DEVELOPMENT OF FAST CALCULATION METHOD FOR AMMONIA REFRIGERATION CYCLE AND PARAMETER ADJUSTMENT WITH GENETIC ALGORITHM

Eisuke Togashi, Shin-ichi Tanabe and Tomohiro Ataku

Waseda University, Dept. of Architecture, 3-4-1 Okubo Shinjuku-ku, Tokyo 169-8555
E-mail : togashi@tanabe.arch.waseda.ac.jp http://www.tanabe.arch.waseda.ac.jp

ABSTRACT

A parameter adjustment method for an ammonia heat pump chiller using a genetic algorithm (GA) was developed. The parameters were automatically adjusted by the data of performance at rated point. Upon using the proposed adjustment method for parameters, output values of the simulation model agreed quite well with the performance data at rated point. The deviation of output was less than 1.2 [%] from the rated value. To speed up the adjustment process, a new approximation method with neural network was also proposed. This method decreases the calculation time required in obtaining refrigerant thermodynamic properties. The time required to calculate saturated and other refrigerant states were decreased by 14 times and 33 times respectively, while the average relative error was less than 0.04 [%] and 0.5 [%] when compared to the exact solution from REFPROP. The time required to calculate the refrigerant cycle decreased 20 times, while relative error was within 3 [%].

KEYWORDS

Ammonia heat pump, Parameter adjustment, REFPROP, Approximation, Refrigeration cycle

INTRODUCTION

Although a detailed physical model of the refrigeration cycle is suitable for evaluating a performance at a low load operation or during a starting up process, the HVAC simulation program uses more of the performance data to simulate the heat source equipment.

There might be two reasons for this. The first reason is because a detailed physical model requires greater computation time than the simple model which utilizes the performance data file. It is mainly due to an iterative computation on calculating the thermodynamic properties. The second reason is because a detailed physical model needs much more physical parameters to simulate; it is usually difficult to look for all the parameters.

In this study, thermodynamic properties of a refrigerant are approximately evaluated by neural network to increase the calculation speed of a refrigeration cycle. The accuracy of the approximation and the calculation speed are evaluated. After that, some parameters are estimated from a performance data at rated point with using the genetic algorithm. Output values from the simulation model are compared with the rated value.

PHYSICAL MODEL OF REFRIGERATION CYCLE

The refrigeration cycle consists of some smaller components. In this study, the model of a compressor, an evaporator, a condenser, and an expansion valve are all combined to calculate the refrigeration cycle. A brief calculation flow chart with each component is described below.

Compressor

A compression work of the compressor can be generally expressed as a function of inlet and outlet pressures as shown in equation (1) (Fujiwara 1985). A flow rate of the refrigerant is a function of a density, and it is calculated by solving an equation of state (EOS).

$$W = \eta_v Vol \frac{pol-1}{pol} P_{in} \left\{ \left(\frac{P_{out}}{P_{in}} \right)^{(pol-1)/pol} - 1 \right\} \quad (1)$$

$$G_{out} = \eta_v \cdot Vol \cdot \rho_{in} \quad (2)$$

$$\rho_{in} = f_{EOS}(P_{in}, H_{in}) \quad (3)$$

Evaporator

In the evaporator, by drawing heat from an ambient air, the two-phase refrigerant could change its state to super heated. Equation (4) shows the heat balance in two-phase region, where $\Delta\theta$ is a logarithmic mean temperature difference (LMTD) expressed in equation (6). Similarly, the heat balance in the super heated region can be expressed in equation (5). Temperatures necessary to calculate the LMTD could be calculated by solving the EOS.

Figure 1 shows a calculation flow chart of the evaporator. The output refrigeration state is either two-phase or super heated, and an iterative

calculation is needed to determine a suitable enthalpy of the output refrigerant.

