stochastic global search and optimization methods based on Darwin's theories of natural evolution and natural genetics. The objective of this work is to optimize the energy efficiency of air-cooled chillers under CTC. For this purpose, an artificial neural network (ANN) is trained to map the chiller performance. Subsequently, a genetic algorithm (GA) is employed to find the optimal set points of condensing temperature under specific conditions such that an improved chiller performance is realized.

2. Chiller model

In this study, a chiller plant installed in an institutional complex was investigated, which comprised of five identical screw chillers connected in parallel. Each chiller had two refrigeration circuits, namely circuit 1 and circuit 2, and each refrigeration circuit was equipped with two compressors, as shown in Fig.1. In this dual-circuit chiller, tubes were designed as a two-pass arrangement for chilled water to enhance the heat transfer. The chilled water passed first through the evaporator of circuit 1, then passed into the evaporator of circuit 2, and then got back through the evaporator of circuit 1.
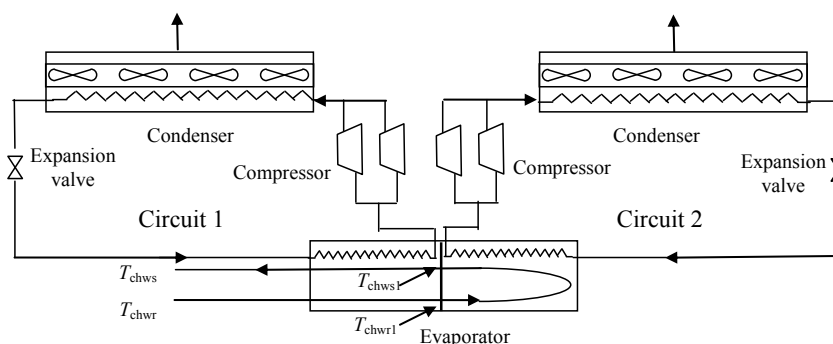

Fig. 1. Schematic of the air-cooled chiller.

The nominal cooling capacity of the studied chiller was 1116 kW, and the rated power of the studied chiller was 398 kW. The air-cooled condensers contained 16 identical condenser fans to deliver a total airflow rate of 85.5 m^3/s

by eight groups, and each refrigeration circuit had four fan groups. The fan speed was 15.8 r/s, and each fan consumed a power of 2.4 kW.

2.1. Chiller model

The chiller model was developed using the simulation program TRNSYS based on mass and energy conservation laws. Classical heat exchanger efficiency method was used to model the evaporator and condenser. The general equations for energy balance and the assumptions made in the chiller model have been reported [1, 5].

The evaporator tubes were designed as a two-pass arrangement for chilled water flow. The heat transfer between the refrigerant and the chilled water was modeled by three heat exchange sections in series, having two sections for refrigerant circuit 1 and one section for refrigerant circuit 2. The heat transfer effectiveness of the evaporator (ε_{ev}) was used to simulate the heat and mass transfer processes in the evaporator as in Eqs. (1-3). The overall heat transfer coefficients (AU_{ev}) of the three heat exchange sections of the evaporator were represented by mechanistic relation in Eq. (4), respectively [5], where the coefficients c1, c2 and c3 were characteristic parameters and had to be evaluated based on the performance data of the specific chiller to be modeled.

$$Q_{11} = (1 - \exp(-AU_{ev11}/(m_w C_{pw}))) m_w C_{pw}(T_{chwr} - T_{ev1}) \tag{1}$$

$$Q_{12} = (1 - \exp(-AU_{ev12}/(m_w C_{pw}))) m_w C_{pw}(T_{chws1} - T_{ev1}) \tag{2}$$

$$Q_2 = (1 - \exp(-AU_{ev2}/(m_w C_{pw}))) m_w C_{pw}(T_{chwr1} - T_{ev2}) \tag{3}$$

where

$$AU_{ev} = 1/(c_1 m_w^{-0.8} + c_2 Q^{-0.745} + c_3) \tag{4}$$

To control the condensing temperature, the set point of condensing temperature (T_{cdsp}) was introduced to determine the number of staged condenser fans to modulate the heat rejection airflow. Cycling on or off the condenser fans was determined by comparing the condensing temperature with the high and low temperature settings, which were 52 °C and 42 °C for the base case under HPC [1], respectively. In each time step, the number of condenser fans would be checked to ascertain whether the staged condenser fans were sufficient to keep the condensing temperature between the high and low boundary. If the staged condenser fans were not sufficient to deliver the airflow required to keep the condensing temperature within the dead band, more or fewer condenser fans would be staged.

