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Application of Hopfield Neural Network to the optimal chilled water supply temperature calculation of air-conditioning systems for saving energy

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ABSTRACT

The values of chilled water supply temperatures of chillers indicate their load distributions due to the chilled water return temperatures of all chillers being the same in a decoupled air-conditioning system. This study employs Hopfield Neural Network (HNN) to find out the chilled water supply temperatures of chillers for solving Optimal Chiller Loading (OCL) problem. HNN overcomes the flaw that Lagrangian method is not adaptable for solving OCL as the power consumption models include non-convex functions. The chilled water supply temperatures are used as the variables to be solved for the decoupled air-conditioning system and solves the problem by using HNN method to improve this defect. After analysis and comparison of the case study, it has been concluded that this method not only solves the problem of Lagrangian method, but also produces results with high accuracy. It can be perfectly applied to the operation of air-conditioning systems.

1. Introduction

The UN Intergovernmental Panel on Climate Change (IPCC) estimates that, by the end of this century, the average global air temperature will increase by 1.8–4.0 °C and sea level will rise by 0.6 meters due to global warming. Global warming is causing glaciers to diminish or disappear. Many island nations are being submerged by the rising sea. Climate change has altered global rainfall patterns, bringing floods, torrential rains, and alternating drought and flood. Global warming thus poses a severe threat to the survival of human civilization. Carbon dioxide accounts for 80% of the greenhouse effect, and rising carbon dioxide levels are the main cause of global warming. The UN will inevitably impose strict limits on carbon dioxide emissions in the future in order to reduce the rate of warming. When that time comes, national governments worldwide will have to focus increasing attention to ways of reducing carbon dioxide emissions.

Taiwan currently depends on thermal power generation for 75% of its power supply, and thermal power plants produce 0.67 kg of carbon dioxide for every kilowatt-hour generated. Air conditioning accounts for approximately 30% of summertime power consumption. Chillers account for the biggest share, roughly 60% of air-conditioning system power consumption [1]. As a consequence, increasing chiller efficiency can save power, reduce power costs for owners, lessen carbon dioxide emissions, and thereby ease greenhouse warming. The question of how to improve chiller operating efficiency is one of the most important issues in contemporary building energy conservation. To maintain efficiency, centralized air-conditioning systems often utilize centrifugal chiller units. Each unit has different features. The longer the machine is run, the more apparent the differences are. Inappropriate operation will waste power. When the usage is substantial, like the semiconductor industries, the effects will be profound.

The common way to allocate the chiller unit capacity in air-conditioning systems has been rather simple (by setting equal chilled water temperature to all on-line units, called ECHWT Method). To solve OCL problem, the Lagrangian method has been adopted in [2,3] based on the convex function of the power consumption model [2] or the kW–PLR (Partial Load Ratio) curve [3]. However, Lagrangian method is not adaptable for solving OCL as the power consumption model is not a simple convex function [4]. This study solves the problem by using HNN to overcome this shortcoming. After extensive experiments, HNN has been modified to provide results with high accuracy within a rapid timeframe.

2. System structure

Fig. 1 depicts the structure of a decoupled system [5], which has many advantages [3] and is used in over 95% of the large air-conditioning systems in Taiwan. The cooling load (in refrigeration tons) of the ith chiller can be calculated as [3,6],

$$Q_{ch,i} = f_i m(T_{chwr,i} - T_{chws,i}) \tag{1}$$

Where f_i = flow rate of chilled water,
m = the specific heat of chilled water.

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Nomenclature

A, B	weighting factors
a_i, b_i, c_i	constant coefficients
a'_i, b'_i, c'_i	constant coefficients
COP	Coefficient of Performance
CL	system cooling load
E	energy function
f_i	flow rate of chilled water
F_i	flow of the ith chiller/total system flow
f_T	system total flow
$g_i(U_i)$	sigmoid input–output function of neuron i
I_i	external input of neuron i
J	objective function
k_0–k_5	regression coefficients
m	the specific heat of chilled water
$P_{\mathrm{ch},i}$	power consumption of the ith chiller
PLR_i	Partial Load Ratio of ith chiller
$Q_{\mathrm{ch},i}$	cooling load of the ith chiller
$\overline{RT_i}$	capacity of ith chiller
s	incline constant of the sigmoid function
$T_{\mathrm{chwr},i}$	return chilled water temperature of ith chiller
$T_{\mathrm{chws},i}$	supply chilled water temperature of ith chiller
T_{ij}	interconnection conductance values
T_r	return temperature of system chilled water
T_s	supply temperature of system chilled water
Δt	differential variation of time t
U_i	input of neuron i
ΔU_i	differential variation of input U_i
V_i	output of neuron i
λ	Lagrangian multiplier
η	accelerated factor
θ_i	threshold of neuron i

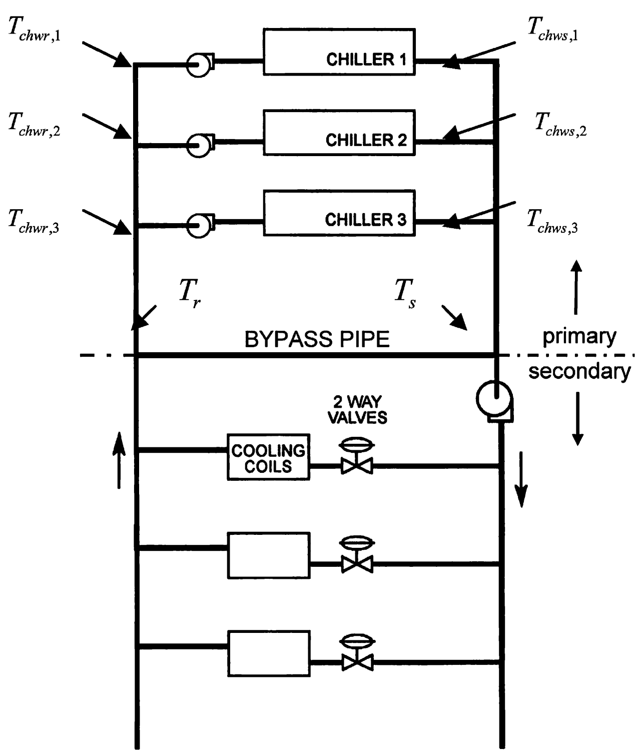


Fig. 1. Decoupled system.