In this model, a cooling air state is assumed to move along the saturation line on the psychometric chart when cooling air is saturated.

$$\begin{aligned} Q_{sh} &= AR_{sh}K_{sh}\Delta\theta_{sh} \\ &= G_{ref}\left(H_{ref,out} - H_{ref,vs}\right) \\ &= G_{air}\left(H_{air,in} - H_{air,sh,out}\right) \end{aligned} \quad (4)$$

$$\begin{aligned} Q_{tp} &= AR_{tp}K_{tp}\Delta\theta_{tp} \\ &= G_{ref}\left(H_{ref,vs} - H_{ref,in}\right) \\ &= G_{air}\left(H_{air,in} - H_{air,tp,out}\right) \end{aligned} \quad (5)$$

$$\Delta\theta = \frac{\left(T_{1in} - T_{2in}\right) - \left(T_{1out} - T_{2out}\right)}{\ln\left(\left(T_{1in} - T_{2in}\right)/\left(T_{1out} - T_{2out}\right)\right)} \quad (6)$$

$$T = f_{EOS}\left(P, H\right) \quad (7)$$

$$T_{vs} = f_{EOS}\left(P_{vs}\right) \quad (8)$$

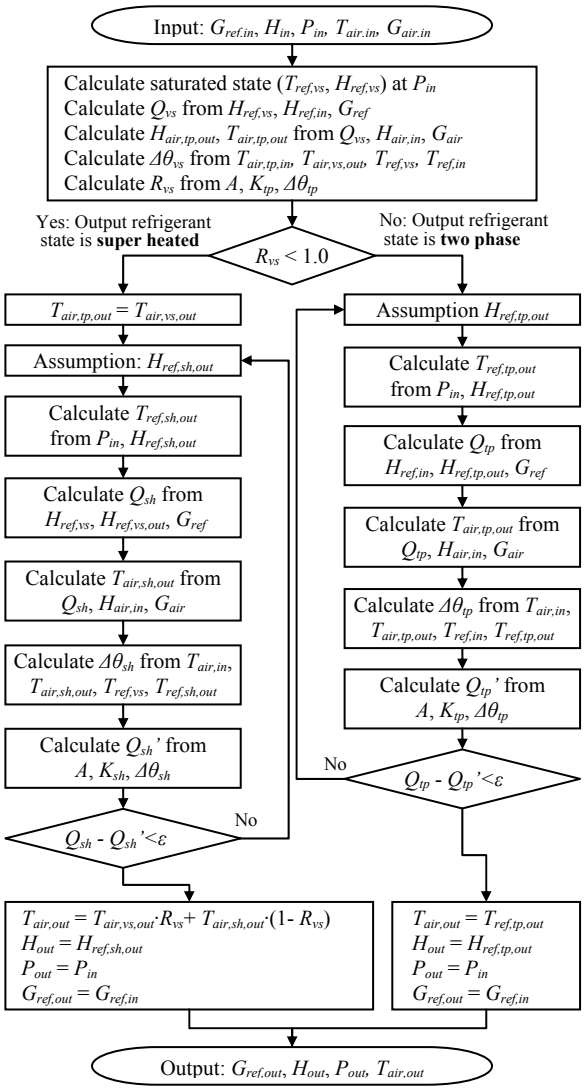

Figure 1 Calculation flow chart of the evaporator

$$G_{in} = Cv\sqrt{\rho_{in}}\sqrt{P_{in} - P_{out}} \quad (9)$$

$$\rho_{in} = f_{EOS}\left(P_{in}, H_{in}\right) \quad (10)$$

Condenser

The model of the condenser is almost as same as that of the evaporator. In this study, though an output state of the refrigerant could be sub cooled, a heat transfer area of sub cooled and two-phase are treated as one unit, because a heat exchange at sub cool state is very low.

Expansion valve

Equation (9) shows pressure drop at an expansion valve at a given flow rate. It is a function of an inlet refrigerant density which can be calculated by solving the EOS.

Refrigeration cycle

Finally, all four components (compressor, evaporator, condenser, expansion valve) are connected together and state variables are solved simultaneously.