2.2. Control algorithm

As HPC is regarded as energy inefficient, CTC is proposed to be an alternative to HPC to improve chiller efficiency. The strategy for implementing CTC is to adjust T_{cdsp} by a certain means, so that the trade-off between the compressor power and condenser fan power can be optimized for any working conditions. The lowest possible T_{cdsp} is 20 °C for ensuring lubrication to the chillers with electronic expansion valves [6]. A logical argument was included in the algorithm of controlling condenser fans to determine the optimum T_{cdsp} ($T_{cdsp,op}$). This argument checked the change in chiller power when T_{cdsp} increased from its lower level of 20 °C or (T_{db} + 3) °C to 45 °C in steps of 0.05 °C, whichever was higher. These steps were small enough to trace the change of the chiller power. For each operating condition, the minimum chiller power along with the optimum T_{cdsp} was able to be identified by resetting T_{cdsp} [5].

2.3. Validation of the chiller model

To verify the effectiveness of the developed modeling technique, the performance of the model was evaluated by comparing the modeled results with the operating data of the chiller system. The measured data collected for validating the chiller model came from the chiller operating data under HPC. Fig. 2 illustrates the comparison between the

modeled and measured chiller COP. For over 86% of the data, the uncertainty (the difference between the modeled value and the experimental value) of chiller COP was less than 10%. The simulation results, therefore, were considered to be satisfactory.
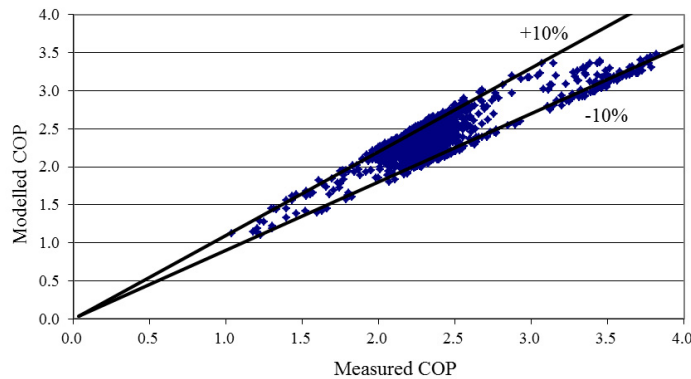

Fig. 2. Comparison between the modeled and measured chiller COP.

3. Optimization strategy

3.1. Formulation of optimization problem

For this study, an optimization problem was formulated to find the solutions (optimal set points of condensing temperature for two refrigeration circuits) that would minimize the chiller energy consumption, when the other parameters were specified. In addition to the energy use, the operation of the chiller system was subjected to constraints for proper operation of the mechanical system and constraints for maintaining indoor thermal comfort. The chilled water supply temperature T_{chws} should be set properly to avoid freezing in the evaporator and to provide dehumidification of the air in the cooling coil. For cooling and dehumidification purpose, the minimum and maximum perturbations of T_{chws} were 5 and 9 °C, respectively [7, 8]. The possible variations degree of subcooling (T_{cdsc}) and the degree of superheat (T_{evsh}) were 1–6 °C and 4–9.5 °C, respectively [8]. The optimal operation problem of this study is mathematically stated as follows:

Min $\qquad J = E_{cc} + E_{cf}$ $\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ (5)

subject to: $\quad 20 \le T_{cdsp1} \le 45$

$\qquad\qquad\quad 20 \le T_{cdsp2} \le 45$

$\qquad\qquad\quad T_{chwr,low} \le T_{chwr} \le T_{chwr,high}$

$\qquad\qquad\quad T_{cdsc,low} \le T_{cdsc} \le T_{cdsc,high}$

$\qquad\qquad\quad T_{evsh,low} \le T_{evsh} \le T_{evsh,high}$

Since the aim was to find a feasible optimal solution, penalty functions were used to penalize infeasible solution for handling the nonlinear constraints whenever any constraints were violated. The set point of condensing temperature should be within [20,45]. The fitness function of GA was revised to accommodate the penalty and was expressed in the following equation.

