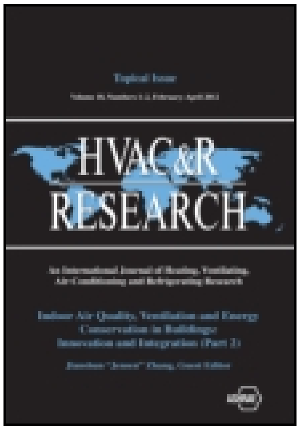

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Cost optimization for a large-scale hybrid central cooling plant with multiple energy sources under a complex electricity cost structure

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Cooling energy costs can account for a significant portion of the total energy costs during summer for a large organization. A hybrid energy system or thermal energy storage can be used to reduce the energy cost. However, without proper operation plans, the advantage of using such systems could be limited. This article presents an energy cost optimization model for a hybrid cooling system under a complex energy cost structure. The model can handle a realistic non-linear complex cost structure incorporating the costs from electricity use, electrical demand, electricity demand ratchet, and fuel consumption. This article also examines the trade-off between chiller operations using different energy sources. The optimization model is constructed as a mixed-integer non-linear program. To reduce computational intensity, a dual-stage solution method is developed by treating a decision variable of the electricity demand limit temporarily as a constraint parameter. This reduced computation allows for the possibility of using the optimization model for real-time implementation. A case study of the central cooling system of an academic institution during a summer month showed that the developed method and model could be used for optimized operation to save energy costs significantly.

Introduction

The energy cost for building cooling can account for a significant portion of the total energy cost of a large organization or building complex. A significant part of the consumed electricity during summer is often used to produce chilled water to meet the high cooling load. The chilled water production could contribute up to one-third of the total electricity cost in summer months.

In fact, a significant portion of the cooling energy cost does not directly come from the electrical energy charge but electrical demand charge. For example, the electrical power used for cooling may occupy more than one-third of the peak electricity demand that sets the demand charge. Moreover, the peak electricity demand during summer sets the electrical demand ratchet for winter, resulting in unnecessary demand charges in winter. In such situations, it is desirable to reduce the peak electricity demand during summer.

The reduction of the peak electricity demand and overall energy cost, however, is a challenging problem. For a non-hybrid cooling system powered by electricity, reducing peak electricity demand usually results in increasing electricity energy use. At the same time, without proper methodology, it may identify ineffective demand reduction, which eventually results in a wrong solution (Sun et al. 2010). For a hybrid cooling system, to reduce the peak electricity demand, part of the cooling load is often shifted from electric chillers to steam turbine chillers using fuel (or a thermal energy storage system). Integrated operating of these two different chiller systems is more challenging than that of only electric chillers. First, although a steam turbine chiller enables load shifting to reduce the peak electricity demand, electric chillers are usually operated more than necessary because of the relatively high efficiency in generating chilled water. Thus, the advantage of using steam turbine chillers is often not fully exploited. Second, when a complex non-linear electricity cost structure (e.g., electricity demand charge and electricity demand ratchet policy) is applied, evaluating the trade-off between fuel and electricity costs can be difficult without complicated computation. The trade-off evaluation is beyond intuitive human judgment. Third, the uncertainty of the cooling demand makes optimal operation even more difficult.

This article presents a cost-optimized model of a hybrid cooling system under a complex non-linear electricity cost structure. The model is constructed as a mixed-integer non-linear program (MINLP) by integrating the models of hybrid cooling system efficiency and multiple energy sources. To reduce the lengthy computation required by the MINLP, a dual-stage solution method is used through an efficient partial enumeration. Although this research focuses on a hybrid cooling system, the methods presented can also be extended to a wide range of cooling systems with multiple energy sources

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or a single-source system with thermal energy storage. In addition, the complex non-linear cost model could help develop and implement global control and smart grid technologies to manage the electricity energy cost.

This article is structured as follows. The next section reviews the literature. The mathematical model of this research is presented in the following section, and a case study follows. The mathematical symbols used in the article are presented in the Nomenclature section.

Literature review

The optimal control of a cooling system can be classified into two categories: local control and global control (Wang and Ma 2008). Local control focuses on the optimal control of individual chillers through coefficient of performance (COP) analysis (Chan and Yu 2002; Chang et al. 2005). On the other hand, global control mainly focuses on the entire cooling system. Previous studies (Wang and Ma 2008) indicated that local control might not be cost effective compared to global control, and thus an analysis of the entire cooling system was necessary and important. A variety of models (Chow et al. 2002; Zhang and Cai 2002; Yao et al. 2004; Lu et al. 2005a, 2005b; Fong et al. 2006, 2009; Wang 2007) have been studied in global control. In addition, when a complex cost structure or multiple energy sources are used, a direct cost optimization model is necessary because a cooling system model based on chiller performance coefficients cannot guarantee the minimum energy cost over the entire planning horizon (Xu et al. 2005).

One common method, known as thermal storage, is extensively reported in the literature (Wang and Ma 2008) for the reduction of the total operation cost when a time-of-use differentiated electricity cost rate exists. Significant savings can be achieved via the proper implementation and control of the thermal storage. Extensive research on active thermal storage methods (Braun 1990; Henze et al. 1997, 2005; Massie 2002; Nagai 2002; Zhou et al. 2005; Ma et al. 2009) has been conducted under a variety of conditions. Several models on passive thermal storage methods (Guo et al. 2005; Henze 2005; Sun et al. 2010) have also been studied and compared with the active thermal storage method. The challenge in achieving the lowest electricity cost and trade-off between electricity demand and energy cost were also discussed by Sun et al. (2010).