Figure 2 shows a calculation flow chart of the refrigeration cycle. According to this chart, the inlet enthalpy and the inlet pressure of each components, compression work, and flow coefficient of expansion are treated as state variables. The object of this calculation is to estimate an electricity consumption

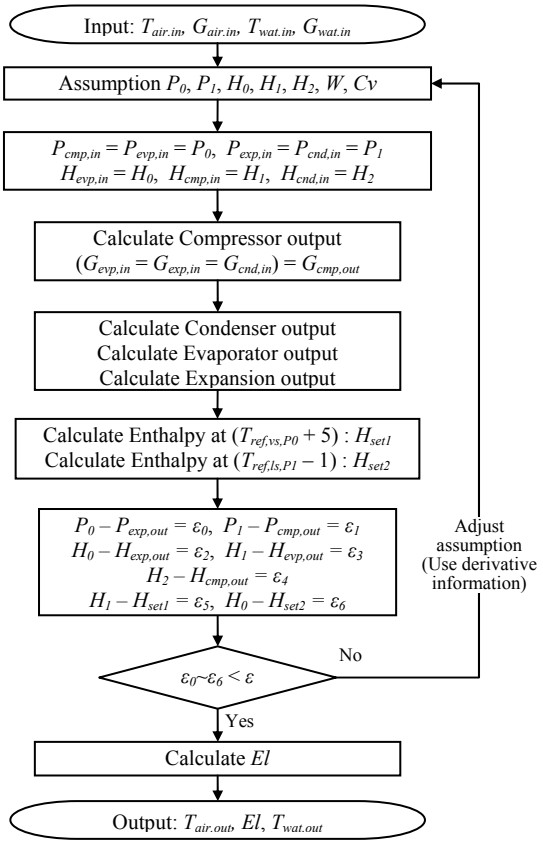

Figure 2 Calculation flow chart of the refrigeration cycle

and a heating rate at a given ambient temperature or under other conditions. State variables and input parameters should be changed in accordance with the intended use. For example, when the flow rate of a cooling air is need provided that a heating rate is given, the heating rate will be the input parameter while the flow rate of the cooling air becomes state variable.

The result of the simulation will be described later.

FAST CALCULATION OF REFRIGERANT PROPERTIES

NIST REFPROP database (Anon.) is mostly used to calculate the thermodynamic properties of refrigerants. Because of unavoidable iterations in calculations, the use of REFPROP leads to high computational time delay.

To accelerate the computation, Cleland (1986) and Charters (1987) has developed some formulae for pure refrigerants approximation. Corberan developed approximation method by linear interpolation. Guoliang (2005, 2006) proposed implicit curve-fitting method which has applicable to mixed refrigerants. Although they achieved significant results for certain range on the mollier diagram, none of them mentioned approximation of density at two-phase state. There was difficulty in approximating density at a two-phase state because of the nonlinearity around the saturated liquid line. As shown in equation (10), the density state is indispensable to evaluate the pressure drop at the expansion valve.

In this section, an approximation method which uses a neural network is proposed to rapidly calculate refrigerant thermodynamic properties. A neural network is a non-linear statistical data modeling tool. Cybenko (1989) showed that every continuous function can be closely approximated by a multi-layer perceptron with just one hidden layer (which means three-layer neural network). Figure 3 shows architecture of a three-layer neural networks. An output value will be calculated by equation (11) and (12). In this study, Levenberg-Marquardt method (Bogdan 1999) was used to train the neural network.

Since the curve of the thermodynamic property inflects around the saturated lines on the mollier diagram, area is divided into three regions by the saturated lines. Different neural networks should be established for different regions. A range with a pressure from 200 [kPa] to 2000 [kPa] and enthalpy from 400 [kJ] to 2000 [kJ] is selected for approximation since it contains the entire range of refrigeration cycle at the rated point. Figure 4 shows a mollier diagram of ammonia with the approximation range and the rated refrigeration cycle.

