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AN ENERGY COST OPTIMIZATION METHOD FOR A LARGE SCALE HYBRID CENTRAL COOLING PLANT WITH MULTIPLE ENERGY SOURCES UNDER A COMPLEX ELECTRICITY COST STRUCTURE

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by

Yin Guo

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AN ENERGY COST OPTIMIZATION METHOD FOR A LARGE SCALE HYBRID CENTRAL COOLING PLANT WITH MULTIPLE ENERGY SOURCES UNDER A COMPLEX ELECTRICITY COST STRUCTURE

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University of Nebraska, 2012

Adviser: Jeonghan Ko

The cooling energy cost could be a significant portion of the total energy cost for a large organization or building complex during summer. A hybrid system or thermal energy storage system is usually applied to reduce the energy cost. However, without proper integration and operation, the advantage of using such systems could be limited.

This study presents a general energy cost optimization methodology and mathematical model for a hybrid cooling system under a complex electricity cost structure. The model considers the efficiency of the hybrid cooling system and multiple energy sources. The energy cost evaluation reflects a complex cost structure including electrical energy cost, electrical demand cost, electrical ratchet cost, fuel cost, and electrical energy consumption from other facilities.

The optimization model is constructed as a mixed integer nonlinear program. To reduce high computational intensity, a dual-stage solution method is used by introducing a decision variable of the electrical demand limit as a constraint. This reduced computation provides the possibility of the real time implementation of the model for practical

purposes. This study also shows how the optimization model can be used with a simple cooling load forecasting strategy to avoid a high electricity cost.

A case study of the central cooling system in an academic institution shows that the developed methodology and model can be used to reduce around \$150,000 in energy cost per year. In particular, the case study shows that the developed optimization model can significantly reduce the high demand punitive costs that are hard to reduce in the current manual operation based on operator experiences. In the case study, this reduction is possible by properly shifting part of the cooling load from electric chillers to steam turbine chillers during peak electrical demand season and thus decreasing the peak electricity consumption under the complex demand charge structure.

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CHAPTER 1

INTRODUCTION

1.1 Background

Energy cost for building cooling can be a significant portion of the energy cost for a large organization or building complex. For example, the University of Nebraska-Lincoln paid approximately \$6,300,000 for electricity for one year period [1], and more than \$1,200,000 of it was for the building cooling.

A significant portion of the cooling energy cost often does not come from the direct electrical energy charge but electrical demand charge. The aforementioned academic institution actually paid more for electrical demand cost than for electrical energy cost in August 2010 [1]. Due to the non-efficient operation of cooling plant in August 2010, it also paid about \$279,000 as an electrical demand charge in additional to the charge for the actual use in the winter season of the same year under the current electrical demand ratchet policy [1].

The reason of the high demand cost is the high peak electrical power used in the summer season to produce chilled water to meet the high cooling load. The electrical demand from the cooling system could contribute up to 35% of the total peak electrical demand in summer months [1]. At the same time, the high peak electrical demand in the summer season would set the high peak electrical ratchet for the winter season. As the electrical ratchet goes higher, more additional meaningless demand charge would occur. Therefore, it could be beneficial for such an organization to reduce the peak electrical demand in the

summer and save unnecessary cost, through a proper operation of the hybrid central cooling plant.

Reducing the peak demand also helps electricity suppliers. The considerable variation of the electrical demand caused by the significant difference of cooling load between peak and off-peak cooling demand periods can not only severely affect the electricity suppliers' production investment and operation, but also greatly increases the burden of the entire electrical power grid. Thus, the high peak demand ultimately raises the cost of electricity production, and the energy purchase rate for other users in the entire grid system. It is therefore economically beneficial to reduce the peak electrical demand for the community.

The reduction of the peak electrical demand and overall energy cost is, however, a challenging problem. To reduce the peak electrical demand, part of the cooling load is usually shifted from electric chillers to steam turbine chillers (or to a thermal energy storage system). Integrating these two kinds of chiller systems of different energy types is more challenging than integrating a multi-chiller system of a single energy type. First, although the steam turbine chiller enables load shifting to reduce the peak electrical demand, electric chillers are usually operated more than necessary because the unit fuel cost for operating steam turbine chillers is usually higher than the unit electrical energy cost for operating electric chillers. Thus, the advantage of using the steam turbine chillers is often not fully utilized. Second, when a complex electricity cost structure or policy is applied, it could be difficult to evaluate the trade-offs between the fuel and electricity cost on the hourly basis or even daily basis. Third, the uncertainty of cooling demand and

the nonlinear cost structure, especially electrical demand charge and electrical demand ratchet policy, makes the optimal operation difficult to determine.

1.2 Research Objectives and Contributions

The objective of this research is to reduce the energy cost by modeling, integration and control of the chiller systems that use dual energy sources. An operation schedule for each chiller in the hybrid multi-chiller cooling system is generated by this energy cost optimization model, using simple cooling load prediction.

The academic contribution of this research is the development of a general methodology and mathematical model that explicitly integrates the hybrid cooling system under a complex electricity cost structure. Although this research focuses on a hybrid cooling system, the methodologies can also be extended to a wide range of cooling systems that use multi-source energy or single source but with a thermal energy storage system.

The practical contribution of this research is the development of a practical energy cost optimization model incorporating cooling load forecasting and an efficiency model of a chiller system for real time implementation. The case study of the cooling plant at the University of Nebraska-Lincoln City Campus shows a potential saving of approximately \$150,000 per year.

This thesis is structured as follows. In Chapter 2, a literature review of the current existing research is presented. The mathematical model is described in Chapter 3. The structure of this research, cost model, plant model, and optimal operation planning model are discussed in detail in this chapter. A case study is shown in Chapter 4. Conclusions and future research directions are shown in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

The optimal control of the cooling system is usually referred to the energy optimization problem or cost optimization problem of the cooling system. The optimal control problem can be classified into two categories depending on the focus – local control and global (supervisory) control [2].

2.1 Local Control

Local control focuses only on the optimal control of chillers through the efficiency analysis, rather than the entire cooling system. Y.C. Chang et al. [3] introduced an optimal chiller sequencing model by branch and bound method to achieve the best performance of a multiple chiller cooling system. However, their result showed a slight energy reduction compared with the maximal peak coefficient of performance method. K.T. Chan et al. [4] proposed a part load efficiency model to optimize the performance of chillers in a cooling plant where an array of air-cooled chillers of the same type was installed. The optimal range of part load ratio was generated when different numbers of chillers were in operation. In their work, they also compared the different weather-load profiles of offices and hotels. Their result also indicated different strategies should be implemented on office and hotel buildings.

Although the chiller plant with multiple chillers of the same type provides benefit and convenience in management and maintenance, more chiller plants are usually equipped with chillers of different capacities, because it could provide more operational flexibility and standby capacity from a chiller plant with an array of the same type of chillers.

2.2 Global Control

Previous studies [2] indicated that local controllers may not be energy-efficient or costeffective, compared with global controllers when the whole system is taken into consideration. Thus the efficiency analysis of the entire cooling system is necessary and important.

The global control mainly focuses on the optimization through the efficiency analysis of the entire cooling system. By modeling the efficiency of the whole cooling system, it becomes possible that the entire system is operated at the best cost efficient level. Therefore improving efficiency and eventually saving cost is achievable by a higher operation level decision, especially when a complex electricity cost rate is applied.

Different methods of modeling have been studied in this field. L. Lu et al. [5, 6] presented a model-based global optimization model for an overall analysis of the HVAC system. The influence of the outdoor temperature was taken into consideration. T.T. Chow et al. [7] developed a global optimization model through genetic algorithm and neural network. S. Wang et al. [8] introduced an online supervisory control model to achieve the lowest energy cost of a central cooling system. K.F. Fond et al. [9] presented an evolutionary programming optimization model to manage the energy of a HVAC system. Later, they developed an optimization model for energy management by using evolutionary algorithm from the evolutionary programming optimization model they proposed previously [10]. Y. Yao et al. [11] introduced an empirical model for optimal

operation of a large cooling system for residential building. Instead of using a traditional coefficient of performance model, they introduced a system coefficient of performance to study the mechanism of the cooling system. H. Zhang et al. [12] explored an optimization model through decentralized nonlinear adaptive control method for an HVAC system.

However, when a complex cost structure (for example, time-of-use differentiated rate, multiple electrical energy sources and demand ratchet policy) is applied or multi-energy types (for example, electricity and fuel, or electricity and thermal energy storage system) are in use, the coefficient of performance model of a chiller system does not always guarantee the minimum energy cost over the entire time horizon of a billing period (usually a calendar month). J. Xu et al. [13] proposed an optimization-based approach to optimize the total operation cost in a cooling system with direct digital control system. The total energy cost consisted of electrical energy cost, monthly electrical demand cost, and 11 months electrical demand/ratchet cost. Instead of optimizing the cost throughout the overall billing period, they tried to minimize the daily cost by scaling the monthly peak demand rate and 11-month peak demand rate to a daily rate. They used multilayer perception neural network to study the mechanism of the cooling system. In order to solve the multistage optimization problem, they applied the Lagrangian relaxation method, and also introduced two variables of the expected peak demands of the current month and of the following 11 months.

2.3 Global Control with Time-of-Use Differentiated Cost Rate

There are two common methods introduced in the literature [2] to reduce the total operation cost when a time-of-use differentiated electrical cost rate or an even more complex cost structure, for example demand ratchet is applied. Significant saving can be achieved by properly implementing these two methods.

The first method, which has been popular in the last decade, is the thermal storage system. Extensive research has been conducted on the topic based on different conditions.

Some of researches were studied under a deterministic case of cooling load. For instance, J. Zhou et al. [14] developed an on-off chiller controller for a campus cooling system with thermal energy storage system to minimize the operation cost under a complicated time-of-use electricity rate schedule. Their optimization model was examined through three different scenarios. However, in their model, only the time-of-use differentiated energy rate was considered. D.D. Massic [15] developed a neural network-based controller to optimize the operation cost of a cooling system with thermal energy storage system. In the model, both time-of-use differentiated energy rate and demand rate were considered. At the same time, the electrical demand from non-cooling purpose was also considered when the demand cost was calculated.