As seen in Fig. 1 and Eq. (1), since the chilled water return temperature in every chiller is the same ($T_{\mathrm{chwr},i} = T_r$), the chiller load can be adjusted by regulating the chilled water supply temperature ($T_{\mathrm{chws},i}$) because the flow is fixed. The system total load can be shown as,

$$CL = f_T m(T_r - T_s) \tag{2}$$

Where f_T = system total flow.

When the load of each chiller is known, Eqs. (1) and (2) can be applied to compute the chilled water supply temperature of each chiller [2]:

$$T_{\mathrm{chws},i} = T_r - \frac{Q_{\mathrm{ch},i}}{F_i * CL}(T_r - T_s) \tag{3}$$

Where F_i = flow of the ith chiller/total system flow.

3. Conventional OCL methods

Braun et al. proposed the power consumption model of the chiller in [2], in which the power consumption model of the chiller is shown with the cooling water return temperature ($T_{\mathrm{cwr},i}$), chilled water supply temperature ($T_{\mathrm{chws},i}$), and chiller load ($Q_{\mathrm{ch},i}$) as independent variables as,

$$\begin{aligned} P_{\mathrm{ch},i} = {} & k_{0,i} + k_{1,i}(T_{\mathrm{cwr},i} - T_{\mathrm{chws},i}) + k_{2,i}(T_{\mathrm{cwr},i} - T_{\mathrm{chws},i})^2 \\ & + k_{3,i} Q_{\mathrm{ch},i} + k_{4,i} Q_{\mathrm{ch},i}^2 + k_{5,i}(T_{\mathrm{cwr},i} - T_{\mathrm{chws},i}) Q_{\mathrm{ch},i} \end{aligned} \tag{4}$$

Where k_0–k_5 are regression coefficients. Then, the OCL problem is to find a set of chiller output which does not violate the operating limits while minimizing the objective function:

$$J = \sum_{i=1}^{I} P_{\mathrm{ch},i} \tag{5}$$

and satisfy the load equilibrium:

$$\sum_{i=1}^{I} Q_{\mathrm{ch},i} = CL \tag{6}$$

When the power consumption model of all chillers is under the hypothesis of convex function, and uses Lagrangian to solve OCL, in other words, when the partial differentials of the individual chiller's power consumption with respect to their cooling loads are equal, the input power is at the minimum,

$$\frac{\partial P_{\mathrm{ch},i}}{\partial Q_{\mathrm{ch},i}} = \frac{\partial P_{\mathrm{ch},j}}{\partial Q_{\mathrm{ch},j}} \quad \text{for all } i \text{ and } j \tag{7}$$

When Eqs. (3) and (4) are substituted into (7),

$$A_i + B_i Q^*_{\mathrm{ch},i} = A_j + B_j Q^*_{\mathrm{ch},j} \tag{8}$$

Where

$$A_i = k_{3,i} + \left[k_{1,i} + 2k_{2,i}(T_{\mathrm{cwr},i} - T_r)\right]\frac{T_r - T_s}{F_i * CL} + k_{5,i}(T_r - T_s)$$

$$B_i = 2\left[k_{4,i} + k_{5,i}\left(\frac{T_r - T_s}{F_i * CL}\right) + k_{2,i}\left(\frac{T_r - T_s}{F_i * CL}\right)^2\right]$$

Eqs. (6) and (8) can be applied to obtain I linear equations, which can obtain the optimal loading ($Q^*_{\mathrm{ch},i}$) of each chiller. Then Eq. (3) is applied to obtain the optimal chilled water supply temperature for each chiller. Since OCL is in search of a manipulation point that minimizes the power consumption of the entire group of chillers while meeting the load requirement, the power consumption of the primary pump is fixed, adding it into Eq. (5) has no effect. Thus, Eq. (5) does not take into consideration of the power consumption of the primary pump.

Since the aforementioned method requires solving linear equations and the deduction process is complicated, the author of this study simplified the method in [3] and substituted $Q_{\mathrm{ch},i}$ with PLR_i given $T_{\mathrm{cwr},i}$ and $T_{\mathrm{chwr},i}$ are known. The power consumption model, Eq. (4), is replaced by COP (Coefficient of Performance) as follows:

$$COP_i = a_i + b_i\,PLR_i + c_i\,PLR_i^2 \tag{9}$$

Where a_i, b_i, c_i are constant coefficients. Then the OCL problem is modified to maximize the objective function,

$$J = \sum_{i=1}^{I} COP_i \tag{10}$$

Simultaneously, the balance equation must be satisfied:

$$\sum_{i=1}^{I} PLR_i \times \overline{RT_i} = CL \tag{11}$$

The Lagrangian method [7] is adopted to find the optimal solution when the COP–PLR curve, Eq. (9), is a concave function (its kW–PLR curve is a convex function). For a system's cooling load CL, the Lagrangian multiplier λ can be evaluated by

$$\lambda = \frac{2\,CL + \sum_{i=1}^{I} \frac{b_i}{c_i}\overline{RT_i}}{\sum_{i=1}^{I} \frac{\overline{RT_i}^2}{c_i}} \tag{12}$$

And PLR_i of ith unit can be expressed as:

$$PLR_i = \frac{\lambda\overline{RT_i} - b_i}{2c_i} \tag{13}$$

Therefore, only two equations, (12) and (13), are required to obtain the optimal loading for the chiller. The above two methods are based on the Lagrangian method, yet the reason that the heat exchanger remains high efficiencies at high load determines the kW–PLR diagram being not a simple convex function and Lagrangian method is not adaptable for solving OCL. The overload design for the a/c system or proper maintenance that allow the heat exchangers maintaining high performance during high load is common, the problem of non-convex function in the kW–PLR curves is unavoidable. Thus, this study uses HNN to solve the OCL problem.