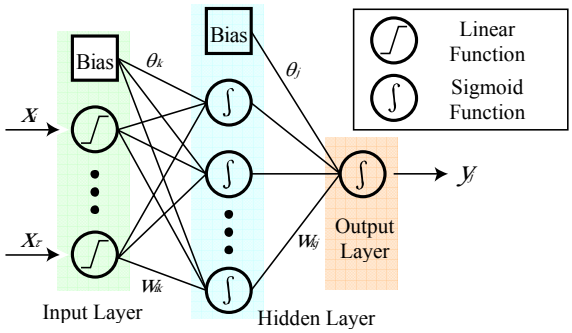

Figure 3 Architecture of three-layer neural network

$$y_j(x) = f_{sig}\left(\sum_{k=1}^{\sigma} w_{kj} \cdot f_{sig}\left(\sum_{i=1}^{\tau} w_{ik} x_i + \theta_k\right) + \theta_j\right) \quad (11)$$

$$f_{sig}(x) = \frac{2}{1+e^{-x}} - 1 \quad (12)$$

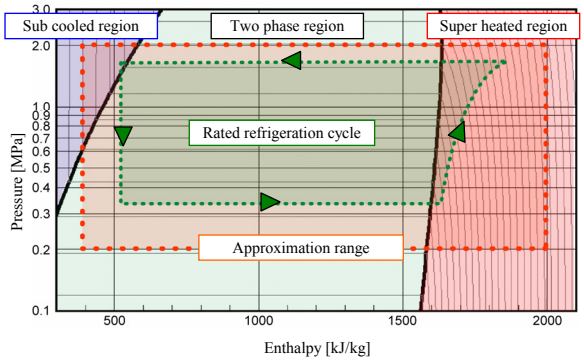

Figure 4 Mollier diagram with approximation range and rated refrigeration cycle

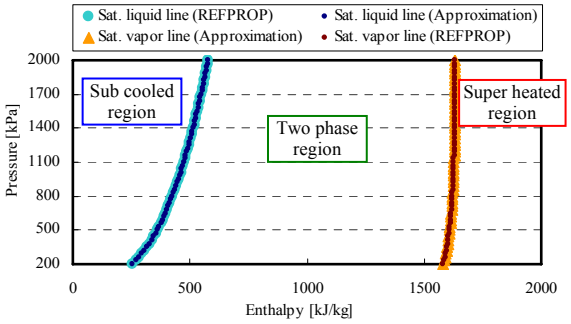

Figure 5 Approximation results of saturated states

Saturated refrigerant properties

For saturated refrigerants, enthalpy, temperature and density are expressed as a function of pressure. Value of pressure is directly used as input value of a neural network.

Figure 5 shows the approximation result of saturated lines of ammonia. In order to check the accuracy of the approximation, 200 points are randomly distributed in the ranges selected above. Table 1 shows the maximum and average value of a relative error, where the relative error is calculated by

equation (13). Table 2 shows a calculation speed of REFPROP and the neural network. It is shown that the average relative error of the output from the neural network is less than 0.01 [%] while the calculation speed is up to 14 times faster than that of REFPROP.

Sub cooled, two-phase and super heated refrigerant properties

For sub cooled, two-phase, and super heated refrigerants, temperature and density are expressed as a function of enthalpy and pressure. Pressure and enthalpy are directly used as input value to calculate temperature and density in the super heated region. Since density increases exponentially around the saturated liquid line, the relative position of enthalpy between saturated lines should be used for an input variable to calculate density at the sub cooled and two-phase region. The relative position of an enthalpy is calculated by equation (14). Densities at saturated states are also used for input variables.

Table 1 Max and average value of relative error

		Sat. liquid line	Sat. vapor line
Ave. relative error [%]	Enthalpy	$9.88 \cdot 10^{-3}$	$9.63 \cdot 10^{-5}$
	Temp.	$4.16 \cdot 10^{-3}$	$6.61 \cdot 10^{-3}$
	Density	$1.29 \cdot 10^{-4}$	$9.63 \cdot 10^{-3}$
Max relative error [%]	Enthalpy	$6.02 \cdot 10^{-2}$	$1.05 \cdot 10^{-3}$
	Temp.	$1.24 \cdot 10^{-2}$	$1.67 \cdot 10^{-2}$
	Density	$2.63 \cdot 10^{-4}$	$5.62 \cdot 10^{-2}$