Min $\qquad J = E_{cc} + E_{cf} + C$ $\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ (6)

where, *C* is a positive constant, and it should be large enough to avoid the corresponding chromosome being selected as the optimal value, and *C* is defined as follow.

$$C = \begin{cases} 500 & \text{If } T_{cdsp} > 45 \text{ or } T_{cdsp} < 20 \\ 0 & \text{If } 20 \leq T_{cdsp} \leq 45 \end{cases} \tag{7}$$

3.2. Optimization plan

The objective was to establish the control strategy for the air-cooled chillers under CTC, and proposed a hybrid artificial intelligent technique for chiller modeling and control to optimize the chiller operation. To solve the above optimization formulation, the technique combining ANN and GA was implored. ANN-GA technique can be considered to be a model-based method of supervisory control, in which ANN was used as an approximator to objective function, and the desired controlled variables were obtained using GA. The optimization process can be described as shown in Fig.3.
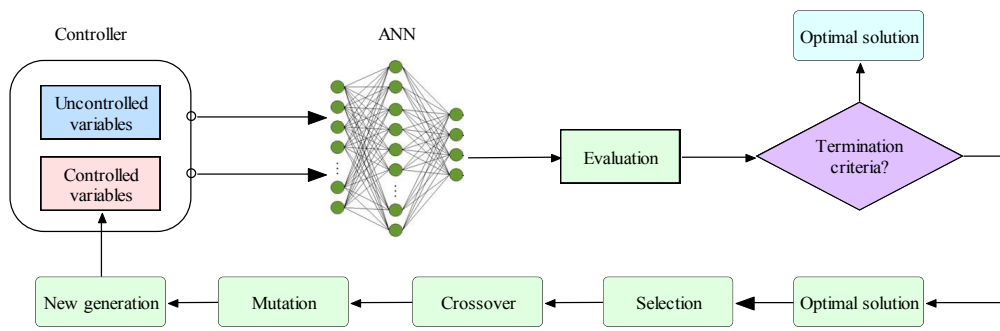

Fig.3. Hybrid intelligent control using ANN and GA.

1. For the air-cooled chiller operating under CTC, the data for developing the chiller model using ANN were generated from the simulation data of chillers under CTC serving the representative office building using TRNSYS. Seven investigated chillers were to serve it with the peak cooling load of 7338 kW [9], and sufficient simulations were performed for the working conditions of a typical weather year.

2. The "operating data" obtained in the previous step was used to train, validate and test the ANN model. Once the training completed, ANN was able to map the chiller performance with a high degree of accuracy.

3. The well-trained ANN was then embedded in the program of GA as a fitness function. The ANN-embedded GA was applied to search for the near-optimal set points of condensing temperature of the two refrigeration circuits for certain conditions, with the goal of minimizing the chiller energy consumption while satisfying the chiller load demand. The results by ANN-GA control were compared with simulation data by TRNSYS to evaluate the accuracy of the proposed approach in the end.

3.3. Artificial neural networks

The simulated "operating data" would be used to train, validate and test the ANN model, and there were total 3051 data patterns for this case. From the operating data set, 60% was selected randomly for the neural network training, 20% was used for validation and the remaining 20% of the total data was employed for testing the network.