4. Hopfield neural network

The American physicist J.J. Hopfield proposed Hopfield neural networks in 1982 [8]. These neural networks have the ability to form associations. HNN employs an associative learning network model, and comprises single-layer feedback neural networks with symmetric weights. While these networks have no data memory areas, they are able to remember training examples. Each neuron receives inputs in parallel from all other neurons, and sends its output in parallel to all other neurons in the network, as shown in Fig. 2. Because outputs are added after modification by synaptic weights along feedback pathways and connective conductance values along links, and are outputted via a transfer function, the relationship between inputs and outputs is continuously revised and adjusted in a dynamic response process. When a new external signal is input, outputs are calculated by neurons, and the outputs are input by other neurons after synaptic weights to the feedback pathways to the input ends of other neurons (or connective conductance values along links) have been revised; new outputs are then calculated, and this process is repeated iteratively. In a stable network, the change in the output of each iterated set of calculations will decrease steadily, until the final output converges on a fixed value.

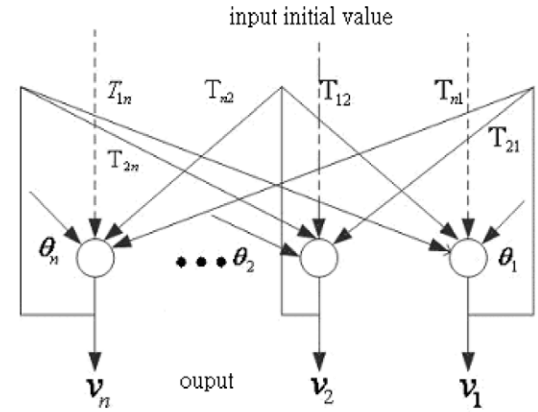


Fig. 2. Hopfield neural network.

In a continuous network, output V_i of neuron i can be any value between the maximum valve and the minimum valve, and the input–output function of neuron i is a continuously and monotonously increasing function, which implies that the time derivative is greater than or equal to zero, so that $g_i'(U_i) \geqslant 0$. The following is a typical input–output function $g_i(U_i)$:

$$V_i = g_i(U_i) = \left(\frac{1}{2}\right)\bigl(1 + \tanh(sU_i)\bigr) = \frac{1}{(1 + \exp(-2sU_i))} \tag{14}$$

Where s = incline constant of the sigmoid function,
U_i = input of neuron i.

The output of each neuron in a network will have values at upper and lower limits if s is set too large. Contrarily, the network will converge very slowly if s is set too small. In a system with a greater number of neurons, s could be set to a smaller value. Otherwise, s has to be set to a large value for small systems. Formula (14) yields curves with different slopes when different sigma values are used. The dynamic characteristics of neurons are expressed using the following differential equation [9]:

$$\frac{dU_i}{dt} = \sum_j T_{ij} V_j + I_i \tag{15}$$

Where T_{ij} = interconnection conductance values,
I_i = external input of neuron i.

When he introduced the Hopfield network in 1982, Hopfield added the energy function concept as a means of determining network stability. Lyapunov's motion stability theory states that if an energy function E is defined to express the "energy" of a motion system, the system can be easily understood from a physical point of view. If the system's energy is limited, and the energy change rate is always negative, then:

$$\frac{\partial E}{\partial t} < 0 \tag{16}$$

If energy always decreases with time, and if all motion in the system is limited, the system will ultimately approach a static, balanced state. The energy function is defined as follows in a continuous Hopfield model [8]:

$$E = -\frac{1}{2}\sum_i \sum_j T_{ij} V_i V_j - \sum_i I_i V_i \tag{17}$$

The following proves that the derivative of the energy function E with respect to time is always decreasing [10]:

$$\frac{dE}{dt} = -\frac{1}{2}\sum_i\sum_j T_{ij}\left[V_j\left(\frac{dV_i}{dt}\right) + V_i\left(\frac{dV_j}{dt}\right)\right] - \sum_i I_i\left(\frac{dV_i}{dt}\right)$$
$$= -\frac{1}{2}\sum_i\left(\frac{dV_i}{dt}\right)\left[(T_{ij}V_j + T_{ji}V_j) + 2I_i\right]$$
$$= -\sum_i\left(\frac{dV_i}{dt}\right)\left(\frac{dU_i}{dt}\right)$$
$$= -\sum_i h_i'(U_i)\left(\frac{dU_i}{dt}\right)^2 \tag{18}$$

Where

$$\frac{dV_i}{dt} = \frac{dV_i}{dU_i} \times \frac{dU_i}{dt} = h_i'(U_i)\left(\frac{dU_i}{dt}\right) \tag{19}$$

Therefore, $\frac{dE}{dt} \leqslant 0$. As a result, in the solution process, the state must inevitably move in the direction of decreasing energy and ultimately reach a minimum stable solution value. We use a continuous HNN in this study to solve OCL problems. When a continuous network is used to solve OCL problems, each neuron represents one chiller, and neuron output consists of chilled water temperatures.

5. Implementation of OCL

5.1. The OCL problem

The method in Section 3 go by obtaining the optimal output ($Q^*_{\mathrm{ch},i}$) of the chiller, then substitute Eq. (3) to obtain the optimal $T_{\mathrm{chws},i}$. Therefore, this study uses $T_{\mathrm{chws},i}$ as the variable to be solved, and modifies the OCL problem as described in the following.