$$Err_{rel} = \left| \frac{X_{App} - X_{REF}}{X_{REF}} \right| \times 100 \quad (13)$$

$$H_r = \frac{H - H_{sl}}{H_{sv} - H_{sl}} \quad (14)$$

Figure 6 and 7 show the approximation result of sub cooled, two-phase and super heated region. Drastic increase of density around the saturated liquid line is clearly represented by the neural network. In order to check the accuracy of the approximation, 40000 points are randomly distributed in the ranges selected above. Table 3 shows the maximum and average value of relative error. Table 4 shows the calculation speed of REFPROP and neural network. It is shown that the average relative error of output from neural network is less than 0.5 [%] while the calculation speed is up to 33 times faster than that of REFPROP.

Table 2 Calculation speed of saturated state

REFPROP vers.7	Approximation
453.13 [msec]	31.25 [msec]

Table 3 Maximum and average value of relative error

		Sub cool	Two-phase	Super heat
Ave. relative error [%]	Temp.	$2.14 \cdot 10^{-2}$	$2.85 \cdot 10^{-2}$	$2.42 \cdot 10^{-3}$
	Density	$4.32 \cdot 10^{-3}$	$4.48 \cdot 10^{-1}$	$3.09 \cdot 10^{-3}$
Max relative error [%]	Temp.	$2.74 \cdot 10^{-1}$	$1.29 \cdot 10^{-1}$	$1.82 \cdot 10^{-2}$
	Density	$3.91 \cdot 10^{-1}$	$2.66 \cdot 10^{-0}$	$5.62 \cdot 10^{-2}$