Although there are many studies related to the aforementioned methods, there are limited studies on implementing a hybrid cooling system. Musgrove and Maher (1988) developed a linear programming optimal control model to minimize the energy cost of a cooling system comprised of electric, steam-driven, and absorption chillers but without the electricity demand cost. Another study (Gibson 1997) introduced a supervisory control model for a hybrid cooling system comprising an electric chiller and gas-fired, engine-driven chiller. In Gibson (1997), a neural network model was developed to examine the performance of the cooling system, and a genetic algorithm was used for optimal scheduling. Ellis et al. (2000) developed an optimization model that considered the life-cycle cost of a hybrid cooling plant. The costs of installation, energy, demand, and maintenance were considered in their model, but auxiliary equipment, such as pumps and cooling towers, was not. Another study (Braun 2007b) introduced near-optimal control strategies based on a chiller sequencing model for a hybrid cooling plant. Both time-of-use differentiated energy cost and demand cost were considered in the work. The proposed chiller sequencing strategy considered the performance coefficient of four different types of chillers. One study (Braun 2007b) also compared the results of the sequencing strategies with and without part-load control under different electricity demand limits.

Mathematical model

This section presents the assumptions, cooling plant model, energy cost model, and cost-optimized operation-planning model used in this study. Because of a large number of mathematical symbols are used throughout the article, each term may not be explained individually in this section. For the complete nomenclature, refer to the Nomenclature section.

Assumptions

The following assumptions were made in the study.

- There exist N electric chillers, M steam turbine chillers, and one boiler in the system.
- The energy efficiency of all the equipment (chillers, boiler, pumps, and cooling towers) does not change over time. In addition, the efficiencies are not affected by other factors such as weather and season.
- The steam generated by the boiler will be used only by the steam turbine chillers to produce chilled water.
- Start-up costs of the electric chillers are insignificant and can be ignored.
- The chillers are turned on or off at the beginning of a time period.

Cooling plant energy consumption

The principal equipment and facilities in a central cooling plant usually include chillers, chilled water pumps, cooling towers, and tower water pumps. The total electricity consumed should account for the electricity used by these four types of equipment. Thus, the total electrical energy consumed by the cooling system through the entire time horizon T is

$$E^{Total} = \sum_{t=1}^{T} E_t = \sum_{t=1}^{T} \left(\sum_{i=1}^{N} E_{t,i}^{EC} + E_t^{TWP} + E_t^{CWP} + E_t^{CT} \right), \tag{1}$$

where E_t is the electrical energy used by the entire cooling system during the time period t. E_t consists of four parts, namely $E_{t,i}{}^{EC}$ (the electrical energy used by the electric chiller i during time period t) and $E_t{}^{TWP}$, $E_t{}^{CWP}$ and $E_t{}^{CT}$ (the electrical energies used during time period t by the tower water pumps, chilled water pumps, and cooling towers, respectively).

General cooling plant models and operation methods were suggested by many researchers (Braun 1990, 2007a). The electricity/fuel consumed during a short time period by the electric/steam turbine chiller can be expressed as a quadratic regression function of its part-load ratio (PLR; Braun 1990). A simplified model without consideration of ambient conditions is as follows:

$$E_i^{EC} = E_i^{EC,D}\left(a_{0,i} + a_{1,i}PLR_i + a_{2,i}PLR_i^2\right), \tag{2}$$

$$F_i^{TC} = F_i^{TC,D}\left(b_{0,i} + b_{1,i}PLR_i + b_{2,i}PLR_i^2\right), \tag{3}$$

where $PLR_i = Q_i/Q_i^D$, and $a_{0,i}$, $a_{1,i}$, and $a_{2,i}$ ($b_{0,i}$, $b_{1,i}$, and $b_{2,i}$) are the coefficients for the power (fuel)-PLR regression function of the ith chiller.

Such assumptions (constant efficiency over time and ambient conditions) are made to simplify non-significant factors in the problem in order to focus on the main topic of this research (complex cost structure and trade-offs). Other black box models, such as COP-PLR or expert-knowledge-based models, can be alternatives to the above models. However, a case study can show that the effect of these chiller efficiency variations would not be numerically significant compared to other factors.

If time period t is an hour, which is the usual measurement period of electricity meters, E_t can be considered as the electrical demand. Consequently, the maximum peak electricity demand, P^{Max}, is the maximum value of E_t throughout the entire time horizon T:

$$P^{\text{Max}} = \max_{1\le t\le T}\{E_t\}. \tag{4}$$

Similarly, the total fuel used by the steam turbine chiller during the entire time horizon T is

$$F^{Total} = \sum_{t=1}^{T}\sum_{i=1}^{M}\left(F_{t,i}^{TC} + F_{t,i}^{S}\right), \tag{5}$$

where $F_{t,i}^{S}$ represents the fuel used for starting steam turbine chiller i in time period t and is a function of binary decision variables representing the on–off status of a chiller, $u_{t-1,i}$ and $u_{t,i}$.

Cost functions under a complex electricity structure

In this article, a complex non-linear cost structure is considered. The cost function for a billing period (usually a month) for a hybrid cooling plant consists of five terms: electrical energy cost, electricity demand cost, electrical facility cost, fuel cost, and demand ratchet punitive cost. Thus, the total operation cost for the current month K is given by

$$C_K^{Total} = C_K^{EG} + C_K^{DM} + C_K^{FC} + C_K^{F} + C_K^{DR}. \tag{6}$$

The first four terms on the right-hand side of the equation are the costs that appear in the bill of each month and are defined as the current-month billing cost. The last term is the demand ratchet punitive cost. It is included in the current-month billing cost in winter months but is calculated based on the operation of the cooling system during summer months.