If $T_{\mathrm{cwr},i}$ and $T_{\mathrm{chwr},i}$ are known, substitute Eq. (1) into Eq. (4), and simplify the power consumption model equation (4) as,

$$P_{\mathrm{ch},i} = a_i' + b_i' T_{\mathrm{chws},i} + c_i' T^2_{\mathrm{chws},i} \tag{20}$$

Where a_i', b_i' and c_i' are constant coefficients. The load equilibrium can be modified as,

$$\sum_{i=1}^{I} f_i m(T_r - T_{\mathrm{chws},i}) = CL \tag{21}$$

Since the maximum output of a chiller is its rated value, the maximum value of PLR_i is 1. The minimum value of PLR_i is 0.3 as surge may occur when the load of chiller is as low as 30%, that is,

$$0.3 \leqslant \frac{f_i m(T_r - T_{\mathrm{chws},i})}{\overline{RT_i}} \leqslant 1.0 \tag{22}$$

Where $\overline{RT_i}$ is the capacity of ith chiller. The upper and lower limits of $T_{\mathrm{chws},i}$ are reorganized as,

$$T_{\mathrm{chws},i,\min} \leqslant T_{\mathrm{chws},i} \leqslant T_{\mathrm{chws},i,\max} \tag{23}$$

Where $T_{\mathrm{chws},i,\max} = T_r - \dfrac{0.3\overline{RT_i}}{f_i m}$

$$T_{\mathrm{chws},i,\min} = T_r - \frac{\overline{RT_i}}{f_i m}$$

Seeking solutions of OCL is to, while meeting the loading demand (Eq. (21)) and the operating constraint Eq. (23), seek a group of $T_{\mathrm{chws},i}$ to minimize the objective function (Eq. (5)).

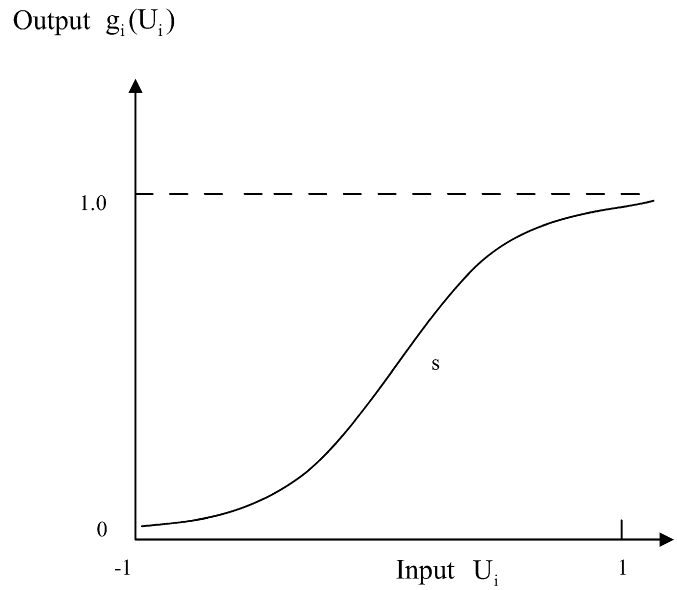


Fig. 3. Sigmoid input–output neuron model.

5.2. Mapping of OCL problems onto Hopfield neural networks

In HNN, n neurons are used to represent n chillers; each neuron represents one chiller. The output of neuron $i(V_i)$ is the chilled water temperature ($T_{\mathrm{chws},i}$) of the ith chiller. The input–output function of each neuron is expressed as a sigmoid function as shown in Fig. 3, and the output of each neuron is set between the maximum and minimum chilled water temperatures as follows:

$$T_{\mathrm{chws},i} = g_i(U_i)(T_{\mathrm{chws},i,\max} - T_{\mathrm{chws},i,\min}) + T_{\mathrm{chws},i,\min}$$
$$= \frac{1}{2}\big(1 + \tanh(sU_i)\big)(T_{\mathrm{chws},i,\max} - T_{\mathrm{chws},i,\min}) + T_{\mathrm{chws},i,\min}$$
$$= \frac{1}{1 + \exp(-2sU_i)}(T_{\mathrm{chws},i,\max} - T_{\mathrm{chws},i,\min}) + T_{\mathrm{chws},i,\min} \tag{24}$$

The OCL objective function F is shown as Eq. (25). The objective function includes two terms; the first term represents the constraint of meeting the air conditioning load balance, and the second term is the chiller operating cost, as follows [11]:

$$F = \frac{A}{2}\left(CL - \sum_{i=1}^{I} K_i \times (T_r - T_{\mathrm{chws},i})\right)^2 + \frac{B}{2}\sum_{i=1}^{I}\left(a_i' + b_i' \times T_{\mathrm{chws},i} + c_i' \times T^2_{\mathrm{chws},i}\right) \tag{25}$$

where $K_i = f_i m$.

Where A and B are weighting factors, and are $\geqslant 0$. By a simple trial and error process, the author found that $A = 0.0001$ and $B = 0.0001$ were appropriate values. If we let $V_i = T_{\mathrm{chws},i}$ in Eq. (17), we can rearrange Lyapunov's energy function as:

$$E = -\frac{1}{2}\sum_i\sum_j T_{ij} T_{\mathrm{chws},i} T_{\mathrm{chws},j} - \sum_i I_i T_{\mathrm{chws},i} \tag{26}$$

Since the objective function shown as Eq. (25) corresponds to the energy function expressed as Eq. (26), T_{ii}, T_{ij} and I_i can be derived as follows:

$$T_{ii} = -AK_i^2 - Bc_i' \tag{27}$$

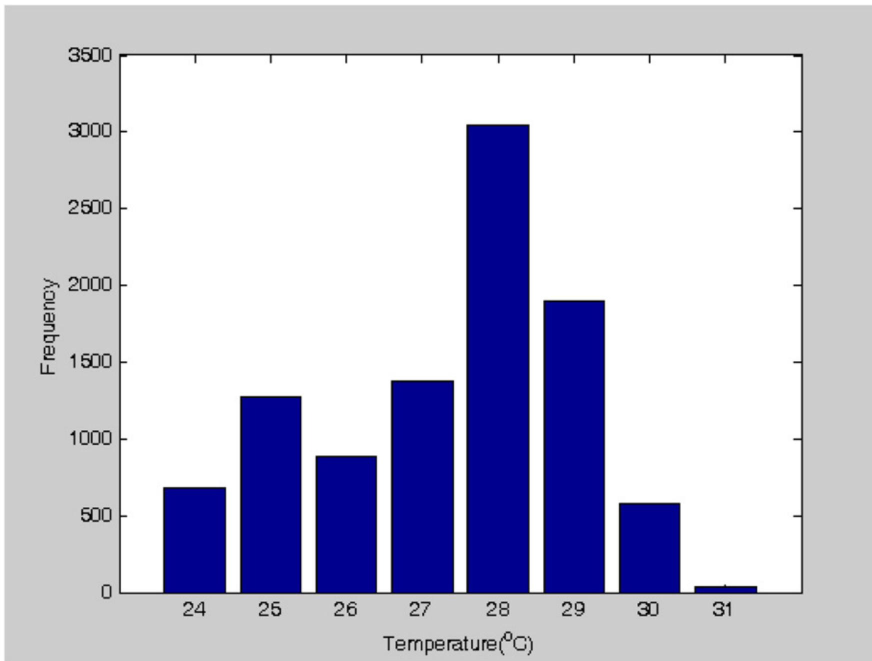
$$T_{ij} = -AK_iK_j \tag{28}$$

$$I_i = -AK_i\left[CL - T_r\sum_{j=1}^{I}K_j\right] - \frac{B}{2}b_i' \tag{29}$$

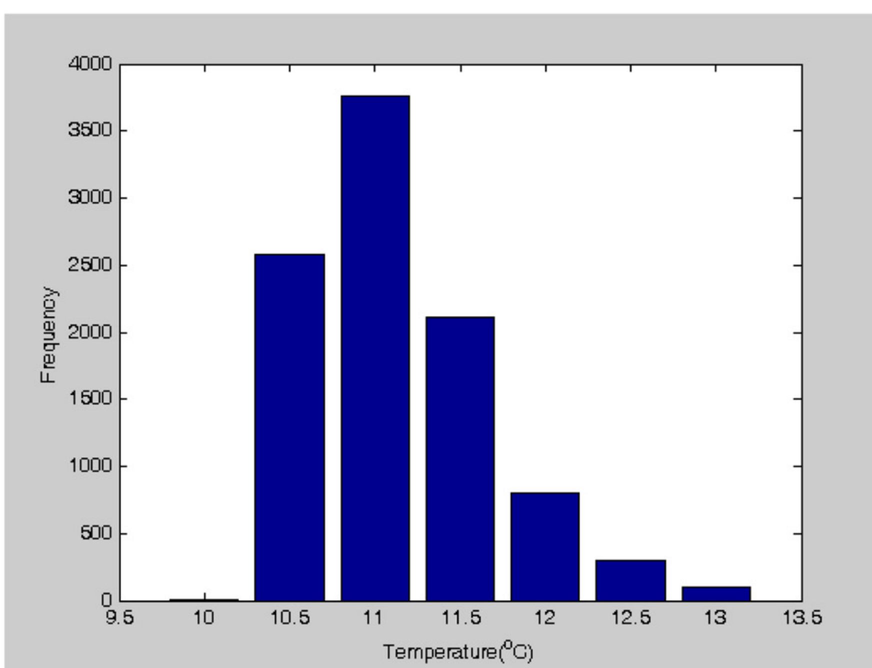
Because the self-conductance values T_{ii} and interconnection conductance values T_{ij} of neuron i are negative, the solution process, as in the case of negative feedback control in a stable system, will

Table 1
k_0–k_5 coefficients.

Chiller	k_0	k_1	k_2	k_3	k_4	k_5	R^2	Capacity
1	213.14	−92.123	148.06	−219.23	353.93	15.427	0.9917	400*RT*
2	228.64	−25.77	92.09	−314.92	410.12	−5.027	0.9924	400*RT*
3	−92.88	55.20	180.76	556.81	−139.90	−237.227	0.9598	400*RT*
4	206.82	−68.63	82.23	−216.23	305.02	25.39	0.9672	400*RT*



(a) Cooling water return temperature (T_{cwr})



(b) Chilled water temperature of system (T_s)

Fig. 4. Scatter diagram of water temperature.

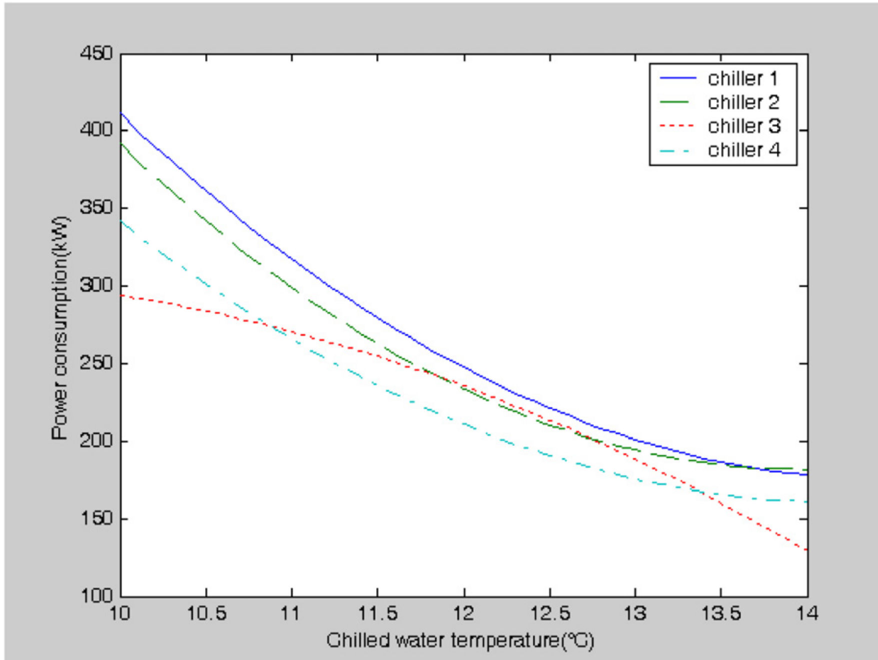


Fig. 5. kW–T_{chws} diagram of four chillers for an office building.