Some of other researches took the predictive control characteristic into consideration. For example, G.P. Henze et al. [16] described a model-based predictive control model for active and passive building thermal storage inventory to save the energy cost under a time-of-use differentiated cost rate. Y. Ma et al. [17] proposed a mixed integer nonlinear program to realize a model-based predictive control model of a building cooling system with thermal energy storage system. By considering both the efficiency performance of the cooling systems and the upper and lower bound of the campus (UC Merced Campus) load in record, they tried to optimize the electrical energy cost through the real time

implementation of the model-based predictive control model. In order to reduce the calculation capacity required by the mix integer nonlinear program problem, they introduced a dual stage optimization strategy to solve the problem. By choosing the tank operation mode profile in the first stage, the problem in the second stage was recast to a nonlinear program problem.

The last group of the researchers tried to focus on the dynamic property of the problem. R.H. Henze et al. [18] introduced a predictive optimal controller model for a cooling system with thermal energy storage system. They developed a dynamic programming model to optimize the operation cost over a planning horizon of 24 hours. In order to optimize the cost, they also considered the performance of the cooling system, the dynamics of the energy rate, and the load forecasting. In their work, they compared the impact from the different levels of the knowledge about the cooling system performance. They also evaluated three different conventional control strategies. J.E. Braun [19] described a dynamic optimization model to reduce the operation cost. In his work, he compared three models with different electrical energy cost structures – minimum energy costs without time-of-use rates, minimum energy costs with time-of-use rates, and minimizing peak electrical demands. T. Nagii [20] introduced a method to minimize annual energy, peak energy demand, and annual energy cost by using a building thermal storage. To solve this multi-objective optimization problem, he used both dynamic programming and Pareto solution method.

Although there are several researches related to the thermal energy storage system, there are only limited studies on the second method -- applying a hybrid cooling system. A.R.

Musgrove et al. [21] developed a linear programming optimal control model to minimize the energy cost of the cooling system that has electric, steam-driven and absorption chillers. However, they did not consider the electrical demand cost and maintenance cost in their study. G.L. Gibson [22] introduced a supervisory control model for a hybrid cooling system where there were an electric chiller and a gas-fired, engine-driven chiller. A neural network model was developed to study the performance of the cooling system, and a genetic algorithm was developed for optimal scheduling. M.W. Ellis et al. [23] developed an optimization model considering life-cycle cost of a hybrid cooling plant. Installation, energy, demand and maintenance costs were considered in their model. However, the auxiliary equipment, such as pump and cooling towers were not considered. J.E. Braun [24] introduced near-optimal control strategies under an electrical demand constraint based on a chiller sequencing model for a hybrid cooling plant. Both time-ofuse differentiated energy cost and demand cost were considered in his work. He proposed a chiller sequencing strategy considering the coefficient of performance of four different types of chiller. He also compared the result from the sequencing strategies with or without part-load control under different electrical demand limits.

2.4 Cooling Load Forecasting Used in Optimal Control

Another important aspect in the cost optimization of a cooling system is the cooling load forecasting. Because the operation of any cooling system is ultimately determined by the cooling demand which is affected ambient weather conditions, building occupancy, indoor activity and other factors, the optimal operation planning is achievable only when the cooling demand forecasting is accurate enough. More cost may occur with the

decrease of the forecasting accuracy. However, many optimization models in the literature were examined under the prefect information of cooling loads.

The current existing research focused more on the short-term cooling demand forecasting, due to the difficulty to achieve high accuracy in mid-term or long-term forecasting. Typically a 24-hour or 48-hour planning horizon was usually used in predictive control model in the literature for a short term scheduling, because a long-term cooling load forecasting with high accuracy is usually impossible due to the uncertainty. Because of this limit, the electrical demand cost and electrical ratchet cost was calculated based on a daily rate which was scaled from the monthly rate.

 However, a longer horizon, one week and month, may be necessary for mid-term and long-term scheduling, if other factors are taken into consideration. For instance, complex electricity cost structure and dynamic fuel prices are considered. Although the monthly electrical demand rate can be scaled to daily rate, it is obviously that the "cost optimization operation" obtained through this method may not be optimal. By focusing on the daily cost, the information and the overall mechanism of the entire month' cooling load profile, cooling system's operation and energy cost are concealed.

On the other hand, different forecasting models have different advantages and disadvantages. One simple method cannot achieve a high accurate forecasting result through the entire planning horizon. By comparing these models, a more sophisticated method could be developed, which combines several models together. Each model will be used to forecast the cooling demand during a specific time period based on it characteristic, so that it can overcome the disadvantage of other models.

Y. Ma et al. [17] used a straightforward method to predict the cooling load. By analyzing the previous cooling load profile, they established the upper and lower bounds of the cooling load, and used that for daily operation scheduling. It is obvious that although this straightforward method buffers the impact of demand uncertainty, the result cannot be considered as optimal.

One of the traditional methods of cooling load prediction is to establish a regression relation between weather parameters and cooling load. K.T. Chan et al. [4] analyzed the cooling load profile against different weather parameter – outdoor temperature, and the product of outdoor temperature and specific humidity. Their result showed there was significant difference between the profile of office and hotel buildings. However, the main problem of this method is there are always other factors, other than weather condition, affecting the cooling load. It is hard to include all the factors into a regression model, because of the availability and measurability of these parameters.

G.P. Henze et al. [18] compared four different load prediction models: unbiased random walk model, bin predictor model, harmonic predictor model and autoregressive network predictor model. They found the bin predictor model gave the best prediction among the four models, and they used the bin predictor model in their future work [16].

Because of the self-learning and self-calibrating ability in nonlinear problems, the neural network was often used for cooling load forecasting. However, an important input to a neural network, the building occupancy is usually difficult to measure. In work of J. Xu et al. [13], the cooling load was divided into two parts: thermal load that usually originated from lighting and other heat generating equipment, and uncontrollable load

that is usually related to outside weather condition, such as building occupancy, time, day, and season. The uncontrollable load is predicted through a multilayer perception neural network.

CHAPTER 3

MODEL

This section presents the structure of the methodology, assumptions, the energy cost model, cooling plant model, cooling load forecasting and cost-optimized operation planning model used in this research.

3.1 Structure of the Methodology

The Figure 3.1 shows the structure of the energy cost optimization operation methodology. In the real time implementation, the cooling plant model will be built based on the plant structure and the data base of operation parameters. Weather condition could be included if consideration of its influence is necessary. Based on the data base of the weather condition and cooling load profile, the cooling load forecasting model will be established and updated as the data base increases. By using the weather forecast from the weather station, the cooling load of the planning horizon is generated. By structuring the cost function, the cost-optimized operation planner will provide the operation decision for the lowest cost, based on the forecasted cooling load and plant model. Operation adjustment will be made after cost-optimized operation decision is generated according to the actual cooling load and the experience of human operators. The actual operation will in the end be recorded in the data base for future use.

Figure 3.1 Structure of cost-optimized operation methodology

Figure 3.2 Methodology structure of cost optimal operation planner

The detailed structure of cost-optimized operation planner is shown in the Figure 3.2. The initial value of electrical demand limit which is usually the lowest boundary of the feasible value is first generated. Then the operation decision of each unit in the system will be generated under the constraint of the electrical demand limit. Electrical chillers will be operated to generate the cooling capacity at the lowest level of electrical energy consumption. However, if the electrical chiller cannot provide enough cooling capacity under the electrical demand limit, the steam turbine chiller will be operated to generate the remaining cooling capacity. Once the operation decision variables for the entire planning horizon are generated, the total electrical energy, peak electrical demand and total fuel usage can be obtained. Total cost will be calculated by summing up the five terms in the cost function. Then incremental adjustment will be made to the peak electrical demand limit, and redo the above process again. After comparing the total cost among all the possible operation situations, the optimal operation decision will be displayed to the operator at last.

3.2 Nomenclature

The following mathematical symbols are used in this research.

Parameters and variables

α Demand ratchet factor

d Total cooling load

 β

E Function or value of electrical energy supply or consumption

- *F* Function or value of fuel consumption
- *M* Total number of steam turbine chiller
- *N* Total number of electric chiller
- *P* Peak electrical power supply or consumption

Subscripts

i Chiller

t Time period

K **Current month**

Superscripts

3.3 Assumptions

In this research, the following assumptions are made.

- There are *N* electric chillers, *M* steam turbine chillers and one boiler in the system.
- All equipment (chillers, boiler, pumps and cooling towers) is considered to have a constant energy efficiency performance over time. In addition, the efficiency will not be affected by other factors, such as weather and seasons.
- The temperatures of inflow and outflow chilled water are constant.
- The temperatures of inflow and outflow cooling tower water are constant.
- The steam generated by the boiler will only be used by steam turbine chillers to produce chilled water.
- There is no start-up cost for electric chillers, due to the insignificant start-up time and cost.
- The chillers can be turned off at the start of any time period and turned on at the start of the next time period, and vice versa.

3.4 Cooling Plant Energy Consumption Model

A central cooling plant generally consists of chillers, chilled water pumps, tower water pump and cooling towers, and the total electricity consumed should account for the electricity used by these four types of equipment.

The electricity consumed during a short time period by the electric chiller can be expressed as a quadratic regression function of its part load ratio (PLR). This general cooling plant modeling method was introduced by J.E. Braun [19].

$$
E_i^{EC} = E_i^{EC,D} \Big(a_{0,i} + a_{1,i} PLR_i + a_{2,i} PLR_i^2 \Big)
$$
 Eq 1

where $PLR_i = Q_i/Q_i^D$, and $a_{0,i}$, $a_{1,i}$, $a_{2,i}$ are the coefficients for the power-PLR regression function of the *i*th electric chiller.

Although the performance of chillers is always affected by the weather condition, the influence of the weather condition is beyond the scope of this research and not considered. However, adjustment can be made to achieve a more accurate result [19].

The electricity consumed by cooling towers and water pumps is complicated: it depends on the type of the driving motor and the structure of the cooling system. Generally, for variable speed drive cooling towers and water pumps, the electricity consumed by each unit can be expressed as a cubic regression function of its PLR. For constant speed drive cooling towers and water pumps, the electricity consumed is considered as a constant value. At the same time, if a chiller is solely served by a certain chilled water pump or tower water pump, then the operation decision of the pumps is related to that of chillers. On the contrary, if a chiller can be served by any of the chilled water pumps or tower water pumps in the system, the operation decision of the pumps is related to the total cooling load. More specific methodology for operation decision of water pumps and cooling towers was described by J.E. Braun [25].