The details of the complex cost structure is further explained as follows. First, the electricity is delivered through two different voltages: 12 kV for the primary service line and 4 kV for the secondary. However, without loss of generality, this study assumes a secondary service line powers the cooling plant. The electrical energy terms for the cooling plant (the amount consumed and their peak values) are calculated with the following equations.

$$E_K^{SC1} = E_K^{Total}, \tag{7}$$

$$E_K^{SC} = E_K^{SC1} + E_K^{SC2}, \tag{8}$$

$$P_K^{SC1} = P_K^{\text{Max}}, \tag{9}$$

$$P_K^{SC} = P_K^{SC1} + P_K^{SC2}. \tag{10}$$

Second, the electricity is provided by two electricity sources with different cost rates: local and national suppliers. The electricity supplied from the local suppliers is charged at different rates depending on the electricity use. On the other hand, the electricity supply and cost rate of the national supplier are fixed by a long-term contract. The amount of primary and secondary services from the local supplier is calculated on the basis of the ratio of the recorded total of the two services. Thus, the electrical energy and demand costs are calculated by the following equations:

$$\begin{aligned} C_K^{EG} = {} & c_K^{EG,W}E_K^W + c_K^{EG,PR,L}\frac{E_K^{PR}}{E_K^{PR}+E_K^{SC}}\left(E_K^{PR}+E_K^{SC}-E_K^W\right) \\ & + c_K^{EG,SC,L}\frac{E_K^{SC}}{E_K^{PR}+E_K^{SC}}\left(E_K^{PR}+E_K^{SC}-E_K^W\right), \end{aligned} \tag{11}$$

$$\begin{aligned} C_K^{DM} = {} & c_K^{DM,W}P_K^W + c_K^{DM,PR,L}\frac{P_K^{PR}}{P_K^{PR}+P_K^{SC}}\left(P_K^{PR}+P_K^{SC}-P_K^W\right) \\ & + c_K^{DM,\text{SC},L}\frac{P_K^{SC}}{P_K^{PR}+P_K^{SC}}\left(P_K^{PR}+P_K^{SC}-P_K^W\right). \end{aligned} \tag{12}$$

In Equation 11, for example, the first term on the right-hand side is the energy cost charged by the national supplier under the contract. The second and third terms are the energy cost for the primary and secondary services charged by the local supplier. The fractions in the second and third terms are the ratio of the energy from the primary and secondary services to the total energy, respectively. The terms inside the parenthesis are the difference between the total energy and the energy supplied by the national supplier, which are equal to the energy from the local supplier.

During winter months, the demand ratchet policy is applied in addition to the previously discussed basic policy. The main idea of the demand ratchet is that the monthly billing demand from the local supplier for a winter month is the higher one between (1) the maximum demand during this winter month and (2) ratio α of the highest maximum demand established from the bills of previous summer months. For example, if the current month is a summer month, the value of the demand ratchet will be the higher of either (1) the demand ratchet of the previous month or (2) the new demand ratchet set by the peak electricity demand established in the current month. If the current month is a winter month, the demand ratchet of the current month would be equal to the demand ratchet of the last month and, thus, be equal to the highest demand ratchet set in previous summer months:

$$R_k = \begin{cases} \max\left\{\alpha\left(P^{PR} + P^{SC} - P_k^W\right),\ R_{k-1}\right\} & \beta_k = 1 \\ R_{k-1} & \beta_k = 0 \end{cases}. \tag{13}$$

In the model above, the first month of the summer period is defined as the first month of the operation year, and the operation year ends in the last month of the winter period. At the end of each operation year, the demand ratchet will be reset to zero.

Thus, the electricity demand cost in winter months is calculated with

$$C_K^{DM} = \begin{cases} c_K^{DM,W} P_K^W + c_K^{DM,PR,L} \dfrac{P_K^{PR}}{P_K^{PR} + P_K^{SC}}\left(P_K^{PR} + P_K^{SC} - P_K^W\right) + c_K^{DM,\mathrm{SC},L} \dfrac{P_K^{SC}}{P_K^{PR} + P_K^{SC}}\left(P_K^{PR} + P_K^{SC} - P_K^W\right) & P_K^{PR} + P_K^{SC} - P_K^W > R_K \\ c_K^{DM,W} P_K^W + c_K^{DM,PR,L} \dfrac{P_K^{PR}}{P_K^{PR} + P_K^{SC}} R_K + c_K^{DM,\mathrm{SC},L} \dfrac{P_K^{SC}}{P_K^{PR} + P_K^{SC}} R_K & P_K^{PR} + P_K^{SC} - P_K^W \le R_K. \end{cases} \tag{14}$$

In some cases, the facility cost exists in addition to the demand cost. The facility cost can be regarded as a special case of the demand costs because it is also charged on the basis of the electrical power. Here, it is assumed that the local supplier charges all the facility costs to make it different from the demand cost. Because the chiller system is powered by the secondary service line in this study, only the facility cost of the secondary service for the current month K is considered, and it is calculated with Equations 13 and 14. The ratchet policy is also applicable to the facility cost:

$$C_K^{FC} = \begin{cases} c_K^{FC} P_K^{SC} & P_K^{SC} > r_K \\ c_K^{FC} r_K & P_K^{SC} \le r_K \end{cases}, \tag{15}$$

$$r_k = \begin{cases} \max\left\{\alpha P^{SC}, r_{k-1}\right\} & \beta_k = 1 \\ r_{k-1} & \beta_k = 0 \end{cases}. \tag{16}$$

According to the ratchet policy, when the actual peak electricity demand in a winter month is lower than the demand ratchet, the customer would pay more than the cost calculated purely based on the actual peak electrical demand of that winter month. The same condition applies in calculating the facility cost. This part of the cost is defined as the winter month's ratchet cost. The sum of the winter month ratchet costs for all winter months is defined as the demand ratchet punitive cost.