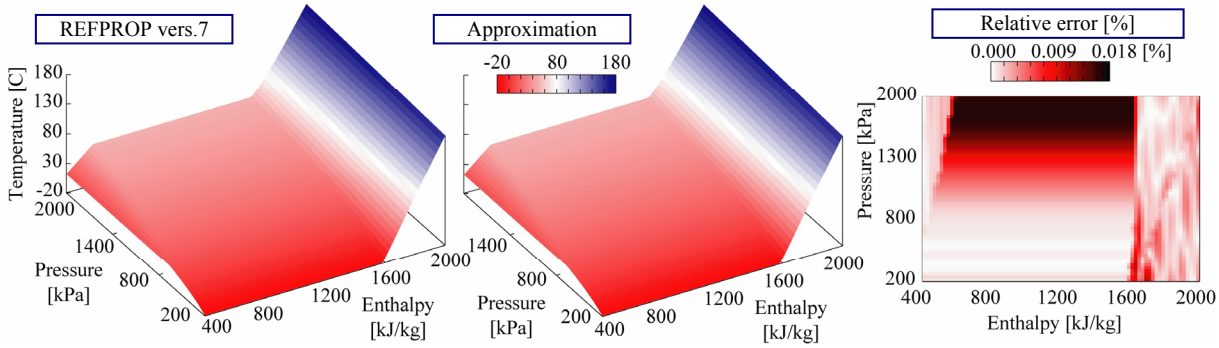

Figure 6 Approximation result of Temperature

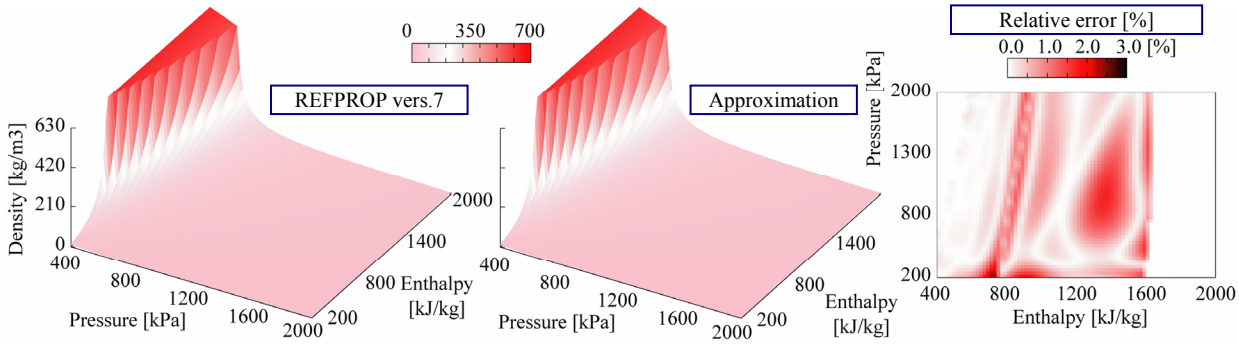

Figure 7 Approximation result of Density

Table 4 Calculation speed of sub cooled, two-phase, super heated region

REFPROP vers.7	Approximation
135234.38 [msec]	4046.75 [msec]

PARAMETER ADJUSTMENT WITH GENETIC ALGORITHM

Although theoretical models are versatile, they normally need number of physical parameters to execute a simulation successfully. In this section, a physical parameters adjustment method using genetic algorithm is proposed.

Genetic algorithm

A genetic algorithm is a random search technique to find optimal solutions. For continuous quantity, a real-coded genetic algorithm is used. Physical parameters such as over all heat transfer coefficient, surface area, and so on, are treated as DNA.

UNDX (unimodal normal distribution crossover) is adopted for cross over method (Ono I. 1997). Figure 8 shows generation of child DNA by UNDX. Two normal distributions (parallel and vertical to deviation vector between parent1 and parent2) are made to generate children randomly.

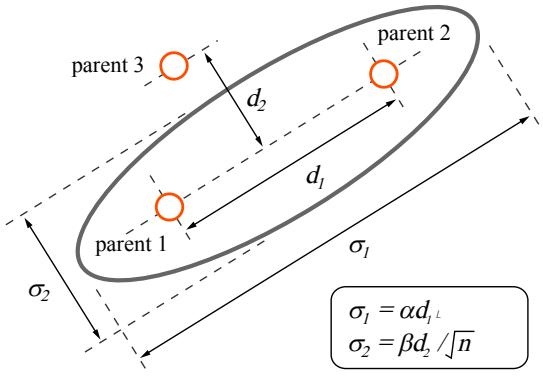

Figure 8 Generation of offspring by UNDX

Figure 9 shows alternation of generations by a MGG (minimum generation gap) method, which has an advantage in avoiding a local solution. First, three parents are selected randomly and a certain number of offspring are generated by UNDX. Then, the fitness of the offspring is evaluated and the most adopted one is selected as the first child. The second child is randomly selected from the rest. Finally, parent 1 and parent 2 are replaced by the selected two offspring.

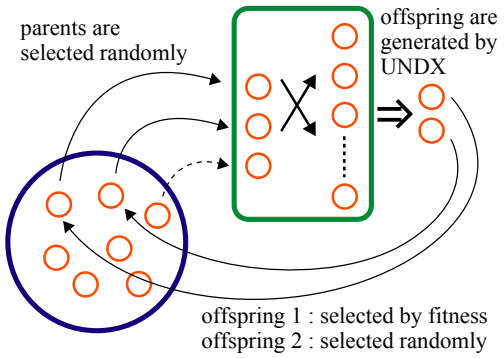

Figure 9 Alternation of generations by MGG

In this study, a value of overall heat transfer coefficients, heat transfer areas, polytropic index, and the volumetric efficiency are the parameters that need to be optimized. In the beginning, these parameters are randomly set within certain bounds. Table 5 shows the minimum and the maximum values of the parameters. Fitness of DNAs is calculated by equation (15). The value of the fitness is between 0 and 1 as a function of a total relative error. The total relative error is defined by the relative error of the heat load and the electricity consumption.