Then the total electrical energy consumed by the cooling system through the entire time horizon *T* is

$$
E^{Total} = \sum_{t=1}^{T} E_t = \sum_{t=1}^{T} \left(\sum_{i=1}^{N} E_{t,i}^{EC} + E_{t}^{TWP} + E_{t}^{CWP} + E_{t}^{CT} \right)
$$
 Eq 2

where E_t is the electrical energy used by the entire cooling system in the short time period *t*. E_t consists of four part: $E_{t,i}^{EC}$ represents the electrical energy used by electric chiller *i* in the time period *t*. E_t^{TWP} , E_t^{CWP} and E_t^{CT} are the electrical energy used in the time period *t* by tower water pumps, chilled water pumps and cooling towers, respectively.

If the time period *t* is short enough or set to be the measurement period of electrical meters, E_t can be considered as electrical power/demand. Then the maximum peak electrical demand, P_{Max} , is the maximum of E_t throughout the entire time horizon T .

$$
P^{Max} = \max_{1 \leq t \leq T} \{E_t\} \qquad \qquad \text{Eq 3}
$$

In the same way, the fuel consumed during any short time period by the steam turbine chiller can also be expressed as a quadratic regression function of its PLR.

$$
F_i^{TC} = F_i^{TC,D} (b_{0,i} + b_{1,i}PLR_i + b_{2,i}PLR_i^2)
$$
 Eq 4

where $PLR_i = Q_i/Q_i^D$, and $b_{0,i}$, $b_{1,i}$, $b_{2,i}$ are the coefficients for the fuel-PLR regression function of the *i*th steam turbine chiller.

Then the total fuel used by the steam turbine through the entire time horizon *T* is

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

where F_t is the fuel used by the steam turbine chiller in the time period *t*, and F_t^S is the start-up cost of steam turbine chillers in the time period *t*. $F_{t,i}^{S}$ is a function determined by zero-one decision variables, $u_{t-1,i}$ and $u_{t,i}$.

Without losing generality, the cooling plant is assumed to be powered by secondary service line in this study. Thus the electrical energy terms described above have the following relations with the terms used in the cost function in Section 3.5.

$$
E_K^{SCI} = E_K^{Total}
$$
 Eq 6

$$
E_K^{SC} = E_K^{SC1} + E_K^{SC2}
$$
 Eq 7

$$
P_K^{SC1} = P_K^{Max} \qquad \qquad \text{Eq 8}
$$

$$
P_K^{SC} = P_K^{SC1} + P_K^{SC2} \tag{Eq 9}
$$

3.5 Cost Function

In this research, the cost function of a billing period (usually a calendar month) for a hybrid cooling plant consists of five terms: electrical energy cost, electrical demand cost, electrical facility cost, fuel cost and demand ratchet punitive cost. The total cost caused by the operation of the current month *K* is formulated as Eq 10.

$$
C_K^{\text{Total}} = C_K^{\text{EG}} + C_K^{\text{DM}} + C_K^{\text{FC}} + C_K^{\text{F}} + C_K^{\text{DR}} \tag{Eq 10}
$$

The first four terms on the right hand side are the costs that appeare in the bill of every month, and are defined as the current month billing cost.

The demand ratchet punitive cost does not appear in the bills of the summer months, but the bills for the following winter months. However, the demand ratchet is taken into account in a summer month, because the demand ratchet punitive cost is caused by the operation of the cooling system in that summer month. Then the demand ratchet cost

incurs as a punitive cost, only if the peak demand set by the summer month affects the demand ratchet level for the following winter months. If the current month is a winter month, then the first four terms make up the total energy cost, and there is no demand ratchet punitive cost, because the operation of the cooling system in the winter month does not affect any of the other 11 months.

In the electricity industry, a simple energy price policy with a single rate is rare for high demand customers [26-31]. Considering the persistent high demand and the burden on the grid, a special plan is usually designated for these customers. In such special plans, a time-of-use differentiated rate policy is usually applied to encourage the cost saving by reducing energy consumption during peak period. In some cases, not only different energy and demand rates are applied in peak and off-peak periods, but also demand ratchet policy is applied.

In this research, a more complex cost structure is studied. First, two electricity sources with different cost rates are considered. Different cost rates are usually applied to the electrical energy or electrical demand consumed from the two sources. One source is usually a national electricity supplier such as Western Area Power Administration (WAPA), and the other is a local supplier. For example, a customer may receive main part of the electrical supply from a national large wind field or large dams, while the rest is provided by local electricity generation plants.

Second, according to the different electrical voltages, the electricity is delivered through the primary service line and secondary one. In order to reduce the electrical energy lost on the electricity line, it is usually recommended that the electrical service be delivered at
a higher voltage, which is usually called primary service. However, a lower voltage service which is usually called secondary service exists due to special needs. The electrical services delivered through the two types of service usually have different cost rates.

Although the electrical service from two sources is delivered through both primary and secondary service lines, usually only the part of supply from the local suppliers is charged at different electrical service rates. The different cost rates based on service type are usually not applicable to national electricity supplier, because the electricity supply and cost rate for the national electricity supplier are fixed number based on the contract. Then the amount of primary and secondary services from local supplier is calculated according to the ratio of these two types of service recorded in total.

For example, if 6,000,000 kWh and 4,000,000 kWh are delivered through primary and secondary services respectively in January, then the total energy supply is 10,000,000 kWh. Therefore the ratios of the primary and secondary services against the total supply are 60% and 40%, respectively. Based on the contract, the national supplier supplied 7,866,000 kWh in January. By subtracting 7,866,000 kWh from the total supply, the balance provided by local supplier is 2,134,000 kWh. This balance of 2,134,000 kWh is then divided into two parts based on the ratio of 60% and 40%. Thus the primary electrical service provided by the local supplier is $2,134,000\times60\% = 1,280,400$ kWh, and the secondary electrical service is $2,134,000\times40\% = 853,600$ kWh.

Thus the electrical energy cost can be calculated through Eq 11.

$$
C_{K}^{EG} = c_{K}^{EG,W} E_{K}^{W} + c_{K}^{EG,PR,L} \frac{E_{K}^{PR}}{E_{K}^{PR} + E_{K}^{SC}} \left(E_{K}^{PR} + E_{K}^{SC} - E_{K}^{W} \right)
$$

+
$$
c_{K}^{EG,SC,L} \frac{E_{K}^{SC}}{E_{K}^{PR} + E_{K}^{SC}} \left(E_{K}^{PR} + E_{K}^{SC} - E_{K}^{W} \right)
$$

Eq 11

The demand cost is calculated in the same way as follows.

$$
C_{K}^{DM} = c_{K}^{DM,W} P_{K}^{W} + c_{K}^{DM,PR,L} \frac{P_{K}^{PR}}{P_{K}^{PR} + P_{K}^{SC}} \left(P_{K}^{PR} + P_{K}^{SC} - P_{K}^{W} \right)
$$

+
$$
c_{K}^{DM,SC,L} \frac{P_{K}^{SC}}{P_{K}^{PR} + P_{K}^{SC}} \left(P_{K}^{PR} + P_{K}^{SC} - P_{K}^{W} \right)
$$
 Eq 12

Because both the energy and demand consumed through the primary service line and secondary service line Part II are stable, the values of the current month are estimated by the average value recorded last year.

During the winter months, the demand ratchet policy is applied in addition to the basic policy mentioned above. The main idea of the demand ratchet is that the monthly billing demand from the local supplier for the winter months is the higher of either (1) the maximum demand during the month or (2) α of the highest maximum demand established by bills rendered in summer months before. Then the electrical demand cost in winter months is calculated by Eq 13.

$$
C_{K}^{DM,PR, L} = \begin{cases} c_{K}^{DM,WR}P_{K}^{W} & P_{K}^{PR} \\ + c_{K}^{DM,PR, L} \frac{P_{K}^{PR}}{P_{K}^{PR} + P_{K}^{SC}} \left(P_{K}^{PR} + P_{K}^{SC} - P_{K}^{W} \right) & P_{K}^{PR} + P_{K}^{SC} - P_{K}^{W} > R_{K} \\ + c_{K}^{DM,SC, L} \frac{P_{K}^{SC}}{P_{K}^{PR} + P_{K}^{SC}} \left(P_{K}^{PR} + P_{K}^{SC} - P_{K}^{W} \right) & \text{Eq 13} \\ c_{K}^{DM, W} P_{K}^{W} + c_{K}^{DM,PR, L} \frac{P_{K}^{PR}}{P_{K}^{PR} + P_{K}^{SC}} R_{K} & P_{K}^{PR} + P_{K}^{SC} - P_{K}^{W} \leq R_{K} \\ + c_{K}^{DM,SC, L} \frac{P_{K}^{SC}}{P_{K}^{PR} + P_{K}^{SC}} R_{K} & P_{K}^{PR} + P_{K}^{SC} - P_{K}^{W} \leq R_{K} \end{cases}
$$

Figures 3.3 and 3.4 illustrate the demand ratchet policy.

Figure 3.3 Billing demand when the actual peak demand is higher than demand ratchet

Figure 3.4 Billing demand when the actual peak demand is lower than demand ratchet

If the current month is a summer month, the value of demand ratchet of the current month is the higher of either (1) the demand ratchet of last month or (2) the new demand ratchet obtained based on the peak electrical demand established in the current month. If the current month is a winter month, then the value of demand ratchet of current month equals to the demand ratchet of the last month, and eventually equals to the highest demand ratchet set in the previous summer months. The demand ratchet is zero at the start of a new fiscal year starting from the first summer month. Thus the demand ratchet is expressed by the following equation.

$$
R_{k} = \begin{cases} 0 & k = 0\\ \max\{\alpha \left(P^{PR} + P^{SC} - P_{k}^{W} \right), R_{k-1} \} & \beta_{k} = 1\\ R_{k-1} & \beta_{k} = 0 \end{cases}
$$
 Eq 14

In some cases, the facility cost exists in addition to the demand cost. The facility cost can be considered as a special term of demand cost, because it is also charged based on the electrical power. The facility cost is the sum of the cost generated through both primary and secondary services, based on the total supply through each service and the different rates of each service. However, the national supplier does not charge the facility cost, while the local supplier charges all the facility cost. Thus even if some part of the electrical energy and demand comes from the national supplier through each service type, the facility cost is charged based on the total usage of each service type by local supplier. Because the operation decision of the chiller system does not affect the primary service line in this research, the facility cost of the current month *K* only includes the cost for the secondary service, and is calculated by the following equation. At the same time, the ratchet policy is also applied to the facility cost.