Although the winter month ratchet cost is included in the billing cost of subsequent winter months, it is rational to consider this cost in summer months as a punitive cost, because it is mainly caused by the peak electricity demand due to the operation of the cooling plant during the summer months. Therefore, if the current month K is a winter month, it is considered that there will be no ratchet punitive cost. However, if the current month K is a summer month, the ratchet punitive cost will be the higher one between (1) the ratchet punitive cost in previous summer months and (2) the ratchet punitive cost calculated based on the new peak electricity demand set in the current month K. Thus, the ratchet punitive cost of the current month K is calculated as

$$C_K^{DR} = \beta_K \max\left\{C_{K-1}^{DR}, \sum_{k=K}^{12} C_k^{DR}\right\}. \tag{17}$$

The winter month ratchet cost of a future month k consists of two terms: the demand ratchet cost and the facility ratchet cost. The two costs are calculated using the basic policy, which is based on the difference between the ratchet value and the actual value. Although the actual peak electricity demand in the winter month k that follows the summer months is unknown, the value recorded in the previous year, p_k, can used to estimate the future value because of its relatively stable values:

$$C_k^{DR} = C_k^{DM}\left(\Delta P_k^{DM}\right) + C_k^{FC}\left(\Delta P_k^{FC}\right), \tag{18}$$

$$\Delta P_k^{DM} = \max\left\{0, \alpha\left(P_K^{PR} + P_K^{SC} - P_K^W\right) - \left(p_k^{PR} + p_k^{SC} - p_k^W\right)\right\}, \tag{19}$$

$$C_k^{DM}\left(\Delta P_k^{DM}\right) = c_k^{DM,PR,L} \Delta P_k^{DM} \frac{p_k^{PR}}{p_k^{PR} + p_k^{SC}} + c_k^{DM,\mathrm{SC},L} \Delta P_k^{DM} \frac{p_k^{SC}}{p_k^{PR} + p_k^{SC}}, \tag{20}$$

$$\Delta P_k^{FC} = \max\left\{0, \alpha P_K^{SC} - p_k^{SC}\right\}, \tag{21}$$

$$C_k^{FC}\left(\Delta P_k^{FC}\right) = c_k^{FC} \Delta P_k^{FC}. \tag{22}$$

Cost-optimized operation-planning model and solution method

The planning horizon in this article is total T periods. The non-negative discrete integer decision variable $x_{t,i}$ is defined as the PLR of chiller i and the binary decision variable $u_{t,i}$ as the on–off status of chiller i. These two variables describe the operational state of chiller i in time period t. A chiller status is OFF at time t if $u_{t,i} = 0$ and $x_{t,i} = 0$, and it is ON if $u_{t,i} = 1$ and $x_{t,i} > 0$ and is within the feasible operation range. The cost-optimized operation-planning model is formulated as an MINLP as follows:

$$\min z = \min_{u,x} C_K^{Total} = \min_{u,x} C_K^{EG} + C_K^{DM} + C_K^{FC} + C_K^{F} + C_K^{DR} \tag{23}$$

subject to

$$\sum_{i=1}^{N} Q_{t,i}^{EC} + \sum_{j=1}^{M} Q_{t,j}^{TC} \geq d_t \quad \forall t, \tag{24}$$

where d_t is the required cooling load in time period t, and $Q_{t,\,i}$ is the cooling load produced by chiller i in t. To calculate the minimum total cost in the objective function (Equation 23), Equations 1 to 22 are used. The constraint by Equation 24 requires that the cooling capacity provided should be equal to or greater than the cooling demand for each hour of the planning horizon.

The non-linear characteristics of the problems reside in the following aspects: (1) the efficiency of chillers with respect to the decision variable of PLR x_i (Equations 1 to 5), (2) the electricity cost objective function with respect to the decision variable of PLR x_i (Equations 7 to 22), and (3) the cost trade-off between electricity cost and fuel cost.

To overcome the computational complexity of the MINLP, a dual-stage solution method is applied by introducing a decision variable y_K, the peak electricity demand limit of the secondary service in month K.

Stage 1: In the first stage, the cooling load d_t and the peak electricity demand limit y_K is set or given first, and the optimal solution for each time period under the given y_K and d_t is recast to an MINLP problem with less complexity. First, the cooling load is checked as to whether it is first provided by the electric chillers under the constraint of y_K. If the electric chiller could not meet the cooling demand under the given y_K, the shortfall is provided by the steam turbine chiller. Thus, the optimal solution at any period can be considered a function of the cooling load and peak electricity demand limit. The optimal solution at the first stage can be pre-processed and stored in a database for convenience.

Stage 2: The second stage is then simplified as a non-linear program with only one decision variable, the peak electricity demand limit y_K.