Table 5 Minimum and Maximum value of parameters

	Name of parameter	Min. value	Max. value
	Polytropic index [-]	0.7	0.85
	Volumetric coefficient [-]	1.17	1.57
Condenser	Heat transfer area [m^2]	1000	1500
Condenser	Overall heat transfer coef [kW/Km^2]	40	60
Condenser	Overall heat transfer coef [kW/Km^2]	40	60
Evaporator	Heat transfer area [m^2]	800	1300
Evaporator	Overall heat transfer coef [kW/Km^2]	40	60
Evaporator	Overall heat transfer coef [kW/Km^2]	40	60

$$Fit = \frac{1}{Err + 1} \tag{15}$$

$$Err = \sum_{j=1}^{n} \left| \Delta load_{rel,j} \right| + \sum_{k=1}^{n} \left| \Delta elec_{rel,k} \right| \tag{16}$$

Result of parameter adjustment for rated value

5 points of rated value (altered to outdoor dry bulb temperature) are used to evaluate the fitness.

200 individuals (DNAs) are initially generated and 6000 generations are passed over to evolve DNAs. Figure 10 shows the value alternation of heat transfer area of the evaporator and the condenser. It is seems that parameters are converged into a certain value

with the passage of generation. Figure 11 shows the alternation of the fitness with the passage of generation. Other parameters are also estimated. Table 6 shows final value of the each parameter gained from the fittest DNA.

Figure 12 and Table 7 shows the calculation result of the refrigeration cycle with estimated parameters against an outdoor dry bulb temperature. The values at rated points are also plotted. Simulation outputs are in good consistent with the rated value. The value of relative error is less than 1.2 [%].

Both REFPROP and the approximation method described above are used to calculate the thermodynamic properties. It seems that there is slight difference at lower temperature but the deviation ratio is not bigger than 3 [%]. Table 8 shows the calculation speed of the refrigeration cycle with the two methods. The rated refrigeration cycles are calculated 50 times. The calculation which uses the approximation method is about 20 times faster than that of using REFPROP.

Table 6 Final value of the each parameter

Name of parameter		Value
Polytropic index [-]		1.00507
Volumetric coefficient [-]		0.736
Condenser	Heat transfer area [m^2]	1580.95
	Overall heat transfer coef [kW/K·m^2]	71.59
	Overall heat transfer coef [kW/K·m^2]	55.16
Evaporator	Heat transfer area [m^2]	1214.98
	Overall heat transfer coef [kW/K·m^2]	46.94
	Overall heat transfer coef [kW/K·m^2]	100.51

Table 7 Calculation result of the refrigeration cycle with estimated parameters

		Outdoor dry bulb temperature [C]				
		7	6	5	4	3
Electricity consumption [kW]	Rated	53.4	52.3	51.2	50.2	49.0
	Ref	53.1	52.3	51.2	50.0	49.4
	App	53.1	52.3	51.2	50.0	48.7
Thermal load [kW]	Rated	219.4	209.6	199.9	190.7	181.5
	Ref	216.7	209.6	200.0	190.8	186.9
	App	216.9	209.7	200.0	190.8	181.5
COP [-]	Rated	4.11	4.01	3.90	3.80	3.70
	Ref	4.08	4.01	3.90	3.82	3.79
	App	4.08	4.01	3.91	3.81	3.73

Table 8 Calculation speed of the refrigeration cycle

REFPROP vers.7	Approximation
99421.88 [msec]	4968.75 [msec]