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

where the facility demand ratchet is as follows.

$$
r_{k} = \begin{cases} 0 & k = 0\\ \max\{\alpha P^{SC}, r_{k-1}\} & \beta_{k} = 1\\ r_{k-1} & \beta_{k} = 0 \end{cases}
$$
 Eq 16

According to the ratchet policy, when the actual peak electrical demand in a winter month is lower than the demand ratchet, the customer would pay more than the cost that calculated based on the actual peak electrical demand that they used during that winter month. The same situation appears in calculating the facility cost. This part of cost is

defined as the winter month ratchet cost. The sum of winter month ratchet costs for all winter months is defined as the demand ratchet punitive cost.

Although winter month ratchet cost does appear in the following winter months, it is rational to consider this cost in the summer months as a punitive cost, because it is mainly caused by the high peak electrical demand set during the summer months. Therefore, if the current month K is a winter month, there is no ratchet punitive cost. However, if the current month K is a summer month, the ratchet punitive cost equals to the greater of (1) the ratchet punitive cost caused by the operation of cooling plant in the previous summer months or (2) the sum of winter month ratchet costs for all winter months calculated based on the new peak electrical demand used in the current month *K*. Then the ratchet punitive cost of the current month *K* is as follows.

$$
C_K^{DR} = \beta_K \max \left\{ C_{K-1}^{DR}, \sum_{k=K}^{12} C_k^{DR} \right\}
$$
 Eq 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 through the basic policy based on the difference of the ratchet value and the actual value.

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

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

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

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

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

Because the actual peak electrical demand in the winter month *k*, after summer months is unknown, the value recorded in the last year, p_k , is used to estimate the future value.

3.6 Cooling Load Forecasting

In this section, two traditional forecasting models are presented and discussed. As this research is not meant to be a research which focuses on cooling demand forecasting, only the basic level work is conducted.

3.6.1 Time Series Model

The time series model is such a model that the current value of the cooling load, *d^t* , is only related to its past values, d_{t-1} , d_{t-2} , d_{t-3} , \dots . Usually, an autoregressive (AR) model or an autoregressive moving average (ARMA) model is applied. The advantage of this model is that it is easy to implement, because there is only one variable to the model which is the past value. In another word, the forecasting result is relatively independent of factors, such as ambient weather conditions and building occupancy. At the same time, this model usually promises an accurate short-term forecasting result. The model also has a quick response to the uncertainty and fluctuation. However, the accuracy decreases as the forecasting lead time increases, because the error in each time step will be accumulated to the next step. So it is not rational to use time series model for mid-term or long-term forecasting.

Different from time series model, the multiple regression model is a straight-forward model which tries to take all the factors into consideration. First order or second order regression is usually studied. The advantage of this model is that it is lead time independent. That is to say, the forecasting result is only related to the number of factors considered and the sufficiency of the data. But on the contrary there are several disadvantages. First, it depends on the accuracy of the estimation of each factor. Second, it is impossible to take all the factors into consideration. Third, the model usually does a bad job in response to the uncertainty. In order to overcome the shortage of the model, usually other works or strategies are needed. For example, one simple method is to take the variance into consideration and then add a safety factor into the forecasting result. Another method is to do an uncertainty analysis through variance analysis or outlier analysis, so that we can structure the uncertainty in the cooling load forecasting.

3.7 Cost-optimized Operation Planning Model and Solution Method

In this research, the planning horizon is *T* periods, which is set to be a billing cycle (a calendar month). If we change the PLR_i in Eq 1 and Eq 4 to the non-negative discrete integer decision variable $x_{t,i}$ and define $u_{t,i}$ as the zero-one decision variable in Eq 5 for the cost-optimized operation planning model, then for each chiller *i* at a time period *t* the operation state of that unit is denoted by these two variables. An electric chiller is off at time *t* if x_t _{*i*}=0, and on if x_t _{*i*}>0 and within the feasible operation range. A steam turbine chiller is off at time *t* if $u_{t,i} = 0$ while also $x_{t,i} = 0$, and on if $u_{t,i} = 1$ while also $x_{t,i} > 0$ and within the feasible operation range as well. Combined with the cooling load forecasting model

and the plant model, the predictive optimal control model is formulated as a mixedinteger nonlinear program (MINLP) as follows:

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

s.t.

$$
\sum_{i=1}^{N} Q_i^{EC,D} x_{t,i} + \sum_{i=1}^{M} Q_i^{TC,D} x_{t,i} \ge d_t \quad \forall t
$$
 Eq 24

where d_t is the cooling load in the time period t . The cooling load constraint ensures the cooling load generated is at least equal to the cooling load from campus.

Due to the general computational complexity of the MINLP, the real time implementation is usually limited. To overcome this problem, a dual stage optimization method is applied in this research by introducing another decision variable, y_K , the peak electrical demand limit of the secondary service in month *K*.

In the first stage, the optimal solution for each time period under the constraint of y_K and d_t is recast to a nonlinear program problem. There are two input values to the problem of first stage: the cooling load, d_t , and the peak electrical demand limit, y_K . For each time period, the cooling load is first met by the electric chillers under the constraint of y_K . If the electric chiller cannot provide enough cooling capacity, the portion of the cooling capacity that is not met by the electric chillers is then filled by steam turbine chiller. Therefore, the optimal solution of any time period is regarded as a function of cooling load and peak electrical demand limit. The optimal solution of the first stage is preprocessed and stored in data base. The second stage is then simplified to be an integer nonlinear program with only one decision variable – peak electrical demand limit, *yK*.

The advantages of this solution strategy are: 1) remove the repeating calculation for each individual time period; 2) greatly reduce the requirement of calculation capacity for real time implementation; 3) as the calculation for each individual time period with different inputs become a separate pre-process, the data base of the solution can be updated every time the plant model is updated.

By applying the dual stage solution strategy, the optimal production planning model becomes:

$$
z = \min_{u,x,y} C_K^{Total} = \min_{u,x,y} C_K^{EG} + C_K^{DM} + C_K^{FC} + C_K^F + C_K^{DR}
$$
 Eq 25

s.t.

$$
\sum_{i=1}^{N} Q_i^{EC,D} x_{t,i} + \sum_{i=1}^{M} Q_i^{TC,D} x_{t,i} \ge d_t \quad \forall t
$$
 Eq 26

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

$$
r_{K-1} \le y_K \tag{Eq 28}
$$

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

CHAPTER 4

CASE STUDIES

In this section, first the cost-optimized operation of the cooling plant at the University of Nebraska-Lincoln (UNL) City Campus in August 2010 is simulated based on the actual cooling load recorded in the same period. This simulation result is compared with the actual manual operation performed at that time. Second, simulated cost-optimized operation plans based on predicted cooling load profiles are also generated for the same period and compared with the above results.

4.1 Description of Case Study Conditions

The central cooling plant of the UNL City Campus is well designed to support the development and implementation of cost efficient technologies and practices, as the UNL has established an enhanced control system as well as a sufficient database.

The UNL City Campus cooling plant currently uses four electric chillers. Electric Chiller 1 has 5000 tons of maximum capacity, Electric Chiller 2 has 4500 ton capacity, and Electric Chillers 3 and 4 have 2000 each. By capacity, Electric Chillers 1 and 2 are called large chillers and Electric Chillers 3 and 4 are called small chillers. The designed electrical energy consumption rates of the four chillers are 4310 kW, 3030 kW, 1324 kW 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. The electric chillers are still responsible for the majority of the cooling load even when cooling load shifting occurs.

In addition, the cooling plant also uses one steam turbine chiller, one boiler, six tower water pumps, five chilled water pumps, three arrays of cooling towers, and a distribution loop serving each building of the campus. The steam turbine chiller has a maximum capacity of 5000 tons/h. It is driven by the 600 psi steam which is generated by the boiler. The pumps and cooling towers are all powered by electricity.

The cooling plant at the UNL City Campus is powered only by the secondary service. The electricity service supplied through 12kV and 4kV lines are considered as the primary service and secondary service respectively. For UNL, there are two lines of the secondary service. The first line is the only one currently supplying the electricity to the cooling plant.

The energy cost function and policy described in Section 3.5 are all applied to the case of UNL. The electricity rates of the local supplier are given in the Table 4.1. The rates and allocations of electrical demand and energy from national supplier are shown in the Table 4.2. The fuel rate is provided in Table 4.3.

| Rates | Winter Energy $(Oct-May)$ (\$/kWh) | Summer Energy $(Jun-Sep)$ (\$/kWh) | Demand (\$/kW) | Facilities (\$/kW) |
|-----------|--|---|-------------------|------------------------------|
| Primary | 0.0205 | 0.0282 | 12.70 | 4.00 |
| Secondary | 0.0200 | 0.0272 | 13.05 | 4.40 |

Table 4.1 Electricity rates of local supplier [32]

Table 4.2 Rates and allocations of electrical demand and energy from national supplier

[33,34]

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

Table 4.3 Fuel cost rate [34]

In this research, the start-up cost only contains the cost for warming up the steam turbine chiller. The boiler is always standby to use, because additional steam is needed to reheat the cooling air to meet the different temperature set points for different sections of the buildings on campus. The steam turbine chiller usually takes about 2 hours to warm up to standard working condition.

4.2 Current Manual Operation

The cooling system at the UNL City Campus is operated manually based on the experience of the human operators by the following strategy. The control system keeps measuring the temperatures of inflow and outflow cooling water. If there is an increase in the difference between the inflow and outflow temperatures, the operator will adjust the part load ratio of the operating chillers or turn on another chiller to increase the cooling capacity, and vice versa if there is a decreased temperature difference.

At the same time, the operator decides the operation of steam turbine chiller to shift cooling load from electric chiller by using the following 10 days' weather forecast (mainly the temperature) every early morning. If there is a high temperature within the near future, for example for the next 2 days, the operators will judge based on their experience if it is necessary to operate the steam turbine chiller in that day to shift part of the cooling load from the electric chillers. If the load shifting is expected, the operator will warm up the steam turbine chiller in the early morning of that day. The operator determines when the steam turbine chiller should be turned on and how much cooling load should be shifted all based on his past experience.

The manual operation profile of August 2010 is shown in Figure 4.1.