By considering the dual-stage solution method, the cost-optimized operation-planning model can be rewritten as

$$\begin{aligned} \min\ z &= \min_{u,x,y} C_K^{Total} \\ &= \min_{u,x,y} C_K^{EG} + C_K^{DM} \\ &\quad + C_K^{FC} + C_K^{F} + C_K^{DR} \end{aligned} \tag{25}$$

subject to

$$\sum_{i=1}^{N} Q_{t,i}^{EC} + \sum_{j=1}^{M} Q_{t,j}^{TC} \geq d_t \quad \forall t, \tag{26}$$

$$P_t^{SC} \leq y_K \quad \forall t, \tag{27}$$

$$r_{K-1} \leq y_K, \tag{28}$$

$$\alpha \left(P^{PR} + y_K - P_K^{W} \right) \geq R_{K-1}. \tag{29}$$

The objective function (Equation 25) is calculated by Equations 1 to 22 as already explained. The constraint Equation 26 requires that the cooling capacity provided should be equal to or greater than the cooling demand for each hour of the planning horizon. Equation 27 ensures that the electricity demand of each hour of the planning horizon is smaller than the electricity demand limit. Equations 28 and 29 give the feasible range of choosing the electricity demand limit y_K.

The advantages of this solution method are as follows: (1) it greatly reduces the required calculation time and memory size for real-time implementation, and (2) the database of the solution can be stored and updated according to the plant change (e.g., unavailability of chillers due to breakdown or maintenance, installation of new chillers, or removal of old chillers).

In addition, although the PLR of chillers (x_i) can be defined as continuous variables, it is defined as a discrete one because of several reasons. First, for an easier management in practice, discrete levels are often chosen by operators. Second, with enough levels of the PLR, the difference between continuous and discrete variable is diminished, and the optimization result is often guaranteed with good accuracy. Third, using a discrete PLR (x_i) is convenient to pre-process and store the solution result in a database as in the dual-stage solution for the purpose of real-time automatic dispatching.

Case studies

This section presents a simulated cost-optimized operation of the cooling plant at a university during a summer month using the actual cooling load recorded. The results are compared with the actual manual operation of the plant at the time.

Description of case study conditions

The central cooling plant of the university is well designed to support the development and implementation of cost optimization technologies and has established an enhanced control system and sufficient database. The university cooling plant currently uses four electric chillers. Electric chiller 1 has a maximum capacity of 5000 ton/h, electric chiller 2 has a maximum capacity of 4500 ton/h, and electric chillers 3 and 4 each have a maximum capacity of 2000 ton/h. By their capacities, electric chillers 1 and 2 are regarded as large chillers, whereas electric chillers 3 and 4 are small chillers. The designed electrical energy consumption rates of the four chillers are 4310, 3030, 1324, and 1324 kW, respectively. The four electric chillers are usually used to meet the entire cooling load when cooling load shifting to the steam turbine chillers is not necessary, and they continue to bear most of the cooling load even when shifting is necessary. The cooling plant also includes one steam turbine chiller, one boiler, three arrays of cooling towers, six tower water pumps, five chilled water pumps, and a distribution loop that serves all the buildings on the campus. The steam turbine chiller has a maximum capacity of 5000 ton/h. It is driven by 600 psi of steam generated by the boiler. The pumps and cooling towers are all powered by electricity.

The energy cost function and policy described in the previous section were applied to this case study. The electricity rates of the local supplier are listed in Table 1. The rates and

Table 1. Electricity rates of local supplier.

Rates	Winter energy, \$/kWh	Summer energy, \$/kWh	Demand, \$/kW	Facilities, \$/kW
Primary	0.0205	0.0282	12.70	4.00
Secondary	0.0200	0.0272	13.05	4.40

allocations of electricity demand and electrical energy from the national supplier are shown in Table 2. The fuel rates are provided in Table 3.

Current manual operation

The university cooling system has been manually operated based on the experience of the human operators. The strategy involves the operator adjusting the PLR of the operating chillers or turning them on or off depending on the observed temperatures of the inflowing and outflowing (chilled) water. Early every morning, based on the weather forecast (mainly the temperature), the operator decides how the steam turbine chiller will be used for handling the cooling load shifting from the electric chillers. If load shifting is expected, the operator would warm up the steam turbine chiller early that day. The operator uses experience to determine when the steam turbine chiller should be turned on and how much cooling load should be shifted to it.

The profile of the manual operation in August of a year is shown in Figure 1.

Under the present manual operation strategy, electric chillers 1 and 2 are often used to provide most of the cooling needs during summer. The cooling load is generally assigned in proportion to their designed capacities. Electric chiller 3 is used to cope with load fluctuation, even if electric chillers 1 and 2 are not at their full PLR. Electric chiller 4 is only operated when there is a breakdown or during maintenance of any of the other electric chillers. The steam turbine chiller is operated when the total campus cooling load is greater than 9000 ton/h.

Table 2. Rates and allocations of electricity demand and electrical energy from a national supplier.

Month	Electrical demand, kW	Electrical energy, kWh	Demand rate, \$/kW	Energy rate, \$/kWh
Jan	14,220	7,866,000	7.65	0.01905
Feb	14,220	7,539,000	7.65	0.01905
Mar	14,220	7,747,000	7.65	0.01905
Apr	14,220	7,499,000	7.65	0.01905
May	17,630	8,491,000	7.65	0.01905
Jun	18,740	9,985,000	7.65	0.01905
Jul	18,965	9,824,000	7.65	0.01905
Aug	18,965	10,581,000	7.65	0.01905
Sep	18,196	9,396,000	7.65	0.01905
Oct	17,745	8,179,000	7.65	0.01905
Nov	14,200	7,580,000	7.65	0.01905
Dec	14,015	7,388,000	7.65	0.01905

Table 3. Fuel cost rate.