The model was developed in the Matlab environment using the neural network toolbox [10]. The architecture of the three-layer BP network for this case was shown in Fig.4. The proposed ANN model in this study has nine inputs, three outputs and one hidden layer, as one hidden layer may be sufficient to map an arbitrary function to any degree

of accuracy. The inputs included the dry bulb temperature (T_{db}) of the entering condenser air, chiller load sharing by refrigeration circuit 1 and circuit 2 (Q_{cl1} and Q_{cl2}), temperature of supply chilled water (T_{chws}), chilled water mass flow rate (m_{chw}), degree of subcooling (T_{cdsc}), degree of superheating (T_{evsh}), set points of condensing temperature of refrigeration circuit 1 and circuit 2 (T_{cdsp1} and T_{cdsp2}), which were easily available to the operating engineers. The outputs from the ANN model were the chiller power consumption (E_{ch}), and the number of operating condensing fans of each refrigeration circuit.

Since there was no explicit rule to determine the number of neurons in the hidden layer, the trial and error method was applied to find the best solution, and different training algorithms and different number of neurons in the hidden layer were performed. The training algorithms included Levenberg-Marquardt backpropagation, Batch gradient descent with momentum, Variable learning rate backpropagation, BFGS quasi-Newton backpropagation and Bayesian regulation backpropagation, which were the popular training algorithms. In the training process, the number of neurons in the hidden layer increased (i.e. from 3 to 15) to obtain the one with best performance. Compared with the different training algorithms with different neurons in the hidden layer, the best one with minimum mean square absolute error (MSE) was selected, which was the Bayesian regularization backpropagation with 11 neurons in the hidden layer and the minimum MSE was 0.002. That is, the best ANN model had 9-11-3 architecture, which meant that there were 9, 11, and 3 neurons in the input, hidden, and output layers, respectively.
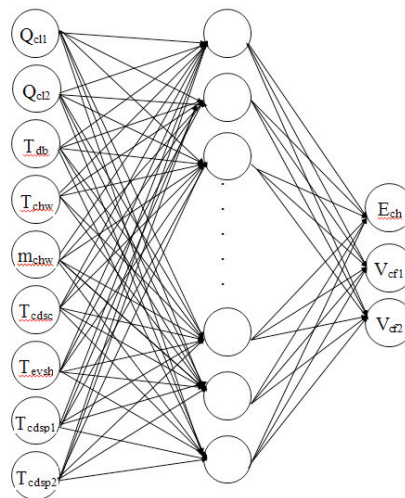

Fig.4. ANN architecture

3.4. Genetic algorithm

A key feature of this work was that the optimal set points of the condensing temperature were obtained from the artificial intelligence (AI) controller based on the specified values for the other 7 uncontrolled input variables. The AI controller applied GA to find the optimal set points of the condensing temperature within the feasible solution space of the system to minimize the chiller energy consumption, while the chiller system satisfied the chiller load. Herein, a possible solution represented a chromosome. Genes in the chromosome were formed by the values of the controlled variables and uncontrolled variables, which were set as continuous and fell in the specified range. The parameter bounds and the precision were determined according to the characteristics of the system.

As one of the objectives of this research was to investigate the possibility of AI control combing ANN and GA to improve the chiller performance, a few working conditions were considered to optimize the chiller operation as shown in Table 1, which were not used for developing the chiller model using ANN. The above problem was optimized by real-coded GA. The population size was 50, and the maximum number of generations was 100. The crossover rate pc

was 0.80, and the mutation rate pm was 0.085. The objective function was a minimum problem of the chiller energy consumption. Through the performance map model based on ANN, the predicted optimal set points of condensing temperature were obtained by GA. Table 1 lists the predicted optimal set points of condensing temperature and the corresponding values of variable combination.

3.5. Verification of the optimization result

There would be some differences between ANN outputs and the simulation results by TRNSYS, even if the ANN was properly trained. Simulation by TRNSYS was performed for the working conditions in Table 1, and the chiller electricity consumption obtained with the hybrid ANN-GA technique was compared with that obtained in the simulation.

Mathematical validation demonstrated that the comparison between the AI control and simulation data had a discrepancy that was lower than 5.8% in the worst case for the set point of condensing temperature. For the chiller power consumption, the discrepancy between the AI control and simulation data was less than 4.5%. It demonstrated that the solutions by AI controller were near optimal. The CPU runtime for GA to search for the optimal solutions was also calculated. The computer used was equipped with an Intel(R) CPU E6750 @2.66GHz, 4GB of RAM. The small relative errors for the variables in conjunction with a computing time of about 80 s indicated that this hybrid artificial intelligent control strategy could be applied with a high level of confidence for the on-line control of the chiller system.