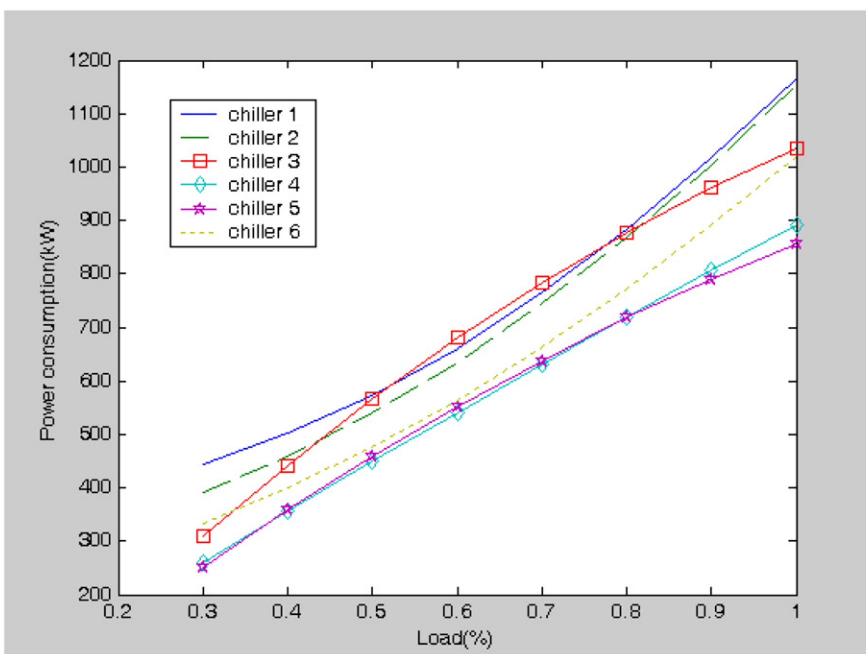


Fig. 6. kW–PLR diagram of six chillers for a SF.

converge to a stable value. When performing iterated operations, the dynamic variation equation for neuron i as follows:

$$\Delta U_i = \left(\sum_j T_{ij} T_{\text{chws},j} + I_i\right)\Delta t$$
$$= \left(T_{ii} T_{\text{chws},i} + \sum_{j=i} T_{ij} T_{\text{chws},j} + I_i\right)\Delta t \tag{30}$$

Here we let $\Delta t = 1$. The speed of convergence can be accelerated by adding momentum in the update processes [12]:

$$U_i(t+1) = U_i(t) + \Delta U_i(t) + \eta \Delta U_i(t-1) \tag{31}$$

Where η is an accelerated factor selected through experimentation. In this problem the author has chose $\eta = 0.95$. The solution steps are stated as follows:

Step 1: First determine weighting factors.
Step 2: Set the initial chilled water temperature $T^{(0)}_{\text{chws},i} = T_s$.
Step 3: Use Eq. (24) to induce neuron input $U^{(0)}_i$.
Step 4: Use Eq. (26) to calculate initial energy function value $E^{(0)}$.
Step 5: Use Eq. (30) to calculate the input variation $\Delta U^{(N)}_i$ of neuron i and update the value of neuron input U_i.
Step 6: Use Eq. (24) to obtain a new chilled water temperatures $T^{(N+1)}_{\text{chws},i}$.

Table 2
Optimal chiller loading for three chillers.

Load (*RT*)	Chiller	Lagrangian method				HNN method					Error
		T_{chws}	*RT*	*kW*	Total *kW* (A)	T_{chws}	*RT*	*kW*	Total *kW* (B)	CPU (sec)	$(A-B)/A$
1080 (90%)	1	11.33	400.00	202.56	604.91	11.33	399.99	202.56	604.85	1.34	0.01%
	2	10.88	319.24	208.62		10.88	319.49	208.70			
	4	10.67	360.76	193.73		10.67	360.52	193.59			
960 (80%)	1	11.03	392.49	202.53	575.91	11.04	390.58	202.12	575.89	1.87	0.00%
	2	10.99	274.02	197.45		10.99	274.62	197.58			
	4	10.97	293.49	175.92		10.96	294.80	176.18			
840 (70%)	1	11.10	333.55	193.51	558.01	11.09	334.27	193.62	558.00	0.81	0.00%
	2	10.89	249.53	194.48		10.90	249.05	194.33			
	4	10.97	256.92	170.10		10.97	256.69	170.06			
720 (60%)	1	11.16	274.60	188.44	548.18	11.16	274.99	188.48	548.18	1.12	0.00%
	2	10.80	225.05	193.01		10.79	225.35	193.03			
	4	10.97	220.35	166.73		10.98	219.66	166.67			

Table 3
Optimal chiller loading for four chillers.

Load (*RT*)	Chiller	1440 (90%)				1280 (80%)				1120 (70%)				960 (60%)			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
ECHWT method	T_{chws}	11.23	10.88	10.94	10.88	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00
	RT	400.00	310.43	400.00	329.57	385.00	265.24	348.18	281.58	336.87	232.08	304.66	246.39	288.75	198.93	261.14	211.19
	kW	210.97	206.09	208.08	184.27	201.34	196.00	187.82	173.69	194.34	192.54	171.51	168.82	189.96	192.14	54.16	166.21
	Total *kW* (A)	809.42				758.85				727.21				702.47			
GA method	T_{chws}	11.25	10.36	11.85	10.21	10.90	10.03	12.71	9.94	10.68	10.46	12.42	10.18	10.68	10.34	12.09	
	RT	397.81	360.59	282.85	398.75	399.73	360.59	127.94	391.75	381.94	284.50	121.92	331.65	334.86	263.70	21.64	239.80
	kW	202.50	225.42	156.14	208.24	204.49	226.81	77.73	206.30	202.32	201.52	77.44	186.51	195.63	198.40	80.57	168.76
	Total *kW* (B)	792.30				715.33				667.80				643.36			
	CPU (sec)	1.38				1.50				1.67				1.94			
SA method	T_{chws}	11.23	10.33	11.78	10.35	10.90	10.06	12.73	9.89	10.63	10.44	12.43	10.25	10.71	10.39	12.08	10.64
	RT	399.86	363.92	292.13	384.09	399.49	357.65	126.26	396.60	388.84	286.74	120.51	323.91	330.23	258.80	22.75	248.22
	kW	202.95	226.96	160.47	202.40	204.44	225.48	76.60	208.27	203.75	202.08	76.63	184.34	195.63	198.40	80.57	168.76
	Total *kW* (C)	792.78				714.94				666.80				643.48			
	CPU (sec)	2.88				0.89				0.72				0.73			
HNN method	T_{chws}	11.23	10.30	11.93	10.20	10.89	10.02	12.78	9.87	10.57	10.43	12.44	10.35	10.67	10.48	12.10	10.58
	RT	400.00	367.40	272.88	399.72	400.00	360.76	120.03	399.21	398.21	287.73	120.00	314.06	335.53	249.84	20.00	254.64
	kW	202.79	228.59	151.41	208.54	204.56	226.87	73.12	209.24	205.79	202.33	76.33	181.71	195.73	196.08	79.62	170.68
	Total *kW* (D)	791.52				713.81				666.15				642.11			
	CPU (sec)	5.16				3.73				3.14				1.64			
Saving power	$(A-D)/A$	2.21%				5.93%				8.39%				8.59%			
	$(B-D)/B$	0.09%				0.21%				0.24%				0.19%			
	$(C-D)/C$	0.15%				0.15%				0.09%				0.21%			