Month	Cost rate, \$/MMBtu	Month	Cost rate, \$/MMBtu	Month	Cost rate, \$/MMBtu
Jan	7.48	May	6.17	Sep	6.68
Feb	7.61	Jun	6.59	Oct	6.39
Mar	7.06	Jul	6.16	Nov	6.03
Apr	6.70	Aug	6.08	Dec	6.42

Simulated cost-optimized operation based on recorded cooling load

This section presents the simulated cost-optimized operation decision for each hour of August of the same year generated from the actual recorded cooling load. The simulation used the models and dual-stage solution method described in the previous section. The optimization is performed by a computer program written with MATLAB®, and it took 9 min for calculation on a workstation with Intel Xeon W3550 CPU at 3.07 GHz and 12 GB memory. The decision variable for the case studies are PLR (x_i) for each hour of the entire planning horizon (T) and electricity demand limit (y_K). The case study was solved based on the two-stage solution method through an implicit enumeration method. One case of the simulation runs is performed based on the data of August of a year with principal 7441 decision variables: 3720 PLRs ($x_{i,t}$), 3720 on–off status ($u_{i,t}$), and one electricity limit. Its cost-optimized operation profile is shown in Figure 2.

The results shown in Figure 2 indicated that the operation of the electric chillers should be primarily based on their efficiency. The results suggested that the main part of the cooling load should be met by using the two small electric chillers, which are more efficient, with electric chiller 2 operated only when extra capacity is needed. Operating electric chiller 1 is the least economical choice. When the cooling load is greater than 7000 ton/h (electric chillers 3 and 4 are operated at the full PLR and electric chiller 2 is operated at a PLR of 80%), it could be more economical to use the steam turbine chiller to cover the remaining portion of the cooling load.

Cost comparison between the manual and cost-optimized operations

The difference between the operation strategies of the current manual and cost-optimized operation can be clearly seen from a comparison of Figures 1 and 2. The manual operation focuses more on operational convenience and management. Its main purpose is to avoid the frequent switching of the on–off status of the chillers, which could also reduce the risk of mechanical failure and promote the longevity of the chillers. This operation (shown in Figure 1) uses the two big chillers to meet the major part of the cooling load, while the two small ones cover some of the peak and fluctuating requirements. However, the simulated operation with the proposed cost-optimized model focused more on reducing the total energy costs.

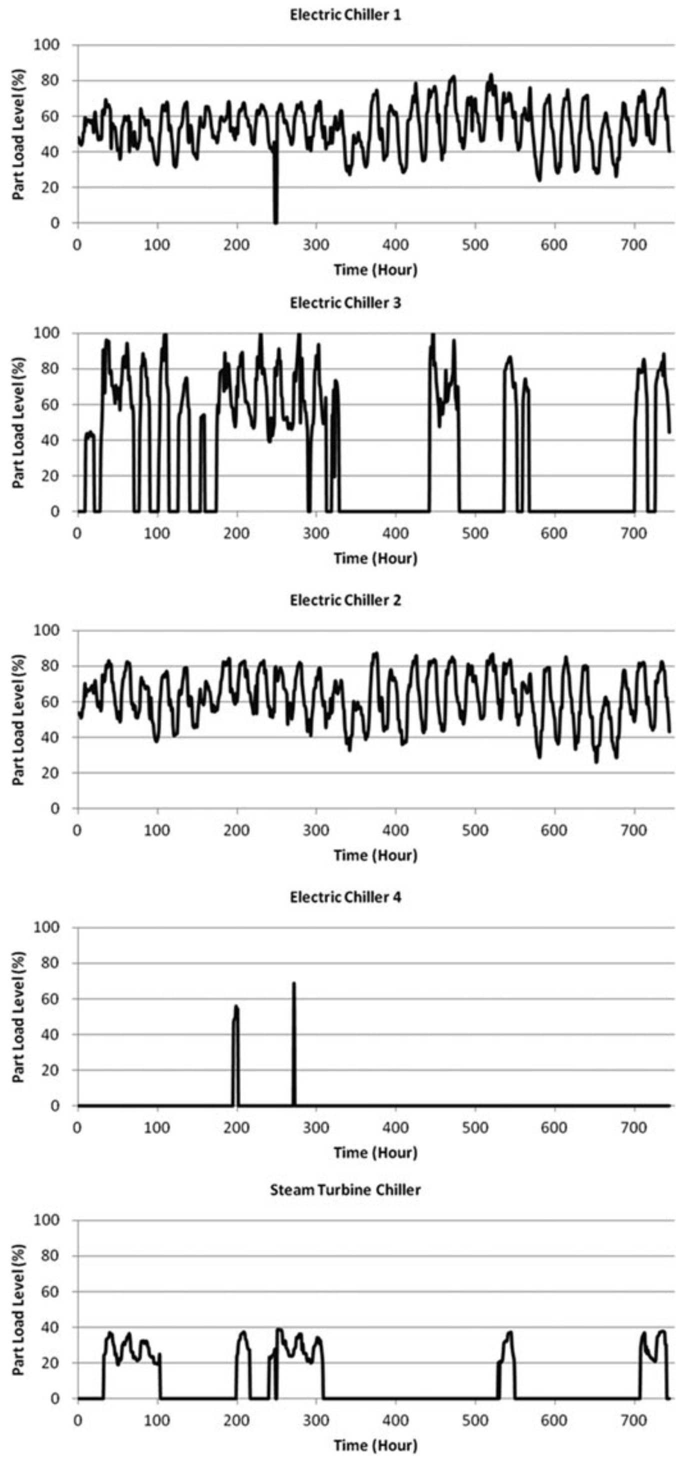

Fig. 1. Manual operation profile in August.