Figure 4.1 Manual operation profile of August 2010 (continues on the next page)

Figure 4.1 Manual operation profile of August 2010 (continued from the previous page)

Under the current manual operation strategy, Electric Chillers 1 and 2 are operated most often. The two big chillers provide most of the cooling capacity. The cooling load is generally assigned to Electric Chillers 1 and 2 according to the ratio of their designed capacity. Electric Chiller 3 is operated to cope with the load fluctuation, even if Electric Chillers 1 and 2 are not at their full part load ratio. Electric Chiller 4 is only operated in case of breakdown or maintenance of other chillers. Generally, the steam turbine chiller is operated when the total campus cooling load is greater than 9000 tons/hour.

4.3 Simulated Cost-optimized Operation under the Perfect Information of the Cooling Load

4.3.1 Simulated Cost-optimized Operation

In this section, the simulated cost-optimized operation decision for each hour is generated through the cost-optimized operation planner based on the 744 data points of actual cooling load of the City Campus recorded in August 2010. The simulation is conducted under the perfect information of the cooling load throughout the entire billing cycle (the colander month of August 2010), and performed using the methodology and modes through the dual-stage solution method described in Chapter 3. The optimization is performed by a computer program written on Matlab \otimes [34]. The time horizon is set to be a billing period (the calendar month of August 2010).

In the current manual operation (shown in Figure 4.1), the two big chillers meet the main part of the cooling load and the two small chillers cover some peaks and fluctuation. But the generated optimal solution indicates operating the chillers based on their efficiency: meet the main part of cooling load by using the two small electric chillers which are more efficient, and operate Electric Chiller 3 only when extra capacity is needed. Operating Electric Chiller 1 is the least economical choice.

The cost-optimized operation planning also suggests that the steam turbine chiller should be operated more often. When the cooling load is greater than 7,000 tons/hour (the Chillers 3 and 4 are operated at the full part load ratio and Chiller 2 is operated at the part load ratio of 80%), it could be more economical to use the steam turbine chiller to cover the rest portion of the cooling load which is higher than 7,000 tons/hour.

The result of cost-optimized operation profile is plotted in Figure 4.2.

Figure 4.2 Simulated cost-optimized operation profile of August 2010 under the perfect information of cooling load (continues on the next page)

Figure 4.2 Simulated cost-optimized operation profile of August 2010 under the perfect information of cooling load (continued from the previous page)

Figures 4.3 and 4.4 illustrate cost terms between the simulated cost-optimized operation and actual manual operation. In those two graphs, the individual cost terms in the current month billing cost and the total cost are compared between the current manual operation and the simulated cost-optimized operation.

Figure 4.3 Comparison of individual cost terms in the current month billing cost between simulated cost-optimized operation and actual manual operation

Figure 4.4 Comparison of monthly and total costs between simulated cost-optimized operation & actual manual operation

Because of the non-linear characteristic of the cost function, especially the demand cost and the demand ratchet punitive cost, the steam turbine chiller is more economical if the cooling load is greater than some threshold value. Shifting more or less cooling load both increases the total cost. The electric chiller is usually more economical than the steam turbine chiller under a simple cost rate, but as it is shown in Figure 4.3, shifting the cooling load from electric chiller to steam turbine results in a reduction in electrical energy cost of \$20,000. However, the cooling load shifting increases the fuel cost by \$29,000.

Determining the cooling load shifting point and the electrical demand limit are critical in achieving the lowest energy cost in summer months. By using more of the steam turbine chiller, the current month billing cost does not reduce significantly in August 2010. That is because as it is shown in Figure 4.3, the reduction of the electrical energy cost,

electrical demand cost and electrical facility cost is not sensitive to the load shifting to the steam turbine chiller, but the fuel cost is. However, the total cost is greatly reduced by reducing the demand ratchet punitive cost significantly. Figure 4.4 indicates that the demand ratchet punitive cost is very sensitive to the load shifting to the steam turbine chiller, because the load shifting to the steam turbine chiller significantly reduces the peak electrical demand. A decrease of 700 kW of peak demand eventually results in a reduction of the demand ratchet punitive cost by half.

4.4 Simulated Cost-Optimized Operations Based on the Predicted Cooling Load¹

In this section, the simulation of cost-optimized operation is generated using the predicted cooling load. The cooling load is predicted using the time series and multiple regression models. The cost of these operation profiles are compared with the actual cost and the cost under the perfect information of the cooling load (Section 4.3).

4.4.1 Cooling Load Forecasting Based on a Time Series Model

Based on the analysis of the cooling load data of August 2010, an auto-regression model is obtained through $SAS \otimes [35]$.

$$
d_{t} = 1.23711 d_{t-1} - 0.10793 d_{t-2} + 0.05339 d_{t-3}
$$

- 0.01545 d_{t-4} - 0.08777 d_{t-5} - 0.02061 d_{t-6}
Eq 30

The forecasting results with different lead time are shown in Figure 4.5. Only the first 250 data points are shown in the graph.

¹ Amey Patwardhan also worked for the forecasting.

Figure 4.5 Cooling load forecasted by AR(6) model with different lead times

The one hour ahead forecasting result shows the best fitting. There is only little difference between the one-hour-ahead forecasting result and actual cooling load. The six hours ahead forecasting still gives good predictions, but with a less, however acceptable accuracy and lag. The 12 hours and 18 hours ahead forecasting result is far away from the actual demand with significant lag, due to the accumulating errors as the lead time increases. The 24 hours ahead forecasting result is better than the 12 hours and 18 hours ahead forecasting result.

In this research, a multiple regression model with independent variables of temperature and humidity is established based on the demand and weather data of August 2010. The regression model obtained through SAS® [35] is given as follows.

$$
d_{t} = 1755 + 224 * temperature_{t} - 10 * humidity_{t}
$$
 Eq 31

By using this model, cooling load is forecasted and compared with actual cooling load in the Figure 4.6.

Figure 4.6 Cooling load forecasted by multiple regression model

The prediction does not show a satisfactory result. The R^2 of the regression model is 0.42, which means some important factors that affect the cooling load from the campus are not included. Out of 744 data points, there are 340 points of predicted cooling load which have a difference less than 1000 tons comparing to the actual values, and 403 points out of 744 which are greater than the actual values.

The multiple regression model fails to predict six critical peaks where the difference between the actual values and predicted values are greater than 1,000 tons. According to the discussion in Section 4.3.2, these peaks are critical to the demand cost and ratchet cost. The separate detailed analysis of the relevant data shows that these unpredicted peaks are usually caused by the uncertainty of building occupancy. For example, oncampus events are one of the factors that result in the uncertainty.

Although the model also fails to predict the some valleys, these are not critical to the total cost and it can be overcome by manual adjustment of the operation. The overestimation of the building occupancy and activity during the night time may have caused these unpredicted valleys. However, accurate prediction of these valleys would have saved the electrical energy cost.

4.4.3 Comparison of Error of Prediction between the Two Models

Figure 4.7 presents the comparison in term of root mean square errors of prediction for planning horizons length of zero to 24 hours between auto-regression model and multiple regression model. Because the load data follows a seasonal pattern of 24 hours, the error of prediction also shows a seasonal pattern. Compared with the simple regression model, the auto-regression model provides a more accurate prediction with a lead time less than 5 hours. As the error increases with the lead time, the multiple regression model has a better performance with a horizon length between 5 hours and 19 hours. Due to the seasonal pattern, the auto-regression model become better when the horizon length is between 19 to 29 hours. Thus a mixed model of auto-regression model and multiple

regression model would have provided a good prediction within the proper horizon length according to the Figure 4.7.

Figure 4.7 Root mean square errors of prediction for different lead time

4.4.4 Simulated Cost-optimized Operation Based on Cooling Load Predicted by Multiple Regression Model

Table 4.3 shows the energy usage and each individual cost terms of simulated costoptimized operation based on the predicted cooling load through multiple regression model. In Table 4.3 the actual values and the values obtained through the simulation in Section 4.3.2 and are also listed for comparison.

| | Simulated Cost- optimized Operation Based on Predicted Cooing Demand | Simulated Cost- optimized Operation Based on Actual Demand | Actual Value |
|---|--|--|---------------------|
| Total Cooling Load (kTons) | 4,414 | 4,414 | 4,414 |
| Total Electrical Energy (MWh) | 4,400 | 4,445 | 4,929 |
| Peak Electrical Demand (kW) | 5,929 | 6,579 | 7,401 |
| Total Fuel (MMbtu) | 10,816 | 8,613 | 3,754 |
| Electrical Energy Cost (\$) | 78,454 | 79,734 | 100,133 |
| Electrical Demand $Cost($ \$) | 74,725 | 82,942 | 93,402 |
| Electrical Facility $Cost (\$)$ | 63,615 | 66,475 | 67,800 |
| Fuel Cost $(\$)$ | 65,764 | 52,366 | 22,824 |
| Monthly Cost $(\$)$ | 282,560 | 281,520 | 284,159 |
| Demand Ratchet Punitive Cost (\$) | 97,444 | 135,810 | 276,976 |
| Total Cost (\$) | 380,000 | 417,330 | 561,135 |

Table 4.4 Simulated cost-optimized results & actual value

The total cooling loads produced are the same for the three cases. But because the multiple regression model fails to predict some critical peaks, the peak electrical demand of simulated cost-optimized operation based on the predicted cooling load through multiple regression model is lower than the value of simulated cost-optimized operation based on the actual cooling load. Therefore, it is more often that steam turbine chiller is operated to shift peak cooling load, as the maximum peak cooling load is lower. Thus the total cost is the lowest among the three cases. However, because there is only about half chance that the predicted cooling loads are greater than the actual cooling loads, the result does not well represent the actual situation.

4.5 Simulated Cost-Optimized Operations with Simple Conservative Strategy

In this section, a Monte Carlo simulation of cost-optimized operations based on the cooling load predicted by multiple regression model with random uncertainty is first conducted. The best and worst cases in term of total cost are compared with the actual operation and the cost-optimized operation under perfect information of cooling load.

A simple conservative strategy of cooling load forecasting is then introduced to buffer the impact of uncertainty in cooling load. The strategy is evaluated, by comparing to the actual operation and the cost-optimized operation obtained through the simulation in Section 4.3.2.