For the purpose of benchmarking, this study conducted a comparison on the chiller electricity consumption between the traditional HPC and the proposed advanced control. Table 1 revealed that the proposed approach outperformed the traditional HPC in terms of the chiller energy consumption, which could be saved up to 21.5% for the listed conditions in Table 1.

Table 1. Comparison of ANN-GA with TRNSYS results.

Test No.	1	2	3	4	5	6	7	8	9	10	11	12
PLR	0.25	0.25	0.25	0.25	0.75	0.75	0.75	0.75	1.0	1.0	1.0	1.0
T_{db} (°C)	20	25	30	35	20	25	30	35	20	25	30	35
m_{chw} (l/s)	53.3	53.3	53.3	53.3	53.3	53.3	53.3	53.3	53.3	53.3	53.3	53.3
T_{cdsc} (°C)	8	8	8	8	8	8	8	8	8	8	8	8
T_{evsh} (°C)	3	3	3	3	3	3	3	3	3	3	3	3
T_{cdsp1} (°C)	31.7	35.7	40.3	44.8	32.8	37.3	41.9	45.0	35.0	39.5	44.3	45.0
$^*T_{cdsp1}$ (°C)	32.6	35.1	41.3	43.9	31.6	37.9	41.5	44.7	33.5	37.3	42.1	44.1
Error (%)	2.8	-1.7	2.5	-2.1	-3.7	1.6	-1.0	-0.7	-4.3	-5.6	-4.9	-2.0
T_{cdsp2} (°C)	-	-	-	-	32.8	37.3	41.9	45.0	35.0	39.5	44.3	45.0
$^*T_{cdsp2}$ (°C)					30.9	37.4	41.6	44.8	33.6	38.3	40.3	43.9
Error (%)					-5.8	0.3	-0.7	-0.4	-4.0	-3.0	-4.5	-2.3
E_{ch} (kW)	58.3	65.1	73.3	83.5	260.3	291.9	331.3	381.3	270.7	304.5	346.8	403.5
$^*E_{ch}$ (kW)	59.6	64.3	75.1	81.7	253.3	291.7	331.6	382.9	258.6	299.0	338.9	387.8
Error (%)	2.2	-1.2	2.5	-2.2	-2.7	-0.1	0.1	0.4	-4.5	-1.8	-2.3	-3.9
$^{**}E_{ch}$ (kW)	75.6	76.4	78.1	83.7	322.7	328.6	341.6	382.1	317.3	326.6	348.7	404.3
Sav. (%)	21.2	15.8	3.8	2.3	21.5	11.2	2.9	0.2	18.5	8.5	2.8	4.1
t (s)	81.3	81.6	81.3	84.1	81.5	81.2	81.6	81.7	81.8	81.5	80.6	81.5

Note: * Values from AI controller;

   ** Chiller power consumption under head pressure control.

4. Conclusions

The hybrid intelligent control combing the artificial neural network and genetic algorithm was developed to obtain the optimum set points of condensing temperature to improve the chiller efficiency. The ANN was trained and validated using simulation results. The database of the chiller operating under CTC for a typical weather year was generated using TRNSYS. By trial and error method with different training algorithms and number of hidden neurons, the optimal architecture was determined. After training and validation, the ANN model proved to be able to map the chiller performance with acceptable accuracy. The performance map based on the ANN was used as the objective function of the optimization problem, and genetic algorithm was adopted in searching optimal set points of condensing temperature based on the predicted fitness values. The proposed AI control outperformed the traditional HPC in terms of the chiller energy consumption, which could be saved up to 21.5%. The results illustrated that the hybrid intelligent control has excellent performance as compared to the traditional HPC. This intelligent control strategy on the optimal set point of condensing temperature will support building operators in setting operating scheme of cooling plant and cutting the electrical bill.

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