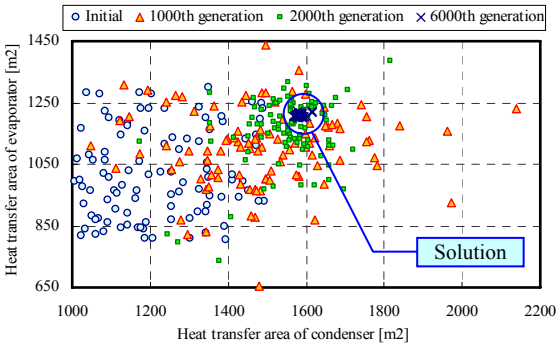

Figure 10 Alternation of the heat transfer area

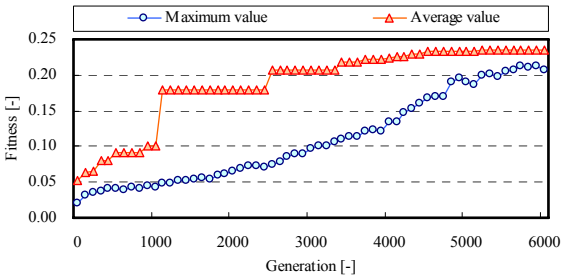

Figure 11 Alternation of the fitness

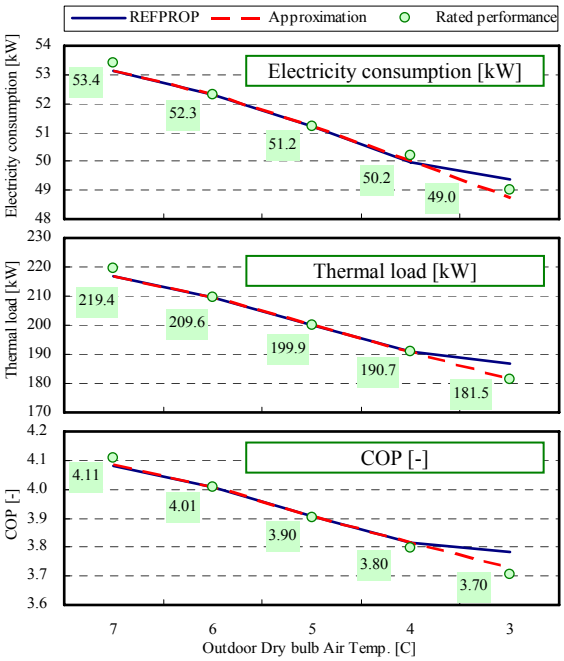

Figure 12 Calculation result of the refrigeration cycle with estimated parameters

CONCLUSION

In this paper, a parameter adjustment method for an ammonia heat pump chiller using a genetic algorithm (GA) was developed. To speed up adjustment process, a new approximation method with neural network is also proposed.

1) The calculation speed of saturated states and other refrigerant states increased 14 times and 33

times respectively, while the average relative error was less than 0.04 [%] and 0.5 [%] when compared to exact solution.

2) The calculation speed of refrigerant cycle increased 20 times faster, while maximum relative error was within 3 [%].

3) Parameter adjustment method by genetic algorithm was applied with the help of the proposed approximation method to speed up the iterative calculation process. Moreover, outputs values of the simulation are consistent with values at rated point as demonstrated using adjusted parameters values.

NOMENCLATURE

Physical model of refrigeration cycle

T	Temperature [K]
P	Pressure [kPa]
ρ	Density [kg/m^3]
H	Enthalpy [kJ/kg]
G	Flow rate [kg/sec]
W	Compression work [kW]
El	Electricity consumption [kW]
Q	Amount of heat exchanger duty [kW]
A	Heat transfer area [m^2]
R	Rate of area [-]
K	Overall heat transfer coefficient [kW/m^2-K]
pol	Polytropic index [-]
η_v	Volumetric efficiency [-]
Vol	Volume [m^3]
Cv	Flow coefficient [m^2]
$\Delta\theta$	Logarithmic mean temp. difference [K]
$f_{EOS}(\cdot)$	Equation of state (EOS)

Subscripts:

sh	super heat	cmp	compressor
tp	two-phase	evp	evaporator
sv	saturated vapor	cnd	condenser
sl	saturated liquid	exp	expansion
in	inlet	air	outdoor air
out	outlet	ref	refrigerant
wat	water	set	setpoint

First calculation of refrigerant properties

$f_{sig}(\cdot)$	Sigmoid function
τ	Number of neurons in input layer
σ	Number of neurons in hidden layer
j	Number of neurons in output layer
θ	Threshold value
w	Connection weight between neurons
x	Input value
y	Output value
Err_{rel}	Relative error
H_r	Relative value of enthalpy

Subscripts:

APP	value calculated from approximation formula
REF	value calculated from REFPROP

Parameter adjustment with genetic algorithm

Fit	Fitness of DNA [-]
Err	Total relative error [-]
$\Delta load$	Relative error of thermal load [-]
$\Delta elec$	Relative error of electricity consumption [-]

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