4.5.1 Monte Carlo Simulation for Evaluation of Uncertainty in Cooling Load

To evaluate the influence of uncertainty, a Monte Carlo simulation is conducted. The set of cooling loads is generated as follows:

$$
d_{t} = 1755 + 224 * temperature_{t} - 10 * humidity_{t} + random_{t}(N(0, \sigma))
$$
 Eq 32

where σ is the standard deviation of 744 data points of actual cooling load, which starts from 12:00 am August $1st$ 2010 to 12 am September $1st$ 2010 and measured by one hour interval.

Table 4.4 gives the best and worst simulation results in terms of the total cost among 100 trails.

| | Monte Carlo Simulation Result | | Simulated Cost-optimized Operation Based on Actual | Actual Value |
|---|----------------------------------|-------------------|--|---------------------|
| | Best Case | Worst Case | Demand | |
| Total Cooling Load (kTons) | 4,623 | 4,500 | 4,414 | 4,414 |
| Total Electrical Energy (MWh) | 4,490 | 4,690 | 4,445 | 4,929 |
| Peak Electrical Demand (kW) | 6,929 | 8,329 | 6,579 | 7,401 |
| Total Fuel (MMbtu) | 11,407 | 7,367 | 8,613 | 3,754 |
| Electrical Energy $Cost($ \$) | 80,985 | 86,567 | 79,734 | 100,133 |
| Electrical Demand $Cost (\$)$ | 87,367 | 105,080 | 82,942 | 93,402 |
| Electrical Facility $Cost($ \$) | 68,015 | 74,175 | 66,475 | 67,800 |
| Fuel Cost $(\$)$ | 69,356 | 44,790 | 52,366 | 22,824 |
| Monthly Cost $(\$)$ | 305,720 | 310,610 | 281,520 | 284,159 |
| Demand Ratchet Punitive Cost (\$) | 159,260 | 264,980 | 135,810 | 276,976 |
| Total Cost (\$) | 464,980 | 575.590 | 417,330 | 561,135 |

Table 4.5 Monte Carlo simulation result

As discussed in Section 4.4.3, by using the multiple regression model, it is more likely that the cooling plant could make saving from shifting part of the peak cooling load from electric chillers to the steam turbine chiller. However, due to the uncertainty of the cooling load, the Monte Carlo simulation shows there is a chance that the operation of the cooling plant may cost more than the actual manual operation. Although in the worst case the steam turbine chiller is used more than actual operation, the cooling plant still hit its peak electrical demand of 8329 kW, which is 900kW higher than actual value. Because of the high cost in the current month, even if the demand ratchet punitive cost is little reduced comparing to the actual value, the cooling plant still needs to pay more in total. However, the best case provides an estimation of the peak electrical demand. The peak

electrical demand in the best case is only 350kW higher than the value obtained through the simulated cost-optimized operation based on actual demand, which is within an acceptable range.

4.5.2 Simulations for Evaluation of a Simple Conservative Strategy

In order to buffer the impact of uncertainty and avoid those unpredicted peaks, a conservative strategy with different levels of safety factor is applied. By applying the simple conservative strategy, the cooling load is predicted as follows:

$$
d_{t} = 1755 + 224 * temperature_{t} - 10 * humidity_{t} + z\sigma
$$
 Eq 33

where *z* is the safety factor and σ was the same standard deviation of the actual cooling load using in Section 4.5.1.

Figure 4.8 Predicted cooling load with different conservative level

As shown in the Figure 4.8, one sigma conservative level prediction does not improve much compared with the non-conservative prediction. It still does not cover some critical peaks. Two sigma conservative level prediction well coveres these peaks, while three sigma conservative level prediction is high than all the peaks.

The cost of simulated operation is given by Table 4.4.

Table 4.6 Simulated cost-optimized operation result based on cooling load forecasting

with different level conservative levels

 Generally, the simple conservative prediction costs more. Although applying simple conservative strategy improves the number of points where the predicted cooling load is higher than actual value, as more production of cooling load is needed, more cost occurs. One sigma conservative level is the most cost efficient one. By applying one sigma conservative level, the number of points where the predicted cooling load is higher than actual value increases from 378 to 610, by 232, while the total cost is still lower than the actual total cost caused by the current manual operation of cooling plant in August 2010. Compared with one sigma conservative level, two and three sigma conservative levels cost much more than the actual total cost. However, one sigma conservative level still fails to predict some peaks, but two sigma conservative level provided a good prediction. On the other hand, the conservative strategy is not necessary for all peaks. As discussed in Section 4.4.2, because the prediction without conservative strategy has already well predicted most of the peaks, it is more appropriate that the conservative strategy is applied if there is a special event on campus which would lead to an unexpected high peak of cooling load. Meanwhile, different conservative levels should be applied based on the analysis of the event's impact on cooling load. Thus according to the Figure 4.7, one to two sigma might be a reasonable range of conservative level.

At the same time, the simple positive conservative strategy is not necessary for night time. As discussed in the Section 4.4.2, the valleys of cooling load during night time are not critical to the cost, and the influence of the difference can be avoided by manual adjustment. More importantly, these valleys of actual cooling load are more likely to be lower than the prediction without conservative strategy, so it is rational to have a negative conservative strategy for night time instead of a positive conservative strategy. According to the Figure 4.7, one to two sigma could also be a reasonable range of negative conservative level.

There is also a trend for high peaks or low valleys in the load profile. If there would be a high peak in a day which is much higher than the predicted peak, the actual cooling load tends to be much higher than the predicted load even at the low cooling load level in the same day. The same situation happens to the low valleys too. That is to say, if the actual cooling load in the early morning, for example 8 am to 11 am, is much high than the predicted cooling load, it is likely that there will be a high peak in that day.

CHAPTER 5

CONCLUSIONS

5.1 Summary and Contributions

This research introduced a general methodology for the cost-optimized operation of a hybrid central cooling plant. This research established a mixed integer non-linear program of the chiller operations, by integrating the complex characteristics of component efficiency, multiple energy sources, electrical energy cost, electrical demand cost, electrical ratchet cost, and energy consumption from other facilities. To reduce the required computation of the mixed integer non-linear program for real time implementation, a dual stage solution method was applied by introducing the electrical demand limit as a constraint. Through the case studies simulated based on the past operation and weather data, the methodology and mathematic model were also verified for their effectiveness. The case study result indicated a good potential saving in the total energy cost if the developed methodology was applied.

This study provides a generalized cost-optimized operation-planning model for a hybrid cooling plant under a complex cost structure. Although the detailed consideration of the utility cost structure is essential for optimal control of a cooling system [18], the majority of the existing research is based on the assumption that the cooling system is powered by a single electrical energy source, and the cooling system is considered as a separate system and charged separately from other facilities in the same organization. For example, for a hybrid cooling plant model by J.E. Braun [24], only time-of-use differentiated

energy cost and demand cost were considered; the cooling plant was considered as an isolated system and powered by a single electrical energy source. Although in the model by J. Xu et al. [13] the 11-months ratchet cost was taken into consideration, the cooling system in their model was also a separate energy system from other facilities. In this research, in addition to the demand ratchet cost, the cooling plant's dual electrical energy sources—national and local suppliers were considered. In addition, this study considers that the electricity is delivered through primary and secondary services with a time-of-use differentiated cost rate. The electricity consumption from other facilities in the same organization is also taken into consideration. Therefore, the model in this research provides more generalized cost functions and enhances the cost-optimized operation decision for a hybrid cooling system.

5.2 Future Work

The first direction of future work is to improve the plant model and the cost-optimized operation planner for a more realistic practice by introducing more operation constraints. For example, because the weather condition will affect the performance of the cooling plant, the performance under different operation condition should be evaluated and the plant model considering the weather condition should be developed. In addition, constraint on the changes of the on-off status of chillers is a necessary, because it is not economic to change the on-off status of chillers too frequently. The frequent change will greatly reduce the reliability and lifetime of the equipment. These considerations are necessary for a more practical model.

The second direction of the future work is to develop a cost-optimized operation planning model with direct digit control technology. Thus a global control of a hybrid cooling system with multiple energy sources under complex electricity cost structure will be developed. In such a cooling system with direct digit control, the temperature of the cooled air will be adjusted by controlling the inflow rates of air and chilled water. More saving can be expected by implementing such a system. Thus, the development of the cost-optimized operation-scheduling model with a direct digit control technology will be one area of the future work.

The third direction of the future work could be the development of a sophisticated cooling load forecasting model combined with a proper conservative strategy and dynamics of cooling load. Because this research focuses more on a deterministic case of cooling load, the planning horizon can easily be set to be a billing period. However, in real time implementation it is not rational or feasible to provide a cooling load forecasting of the entire billing period. Ten days is usually the maximum time length for reliable weather forecasting, and thus the maximum time length for cooling load forecasting. Therefore, it is necessary to conduct a more sophisticated study on the dynamics of the cooling load.
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APPENDIX A

MAT LAB PROGRAM CODE

clc;

alpha= 0.65 ; beta=0.415795; gama=0.005; $a=[1 1 1 1 0 0 0 0 0 0 0 0$;]; $k=3$; T=744; Y=[16002 16816 16537 15979 12278 9320 7715 7268 8885 8953 9029 11011;];

%% Actual number %% e_pr=10217; %% Average number %% e_pr=9897; e_pr=[9291 9975 10436 10217 9732 10240 9581 8493 9070 9826 8335 8389;];

%% Actual number E_pr=5154251; %% Average number %% E_pr=4890099;

%% Actual number

e_sc2=7858;

%% e_sc2=[6811 7963 7963 7753 6725 6437 6277 6413 6631 6982 7697 7025;];

%% Average number

%% e_sc2=7056;

%% Actual number

E_sc2=3847282;

%% Average number

%% E_sc2=3503423;

e_w=[18740 18965 18965 18196 17745 14220 14015 14220 14220 14220 14220 17630;]; E_w=[9985000 9824000 10581000 9396000 8197000 7580000 7388000 7866000 7539000 7747000 7499000 8491000;];

c_dm_pr_l=[12.40 12.40 12.40 12.40 12.40 12.40 12.40 12.70 12.70 12.70 12.70 12.70;]; c_eg_pr_l=[0.0272 0.0272 0.0272 0.0272 0.0200 0.0200 0.0200 0.0200 0.0200 0.0200 0.0200 0.0200;];

c_dm_sc_l=[12.75 12.75 12.75 12.75 12.75 12.75 12.75 13.05 13.05 13.05 13.05 13.05;]; c_eg_sc_l=[0.0282 0.0282 0.0282 0.0282 0.0205 0.0205 0.0205 0.0205 0.0205 0.0205 0.0205 0.0205;];

c_fc=[4.40 4.40 4.40 4.40 4.40 4.40 4.40 4.40 4.40 4.40 4.40 4.40;];