Step 7: Use $T_{\text{chws},i}^{(N+1)}$ to derive anew energy function $E^{(N+1)}$.

Step 8: Calculate $\Delta E = E^{(N+1)} - E^{(N)}$; calculation can terminate when ΔE less than permissible error, otherwise return to Step 5.

6. Examples and results

Although the air-conditioning system of semiconductor plants demand a great amount of power, the energy saving has not attracted enough attention and most manufactures set all chillers to the same chilled water supply temperature (5 °C) to get stable operation, and the chiller OCL is not yet applied (yet the cooling water return temperature and the chiller load may vary due to the weather conditions and the load). Therefore, it is unable to collect related data on the different chilled water supply temperatures in the semiconductor plants for determining the power consumption model, Eq. (4). Since the air-conditioning capacity for conventional office buildings is smaller, and the chilled water supply temperature is not fixed, it is suitable for OCL simulation. Therefore, this study selected the air-conditioning system of an office building in Taipei City for OCL simulation analysis. This paper tests the data of four chillers in this building, namely the respective power consumption of each chiller, and the chilled water temperatures and the cooling water temperatures from April, 2004 to June, 2004 to establish the power consumption mode. The relevant regression coefficients are shown in Table 1, which also shows R^2 values (all no less than 0.9598). Although these four units are identical in type and capacity, extensive operating period and system structure have caused chilled water temperature and flow rate to be different, and have resulted in different coefficients. Fig. 4 shows the scatter diagrams of the cooling water return temperature (T_{cwr}) and the chilled water temperature of system (T_s), and the most data are $T_{\text{cwr}} = 28$ °C and $T_s = 11$ °C. The chilled water return temperature ($T_{\text{chwr},i} = T_r$) can be obtained from Eq. (2) for a given system load (CL). Therefore T_{cwr} and T_s are entered in Eq. (2) to acquire coefficient a_i', b_i' and c_i' in Eq. (20). The kW–T_{chws} diagram is drawn as shown in Fig. 5. As seen, the power consumption of the chillers decreases as the chilled water temperature increases. The kW–T_{chws} diagram clearly shows that the power consumption curves of Nos. 1, 2, 4 chillers are convex functions whose kW/RT values rise up as the cooling load increases and No. 3 chiller is non-convex functions whose kW/RT values drop down

Table 4
Optimal chiller loading involving chiller number selection.

Load (RT)	4 chillers	3 chillers									
	1, 2, 3, 4	Chiller	1	2	3	1	2	4	2	3	4
1440 (90%)	791.52kW			–			–			–	
1280 (80%)	713.81kW			–			–			–	
1120 (70%)	666.15kW	T_{chws}	11.25	10.54	11.11	11.44	10.82	10.56	10.93	11.34	10.66
		RT	400.00	342.89	377.11	400.00	336.13	383.87	339.15	392.73	388.13
		kW	203.02	217.84	197.27	202.04	214.30	201.72	214.95	201.19	203.02
		Total kW		618.12			618.05			619.16	
960 (60%)	642.11kW	T_{chws}	10.79	9.60	12.30	11.04	10.99	10.96	10.01	12.52	10.06
		RT	400.00	391.69	168.31	390.58	274.62	294.80	381.80	178.43	399.77
		kW	205.05	242.80	101.31	202.12	197.58	176.18	236.30	104.31	208.93
		Total kW		549.16			575.89			549.54	

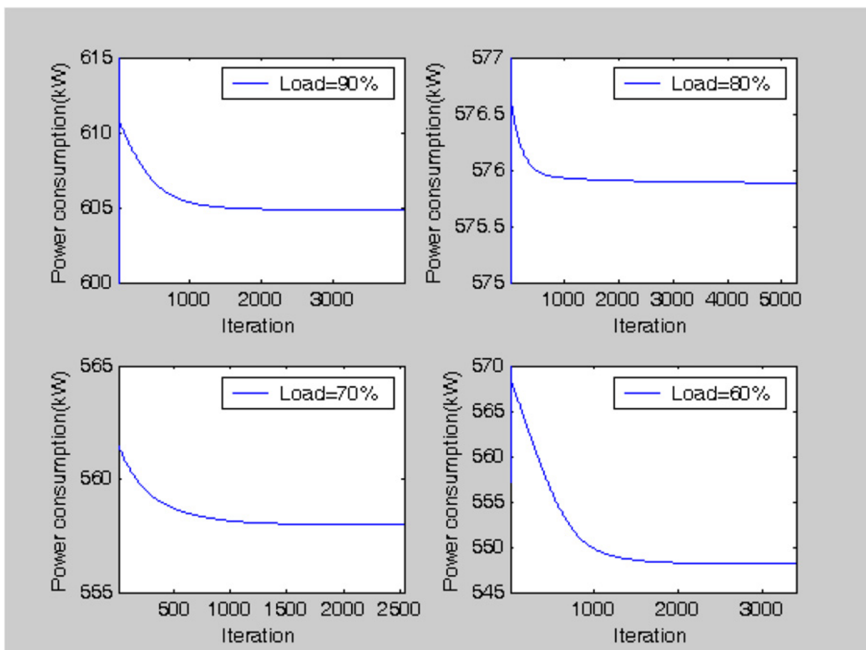


Fig. 7. Cost evolution for three chillers.

as the cooling load increases due to the thermal heat exchanger of No. 3 chiller remaining high efficiency at high cooling load. The same situation occurs to the chiller in semiconductor plants. Fig. 6 shows the kW–PLR curves of six chillers in a semiconductor plant in Hsinchu Science-based Park at temperatures of $T_{\text{cwr}} = 28\,^\circ\text{C}$ and $T_s = 5\,^\circ\text{C}$. Obviously, the third, fourth, and the fifth chillers are not of convex function.