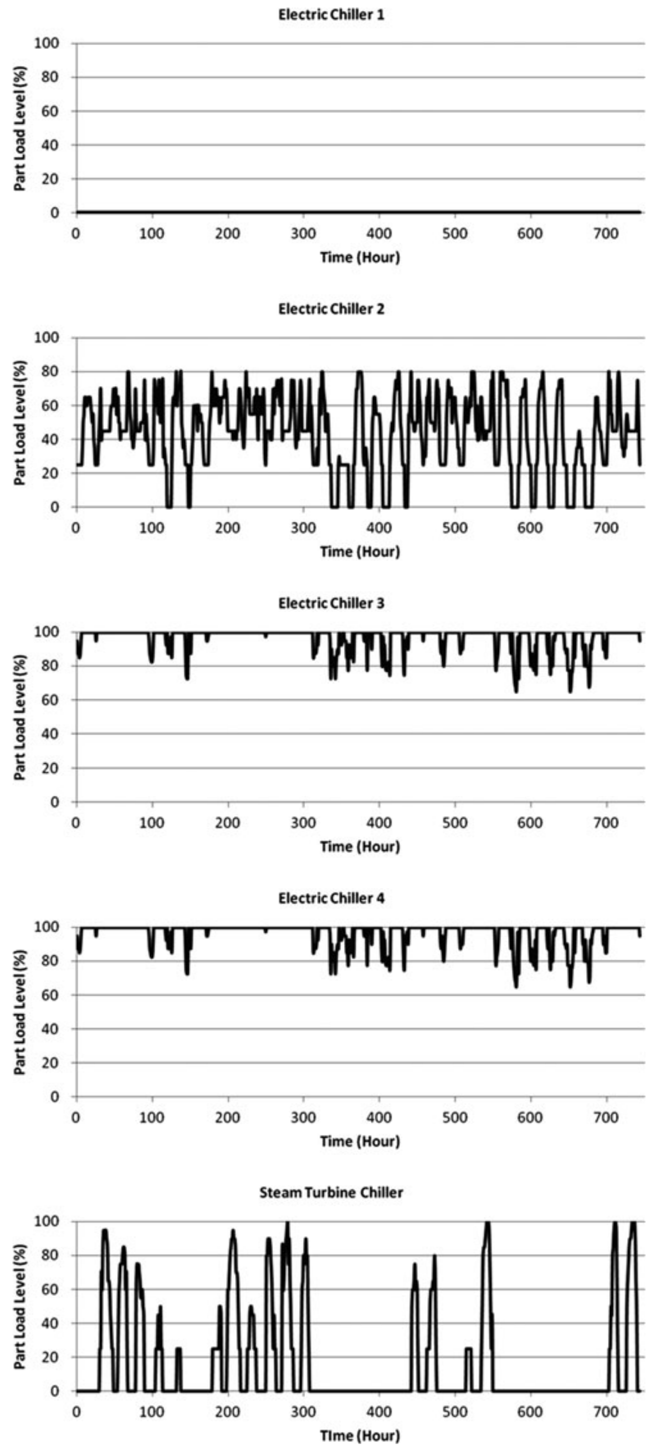

Fig. 2. Simulated cost-optimized operation profile for August using actual cooling load information.

Figures 3 and 4 compare the cost terms of the two operations. The individual cost terms in the current-month billing and total cost are compared.

As can be seen in Figures 3 and 4, the optimized operation during only August could save around $140,000 for a fiscal year. The main part of the savings in this summer month comes from the reduction of the electricity demand ratchet punitive cost rather than from the current-month billing cost itself.

These results provide some insights into the trade-off between different energy sources and operation policies. First, because of the non-linearity of the cost functions, especially

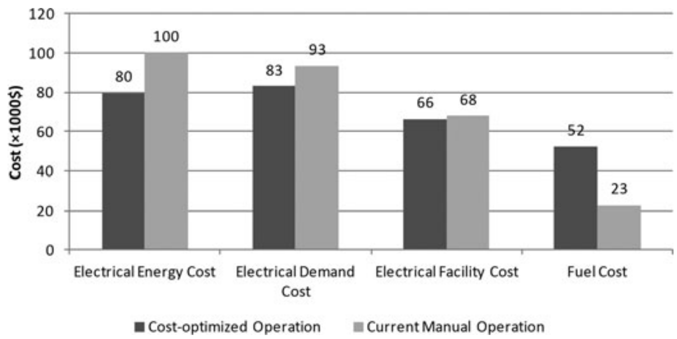

Fig. 3. Comparison of individual cost terms in current-month billing cost for simulated cost-optimized and actual manual operation.

the demand cost and demand ratchet punitive cost, the steam turbine chiller is more economical when the cooling load is greater than a threshold value for a given fuel cost rate and cooling load profile. As shown in Figure 3, the cooling load shifting from an electric chiller to the steam turbine chiller results in reductions of $20,000 in electrical energy cost, $10,000 in electricity demand cost, and $2,000 in electrical facility cost. However, the shifting increases the fuel cost by $29,000.