 $c_f = 6.08$;

r=10919;

R=4400;

r e sc2=6400;

P_EC1=500;

P_EC2=450;

P_EC3=200;

P_EC4=200;

P_TC=250;

E_EC1=431.08;

E_EC2=302.99;

E_EC3=132.42;

E_EC4=132.42;

 $E_TC=2.8;$

 T SU=3;

mintotalcost=100000000000000;

demand=zeros(1,T);

%% Actual demand

B3

%% Predicted demand

%% for $i=1:1:T$

 $%%$ demand(1,i)=161.72*tf(1,i)-6081;

 $%$ % end

```
%% Predicted demand plus one SD 
%% for i=1:1:T%% demand(1,i)=161.72*tf(1,i)-6081+1264; 
%% end
```

```
%% Predicted demand plus two SDs
```
%% for $i=1:1:T$

%% demand(1,i)=161.72*tf(1,i)-6081+2*1264;

%% end

%% Predicted demand plus three SDs

%% for $i=1:1:T$

%% demand(1,i)=161.72*tf(1,i)-6081+3*1264;

 $\%$ % end

%% Monte Carlo Simulation

%% actualdemand=[4827 4624 4716 4483 4574 4838 5119 5381 6131 6385 6807 6747 6699 6690 6768 6764 6783 6848 6613 6326 6174 6360 5776 5385 5071 4913 5132 5027 5522 5953 7721 8272 9291 8996 10087 10587 10406 10582 10694 10310 10157 9114 9204 9002 8542 8340 7751 7746 7066 6556 6793 6967 6259 6656 8035 8935 9292 9527 9711 9653 9948 10205 10158 9946 9018 9332 7832 7413 7496 6875 6328 6172 5605 5598 5441 5635 5808 7003 9028 9692 9393 9607 9339 9256 8985 9092 9025 8727 8592 7330 5797 6382 5818 5606 5397 4870 4570 4433 4363 4357 4554 5760 7214 6967 7775 8326 8364 8505 8495 8274 8730 8317 8069 7173 5221 5517 5288 4881 4763 3987 3474 3477 3443 3548 3815 4444 6387 6770 6680 6789 7100 7426 7889 8254 8302 8371 8449 7514 6187 5996 5481 5584 5424 4820 4121 3993 4004 3995 3998 3877 4548 5051 5491 6001 6532 6594 6528 6395 6563 5974 6491 6421 6397 6348 6172 6038 5775 5340 5056 5025 5063 4887 4836 4960 5670 6133 6450 6761 7390

7150 7345 7192 7379 6990 6699 5981 5675 5388 4668 4603 3991 3416 2947 3392 3153 3200 3860 4915 4960 5697 6282 6838 7122 6991 7154 7179 7098 7170 5917 5406 5008 4697 4631 4564 3543 3081 3022 3092 2590 2611 2984 3017 3392 3930 4524 4992 5130 5381 5503 5751 5919 5774 5486 5402 5087 4677 4749 4324 3666 3420 3189 3131 3018 2612 2704 3629 3543 3790 4999 5058 5874 6096 6800 6849 6835 6441 6030 5920 5990 5704 5400 5200 4713 4881 4640 4484 4495 5624 6148 7504 8079 8421 8829 8667 9989 10232 10595 10866 10915 10616 9165 8495 7583 7217 6588 6240 5769 5504 5447 5349 5351 5468 6079 8900 9322 9724 10211 10348 10465 10605 10959 11054 10753 10912 10417 9251 8644 7179 6602 5700 4853;];

- %% expectdemand=161.72*tf-6081;
- %% maxsimucost=0;
- %% minsimucost=1000000;

%% for $x=1:1:50$

- $%%$ demand=zeros(1,T);
- $%$ % randomdemand=normrnd $(0,1264,1,T);$
- %% demand=expectdemand+randomdemand;

```
for y=7200:50:7600
```

```
%%for y=r_e_sc2:200:12000
```

```
%%for y=r_e_sc2:400:18400
```

```
 tempoperation=zeros(5,T);
```
judge=1;

totalenergy=0;

totalgas=0;

```
 startup=0;
```

```
for t=1:1:T
```

```
 hourlygas=0;
```

```
if judge==0
```
break

```
 end
```

```
 minhourlyenergy=100000000000; 
 maxsupply_ec=0; 
 for ec1=0:1:10 
   for ec2=0:1:10 
      for ec3=0:1:10 
        for ec4=0:1:10 
           if ec1<5 
             partload(1,1)=0; else 
             partload(1,1)=ec1;
           end 
           if ec2<5 
             partload(2,1)=0; else 
             partload(2,1)=ec2; end 
           if ec3<5 
             partload(3,1)=0;
           else 
             partload(3,1)=ec3;
           end 
           if ec4<5 
             partload(4,1)=0;
           else 
              partload(4,1)=ec4; 
           end 
          E_se=0;
           if demand(1,t)>0.1 && demand(1,t)<2000.1 
              E_se=946.6; 
           end 
           if demand(1,t)>2000.1 && demand(1,t)<4000.1
```

```
 E_se=1127.6; 
 end 
 if demand(1,t)>4000.1 && demand(1,t)<4500.1 
   E_se=1530.1; 
 end 
if demand(1,t)>4500.1 && demand(1,t)<6500.1
   E_se=1847.8; 
 end 
if demand(1,t)>6500.1 && demand(1,t)<8500.1
   E_se=2086.4; 
 end 
 if demand(1,t)>8500.1 && demand(1,t)<9000.1 
   E_se=2852; 
 end 
 if demand(1,t)>9000.1 && demand(1,t)<9500.1 
   E_se=2993.8; 
 end 
 if demand(1,t)>9500.1 && demand(1,t)<11500.1 
   E_se=3174.8; 
 end 
 if demand(1,t)>11500.1 && demand(1,t)<13500.1 
   E_se=3940.4; 
 end
```

```
E_ec=E_EC1*partload(1,1)+E_EC2*partload(2,1)+E_EC3*partload(3,1)+E_EC4*partlo
ad(4,1);
```
if E_ec+E_se<y

supply_ec=P_EC1*partload(1,1)+P_EC2*partload(2,1)+P_EC3*partload(3,1)+P_EC4*p $artload(4,1);$

if supply_ec<demand(1,t)

```
if partload(4,1)=10if partload(3,1)=10if partload(2,1)=10if partload(1,1)=10 for tc=0:1:20 
                                                       if tc<5 
                                                           partload(5,1)=0;
                                                       else 
                                                           partload(5,1)=tc; end 
                                                       supply_tc=P_TC*partload(5,1); 
                                                       if supply_tc>demand(1,t)-supply_ec 
                                                           for i=1:1:5tempoperation(i,t)=partload(i,1);end on the contract of the con
                                                            hourlyenergy=E_se+E_ec; 
                                                            minhourlyenergy=hourlyenergy; 
                                                           hourlygas=E_TC*partload(5,1);
                                                            break 
                                                       end 
end and the state of the st
```
else

adjustpartload=partload(1,1)+1;

adjust_E_ec=E_EC1*adjustpartload+E_EC2*partload(2,1)+E_EC3*partload(3,1)+E_EC 4*partload(4,1);

> if adjust_E_ec+E_se>y if supply_ec>maxsupply_ec if demand(1,t)-supply_ec>20*P_TC hourlyenergy=1000000000; else

```
 maxsupply_ec=supply_ec; 
                                                                   for tc=0:1:20 
                                                                       if tc<5 
                                                                           partload(5,1)=0;
 else 
                                                                           partload(5,1)=tc;end of the state of the sta
                                                                      supply_tc=P_TC*partload(5,1);
                                                                       if supply_tc>demand(1,t)-supply_ec 
                                                                           hourlyenergy=E_se+E_ec; 
                                                                           if hourlyenergy<minhourlyenergy 
                                                                               for i=1:1:5tempoperation(i,t)=partload(i,1); end 
                                                                                minhourlyenergy=hourlyenergy; 
                                                                               hourlygas=E_TC*partload(5,1);
end on the state of the sta
break break break and the state of the s
```
end

end of the contract of the con

end on the contract of the con

end

else

hourlyenergy=1000000000;

end

end

else

adjustpartload=partload(2,1)+1;

adjust_E_ec=E_EC1*partload(1,1)+E_EC2*adjustpartload+E_EC3*partload(3,1)+E_EC 4*partload(4,1);

```
 if adjust_E_ec+E_se>y 
                                                           if supply_ec>maxsupply_ec 
                                                               if demand(1,t)-supply_ec>20*P_TC 
                                                                     hourlyenergy=1000000000; 
                                                                else 
                                                                     maxsupply_ec=supply_ec; 
                                                                     for tc=0:1:20 
                                                                          if tc<5 
                                                                              partload(5,1)=0;
 else 
                                                                              partload(5,1)=tc;end of the contract of the con
                                                                         supply_tc=P_TC*partload(5,1);
                                                                         if supply_tc>demand(1,t)-supply_ec 
                                                                               hourlyenergy=E_se+E_ec; 
                                                                               if hourlyenergy<minhourlyenergy 
                                                                                   for i=1:1:5tempoperation(i,t)=partload(i,1); end 
                                                                                    minhourlyenergy=hourlyenergy; 
                                                                                   hourlygas=E_TC*partload(5,1);
end of the state of the sta
                                                                               break 
end of the state of the sta
end on the contract of the con
 end 
end and the state of the st
                                                      else 
                                                          hourlyenergy=1000000000;
                                                      end
```
end

else

adjustpartload=partload(3,1)+1;

```
adjust_E_ec=E_EC1*partload(1,1)+E_EC2*partload(2,1)+E_EC3*adjustpartload+E_EC
4*partload(4,1); 
                       if adjust_E_ec+E_se>y
```
 if supply_ec>maxsupply_ec if demand(1,t)-supply_ec>20*P_TC hourlyenergy=1000000000; else maxsupply_ec=supply_ec; for tc=0:1:20 if tc<5 partload $(5,1)=0$; else $partload(5,1)=tc;$ end on the contract of the con supply_tc=P_TC*partload(5,1); if supply_tc>demand(1,t)-supply_ec hourlyenergy=E_se+E_ec; if hourlyenergy<minhourlyenergy for $i=1:1:5$ $tempoperation(i,t)=partload(i,1);$ end and the state of the st minhourlyenergy=hourlyenergy; hourlygas=E_TC*partload(5,1); end of the contract of the con break end on the state of the sta end end