Since Lagrangian method cannot be applied to solve OCL with non-convex functions, this paper employs HNN method to solve the OCL of the system. Since the power consumption curves of Nos. 1, 2 and 4 chillers in Fig. 5 are convex functions, and the Lagrangian method can acquire optimal solution and HNN for near optimal solution, the three chillers are used to simulate and solve the OCL to test the accuracy of HNN. As the load shifts from 90% of the system's total capacity to 60% of the system's total capacity, the results acquired by using the two methods are shown in Table 2. As seen in the table, the results obtained from HNN are almost the same as those from the Lagrangian method. The maximum error of HNN method is only 0.01%, which suggests high accuracy of HNN employed by this paper. Table 3 is the OCL results when considering all four chillers (as there is a non-convex function and Lagrangian method is not suitable, HNN method is employed). Compared with the ECHWT Method, which is commonly used now, the table shows that the presented method can save 1.02–8.60% of power as the load varies. For comparison with other methodology, the OCL results by the GA (genetic algorithm) method [13] and SA (simulated annealing) method [14] are also shown in Table 3. The HNN method has less power consumption than the GA method and the SA method, saving 0.09–0.24% and 0.09–0.21% of powers respectively. Table 4 shows OCL considering chiller number selection. Due to the cooling load being restricted between $0.3\sum_{i=1}^{I}\overline{RT_i}$ and $\sum_{i=1}^{I}\overline{RT_i}$ according to Eq. (22), only four online chillers and three online chillers with cooling loads at 960RT and 1120RT are feasible. It is obvious that the case of three online chillers saves more energy than four online chillers when the load shifts below 70% of the system's total capacity. So, the optimal online chillers are 1, 2, 3 and 4 at 1440RT and 1280RT; 1, 2 and 4 at 1120RT; 1, 2 and 3 at 960RT.

Although low execution speed is the weakness in HNN, it does not become a limitation because the number of air-conditioning units is low. The CPU times are less than 6 seconds in this case, as shown in Table 3. Figs. 7 and 8 show the process of convergence with the cost function (power consumption) for these two cases. Table 5 shows that the assigned value of parameter when

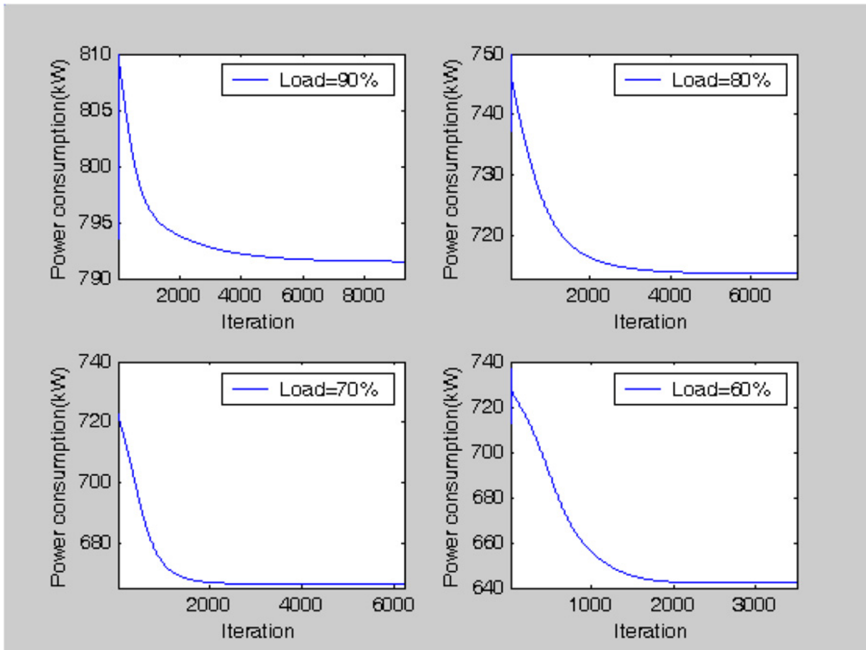


Fig. 8. Cost evolution for four chillers.

Table 5
Control parameters by HNN.

A	0.0001
B	0.0001
S	0.4
η	0.95

the OCL is executed in HNN. The testing software used is written in MATLAB program and run on an Intel Core(TM)/1.73 GHZ personal computer. The OCL program should be executed once every 5 minutes if the system load is changed quickly (for example, in an office building) [15]. However, it should be executed once every 15–20 minutes if the system load is changed slowly (for example, in a semiconductor factory).

7. Conclusion

With more traditional centralized air-conditioning systems (such as in office building, hotels and hospitals), the total cooling capacity is not very substantial, the number of units is low, the operation method is simple, and the OCL is not well thought-out. As the requirement increases due to the development of semiconductor industry, however, cooling capacity and the number of units multiply. The OCL of chiller unit has to be taken seriously. Each unit has to run with highest efficiency, and the power consumption has to be minimized. The saving of power consumption on air conditioning could decrease the operating cost of the company, lessen carbon dioxide emissions, and ease greenhouse warming. This study utilizes HNN to work out OCL problem, and solves Lagrangian method's problem of not being able to deal with a system with non-convex functions. By utilizing HNN, we can obtain the OCL result with high accuracy. It can be concluded that HNN is a highly recommendable method. Since the control panel of every chiller can set the chilled water supply temperature to control the output capacity, this method can be easily executed on the modern chiller.

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