Second, determining the cooling load shifting point and the electricity demand limit (y_K) are critical and challenging in achieving the lowest energy cost in summer months. Increasing the use of the steam turbine chiller in August does not significantly reduce the current-month billing cost itself. However, the total cost is greatly reduced by significantly decreasing the demand ratchet punitive cost. This is because, as shown in Figures 3 and 4, the trade-off is mainly between fuel cost and electricity demand ratchet punitive cost. Figure 4 also indicates that the demand ratchet punitive cost is very sensitive to shifting of the load to the steam turbine chiller. A reduction of 700 kW in the peak demand (around 3%) eventually lowered the demand ratchet punitive cost to a half.

Generally, if the electricity demand limit (y_K) is not properly chosen, it would give a wrong solution, which results in an increase in the final cost: (1) if the selected electricity demand limit (y_K) is greater than the optimal value ($y_K{}^*$), the increase in demand ratchet punitive cost will be greater than the reduction in fuel cost; (2) if the selected electricity demand limit is smaller than the optimal value ($y_K{}^*$), the increase in fuel cost will be greater than the reduction in demand ratchet punitive cost. However, if the fuel cost rate is very cheap, then the steam turbine chillers should be the first choice and operated as much as possible. Furthermore, if the steam turbine chillers have enough capacity, operation of the electric chillers will be unnecessary. Thus, with different fuel cost rates, the optimal electricity demand limit would be different under the same cooling demand profile. On the other hand, due to the capacity limit of steam turbine chillers in real operation, the ideal electricity demand limit may not be reachable. Therefore, determining the optimal is a challenging problem.

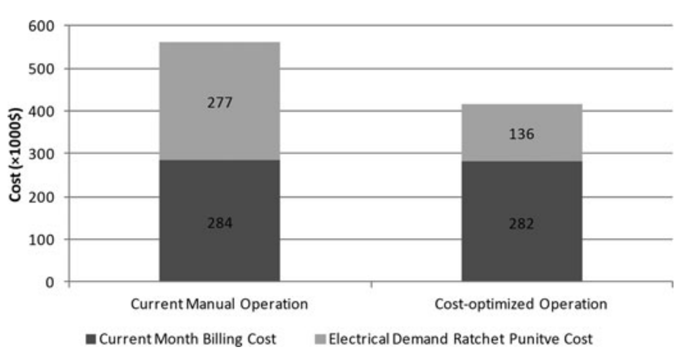

Fig. 4. Comparison of monthly and total costs of simulated cost-optimized operation and actual manual operation.

Therefore, the reasons why the current manual operation cannot reduce energy costs are as follows: (1) energy costs are charged as both electrical energy cost and demand cost; (2) demand ratchet policy brings the demand cost charged in winter months into consideration in summer month operation; (3) dual electrical energy sources, dual electrical service delivery lines, and differentiated cost rates complicate the cost rate of operating the electric chillers; (4) the cost of operating the electric chillers correlates with the electrical energy consumed by other facilities; and (5) the floating fuel cost rate makes it more difficult to evaluate the trade-off between using electrical and fuel energy. As a result of the reasons, the human operator experience is not sufficient for operating the hybrid system efficiently for an extended time period even with an almost known cooling load. In addition, the common knowledge among operators that the electric chillers are more energy efficient than steam turbine chillers often causes the electric chillers to be operated more than necessary.

Conclusions

This article introduced a cost-optimized operation-planning model for a hybrid central cooling plant. The proposed model provides profound insight into the trade-off of chiller operations using different types of energy sources under a complex electricity cost structure. The model was formulated as an MINLP by integrating the complex characteristics of component efficiency, multiple energy sources, a complex non-linear cost structure, and energy consumption by other facilities. To reduce the computation required by the MINLP and to facilitate real-time implementation, a dual-stage solution method was devised by introducing the electricity demand limit variable. A case study verified the effectiveness of the method and mathematic model. The results of the case study also revealed that the developed method had the potential to make significant savings in the total energy cost.

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Nomenclature

Parameters and variables:

c = cost rate
C = cost function
d = total cooling load
E = function or value of electrical energy supply or consumption
F = function or value of fuel consumption
M = total number of steam turbine chillers
N = total number of electric chillers
p = actual peak electrical power supply or consumption recorded in the last year
P = peak electrical power supply or consumption
Q = cooling capacity produced by chillers
r = electrical facility ratchet
R = electricity demand ratchet
T = time horizon
u = decision variable of on–off status of a chiller
x = decision variable of part-load ratio of a chiller
y = decision variable of peak electricity demand limit
α = demand ratchet factor
β = summer month indicator; 1 if current month is a summer month, and 0 otherwise
ΔP = difference between demand ratchet and actual peak demand for the same winter month; non-negative number

Subscripts

i, j = electric/steam turbine chiller
t = time period
k = month in the planning year starting from first summer month
K = current month

Superscripts

CT = cooling tower
CWP = chilled water pump
D = designed value
DM = electricity demand cost
DR = electricity demand ratchet cost
EC = electric chiller
EG = electrical energy cost
F = fuel
FC = electrical facility cost
L = local electricity supplier
Max = maximum value
PR = primary service
S = start up
SC = secondary service
$SC1$ = secondary service part I, for cooling plant
$SC2$ = secondary service part II, for other facilities
TC = steam turbine chiller
$Total$ = total terms
TWP = tower water pump
W = national electricity supplier

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