 end else hourlyenergy=1000000000; end end else adjustpartload=partload(4,1)+1;

```
adjust_E_ec=E_EC1*partload(1,1)+E_EC2*partload(2,1)+E_EC3*partload(3,1)+E_EC4
*adjustpartload;
```
 if adjust_E_ec+E_se>y if supply_ec>maxsupply_ec if demand(1,t)-supply_ec>20*P_TC hourlyenergy=1000000000; else maxsupply_ec=supply_ec; for tc=0:1:20 if tc<5 partload $(5,1)=0$; else partload(5,1)=tc; end supply_tc=P_TC*partload(5,1); if supply_tc>demand(1,t)-supply_ec hourlyenergy=E_se+E_ec; if hourlyenergy<minhourlyenergy for $i=1:1:5$ $tempoperation(i,t)=partload(i,1);$ end of the state of the sta minhourlyenergy=hourlyenergy; hourlygas=E_TC*partload(5,1);

```
end on the contract of the con
                                                                 break 
                                                            end 
end and the state of the st
                                                   end 
                                              end 
                                          else 
                                              hourlyenergy=1000000000; 
                                          end 
                                     end 
                                 else 
                                     hourlyenergy=E_se+E_ec; 
                                     if hourlyenergy<minhourlyenergy 
                                         minhourlyenergy=hourlyenergy; 
                                        for i=1:1:4tempoperation(i,t)=partload(i,1);
                                         end 
                                        tempoperation(5,t)=0;
                                     end 
                                 end 
                            else 
                                hourlyenergy=1000000000000; 
                            end 
                       end 
                  end 
         if minhourlyenergy>1000000000 
             judge=0*judge; 
              totalgas=totalgas+hourlygas;
```
end

end

else

```
 totalenergy=totalenergy+minhourlyenergy; 
   end 
 end 
 if judge==1 
  for i=2:1:Tif tempoperation(5,i-1)==0 && tempoperation(5,i)>1
        startup=startup+10*E_TC*T_SU; 
      end 
   end 
   totalgas=totalgas+startup; 
   totalcost=0;
```

```
cost_energy1=c_eg_pr_l(1,k)*(E_pr/(E_pr+totalenergy+E_sc2))*(E_pr+totalenergy+E_s
c2-E_w(1,k);
```

```
cost_energy2=c_eg_sc_l(1,k)*((E_sc2+totalenergy)/(E_pr+totalenergy+E_sc2))*(E_pr+t
otalenergy+E_sc2-E_w(1,k));
     cost_energy=cost_energy1+cost_energy2; 
    cost_fuel=c_f*totalgas;
```

```
if e_pr(1,k)+y+e_sc2-e_w(1,k)>R
```

```
cost_demand=c_dm_pr_l(1,k)*(e_pr(1,k)/(e_pr(1,k)+y+e_sc2))*(e_pr(1,k)+y+e_sc2-
e_w(1,k))+c_dm_sc_l(1,k)*((e_sc2+y)/(e_pr(1,k)+y+e_sc2))*(e_pr(1,k)+y+e_sc2-
e_{w(1,k)};
     else
```

```
cost_demand=c_dm_pr_l(1,k)*(e_pr(1,k)/(e_pr(1,k)+y+e_sc2))*R+c_dm_sc_l(1,k)*((e_s
c2+y)/(e_pr(1,k)+y+e_sc(2))*R; end 
     if e_sc2+y>r 
      cost_facility=c_fc(1,k)*(y+e_sc2);
```
 else cost_facility=c_fc $(1,k)^*$ r; end cost_punitive=0; $K=k+1$: for $i=K:1:12$ if alpha*(e_pr(1,k)+y+e_sc2-e_w(1,k))-(e_pr(1,i)+Y(1,i)-e_w(1,i))>0 delta_e=alpha*(e_pr(1,k)+y+e_sc2-e_w(1,k))-(e_pr(1,i)+Y(1,i)-e_w(1,i)); else delta e=0; end if alpha*(y+e_sc2)- $Y(1,i) > 0$ delta_Y=alpha*(y+e_sc2)- $Y(1,i)$; else delta_Y=0; end $\%$ %

```
cost_punitive=cost_punitive+a(1,k)*(c_dm_pr_l(1,i)*delta_e*(e_pr(1,i)/(e_pr(1,i)+Y(1,i)
))+c_dm_sc_l(1,i)*delta_e*((Y(1,i))/(e_pr(1,i)+Y(1,i)))+c_fc(1,i)*delta_Y);
```

```
cost_punitive=cost_punitive+a(1,k)*(c_dm_pr_l(1,i)*delta_e*(e_pr(1,i)/(e_pr(1,i)+Y(1,i)
))+c_dm_sc_l(1,i)*delta_e*((Y(1,i))/(e_pr(1,i)+Y(1,i)))+c_fc(1,i)*delta_Y)/((1+gama)^(i
-k);
```
end

```
 totalcost=cost_energy+cost_demand+cost_facility+cost_fuel+cost_punitive;
```
monthlycost=cost_energy+cost_demand+cost_facility+cost_fuel;

if totalcost<mintotalcost

energycost=cost_energy;

demandcost=cost_demand;

facilitycost=cost_facility;

punitivecost=cost_punitive;

```
 fuelcost=cost_fuel; 
       Yy=y; mintotalcost=totalcost; 
        MonthlyCost=monthlycost; 
        operation=tempoperation; 
        TotalEnergy=totalenergy; 
       PeakDemand=y+e_pr(1,k)+e_sc2-e_w(1,k);
        TotalFuel=totalgas; 
     end 
     tempmincost=10000000000000000; 
   end 
   if totalgas==0 
     break 
   end 
end 
Operation=operation 
Yy=Yy 
TotalEnergy=TotalEnergy 
PeakDemand=PeakDemand 
TotalFuel=TotalFuel 
EnergyCost=energycost 
DemandCost=demandcost 
FacilityCost=facilitycost 
PunitiveCost=punitivecost 
FuelCost=fuelcost 
MonthlyCost=MonthlyCost 
MinTotalCost=mintotalcost 
%% if MinTotalCost<minsimucost
```
%% minsimucost=MinTotalCost;

%% minsimu_Operation=Operation;

- %% minsimu_Y=Yy;
- %% minsimu_TotalEnergy=TotalEnergy;
- %% minsimu_PeakDemand=PeakDemand;
- %% minsimu_TotalFuel=TotalFuel;
- %% minsimu_EnergyCost=EnergyCost;
- %% minsimu_DemandCost=DemandCost;
- %% minsimu_FacilityCost=FacilityCost;
- %% minsimu_PunitiveCost=PunitiveCost;
- %% minsimu_FuelCost=FuelCost;
- %% minsimu_MonthlyCost=MonthlyCost;
- %% minsimu_TotalCost=MinTotalCost;
- %% NoAccuracy=0;
- $%$ % for i=1:1:T
- %% if actualdemand(1,i)>demand(1,i)
- %% NoAccuracy=NoAccuracy+1;
- $\%$ % end
- $%$ % end
- %% mindemand=demand;
- %% minsimu_Accuracy=NoAccuracy;
- %% end

%% if MinTotalCost>maxsimucost

- %% maxsimucost=MinTotalCost;
- %% maxsimu_Operation=Operation;
- %% maxsimu_Y=Yy;
- %% maxsimu_TotalEnergy=TotalEnergy;
- %% maxsimu PeakDemand=PeakDemand;
- %% maxsimu_TotalFuel=TotalFuel;
- %% maxsimu_EnergyCost=EnergyCost;
- %% maxsimu_DemandCost=DemandCost;
- %% maxsimu_FacilityCost=FacilityCost;
- %% maxsimu_PunitiveCost=PunitiveCost;
- %% maxsimu FuelCost=FuelCost;
- %% maxsimu_MonthlyCost=MonthlyCost;
- %% maxsimu_TotalCost=MinTotalCost;
- %% NoAccuracy=0;
- $% \%$ for i=1:1:T
- %% if actualdemand(1,i)>demand(1,i)
- %% NoAccuracy=NoAccuracy+1;
- %% end
- %% end
- %% maxdemand=demand;
- %% maxsimu_Accuracy=NoAccuracy;
- $%$ % end
- %% end
- %% minsimu_Operation=minsimu_Operation;
- %% minsimu_Y=minsimu_Y
- %% minsimu_TotalEnergy=minsimu_TotalEnergy
- %% minsimu_PeakDemand=minsimu_PeakDemand
- %% minsimu_TotalFuel=minsimu_TotalFuel
- %% minsimu_EnergyCost=minsimu_EnergyCost
- %% minsimu_DemandCost=minsimu_DemandCost
- %% minsimu_FacilityCost=minsimu_FacilityCost
- %% minsimu_PunitiveCost=minsimu_PunitiveCost
- %% minsimu_FuelCost=minsimu_FuelCost
- %% minsimu_MonthlyCost=minsimu_MonthlyCost
- %% minsimu_TotalCost=minsimu_TotalCost
- %% minsimu_Accuracy=minsimu_Accuracy
- %% mindemand=mindemand
- %% maxsimu_Operation=maxsimu_Operation;
- %% maxsimu_Y=maxsimu_Y
- %% maxsimu_TotalEnergy=maxsimu_TotalEnergy
- %% maxsimu_PeakDemand=maxsimu_PeakDemand
- %% maxsimu_TotalFuel=maxsimu_TotalFuel
- %% maxsimu_EnergyCost=maxsimu_EnergyCost
- %% maxsimu_DemandCost=maxsimu_DemandCost
- %% maxsimu_FacilityCost=maxsimu_FacilityCost
- %% maxsimu_PunitiveCost=maxsimu_PunitiveCost
- %% maxsimu_FuelCost=maxsimu_FuelCost
- %% maxsimu_MonthlyCost=maxsimu_MonthlyCost
- %% maxsimu_TotalCost=maxsimu_TotalCost
- %% maxsimu_Accuracy=maxsimu_Accuracy
- %% maxdemand=maxdemand

%% r=normrnd(0,1078.754);

APPENDIX B

COOLING LOAD AND WEATHER DATA

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