Model Development and Case Study of an Optimal Control Strategy of Central Ice Storage System for a District Cooling System

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ABSTRACT
Heating and cooling systems can be one of the largest contributors to peak electrical loads in a large building or multiple buildings. Ice storage is an effective mean to reduce peak energy consumption and to avoid high demand charges. A common ice storage control scheme would be to charge the storage tanks at a full capacity during cooling season and allow for the ice to take the place of cooling systems until the ice is completely consumed from the beginning of scheduled hours. Depending on weather conditions and cooling demand from a building(s), this strategy may prevent using stored energy during peak hours (i.e., the stored energy may be used up before peak hours). When an optimal control with proper load forecasting is available, the use of stored energy can be better planned to reduce peak electric demand and lower demand charge. This paper proposes a control system integrated with an artificial neural network (ANN) load prediction model to optimize the operation of central ice storage for district heating and cooling systems. A case study using data from the ice storage and central heating and cooling plant at Mississippi State University is carried out in this paper to demonstrate the feasibility of the proposed control system. 24-hour-ahead central plant cooling load is forecasted using the ANN model based on forecasted weather data and past hour cooling loads. Then optimal operational schedules for the ice storage and chillers in the central plant are determined based on the predicted cooling load of the central plant. The results from this case study demonstrate that the proposed control system for ice storage systems can be effectively used to reduce peak energy consumption and to avoid high electricity rates.

KEYWORDS
Ice storage, Peak shaving, Load prediction, Neural network, Optimization

INTRODUCTION
The need for peak load reduction in various countries is becoming more abundant with already stressed power grids. As alternative energy production becomes a greater portion of the electrical power supply, this need only increases (Qureshi et al. 2011). Thermal energy storage has shown to be effective in peak load and cost reduction, especially in larger systems (Dincer & Rosen 2001). While many retrofits have

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included ice storage in district cooling systems, the controls for when to use the ice storage is often a static schedule. This paper presents a simple and effective way to further reduce costs by determining the optimal time to charge and discharge the ice storage system while also determining the amount of energy to store for the next day. The study is based on a real district cooling system located at Mississippi State University in Starkville, MS, USA.

Much research has been focused on the optimization of thermal energy storage in air conditioning systems resulting in a variety of techniques to formulate the problem. Chan et al. (2006) perform a detailed simulation study of a district cooling plant with ice storage. The study discusses the best configurations and the most effective control strategies for each configuration. They presented the estimated savings in relation to storage capacity, configuration, and simple control strategy (i.e. chiller priority or storage priority). Although the study did not investigate an optimal control method, the results show the ice storage can be a cost effective option if designed properly. Chen et al. (2005) conducted a study that formulates the control strategy as a dynamic programming problem. By modeling each component of the air conditioning system based on manufacturer's data, dynamic programming can be used to pick the best operational mode of the system. In addition, the optimal charge capacity and life-cycle cost are studied under different control scenarios. Lee et al. (2009) performed a similar study in which they use particle swarm optimization to find the minimal life cycle cost. Also, the increase in CO_2 emissions due to thermal storage is also analyzed. Powell et al. (2013) showed optimal control scheme formulated as a dynamic programming problem. Their study uses a real district cooling system with thermal storage. By modeling all the chillers into a single optimal chiller, the optimization problem is greatly simplified and the optimal chiller and thermal storage load is then found. Each component of the chilled water system is modeled using semi-empirical correlations. This is useful when needing to extrapolate beyond the range of the input variables used to create a purely empirical model.

This study intends to reduce the method into an even simpler problem that can be easily implemented and integrated into a building energy management system, especially with limited data.

DESCRIPTION OF DISTRICT COOLING SYSTEM

The district cooling system for Mississippi State University originally consisted of 4 5275 kW chillers with three cooling towers. The chillers are sequenced based on chilled water supply temperature and part load ratio (PLR) being over 0.95. For the ice storage installation, a 5000 kW chiller is installed to make the ice while also being able to supply cooling power directly to the chilled water loop. 18 ice storage modules, shown in Figure 1, are installed totaling capacity of 34,300 kWh of cooling energy. Currently the ice storage is set to make ice beginning at 21:00 until full capacity during the weekdays and is set to supply cooling energy beginning at 12:00

until 10% estimated capacity. The ice storage system is designed to be able to take the place of one main cooling chiller.

Figure 1. *Ice Storage Modules at Mississippi State University*

MODEL DEVEOPMENT

To be able to estimate the electricity consumption of the cooling plant, performance curves were generated. Due to a lack of measurement data, each individual component of the cooling plant (i.e. chillers and cooling towers) were not able to be assessed individually. Therefore, performance curves were generated for the entire cooling plant based on campus cooling load and outdoor wet bulb temperature (Twb). The plant has up to 4 chillers running at once with ice storage being either on or off to effectively replace one chiller. This makes for a possible 8 different operational modes. The data is split up based on these modes and a biquadratic curve, given in Eq. (1), is generated as a function of part load ratio (PLR) and Twb. Table 1 shows the correlation coefficient (R) of the performance curve for each operational mode.

$$EIR(T_{wb}, PLR) = m_1 T_{wb} + m_2 {T_{wb}}^2 + m_3 PLR + m_4 PLR^2 + m_5 T_{wb} PLR + b \quad (1)$$

where *EIR* is the energy input ratio, *m* is the regression coefficient found by the least squares method, *b* is a constant, *PLR* is the part load ratio of the cooling plant, and *Twb* is the outdoor wet-bulb temperature. With the EIR now able to be estimated, the power demand by the cooling plant can be calculated using Eq. (2).

$$P_e = EIR \cdot P_c \quad (2)$$

where P_e is electrical power and P_c is cooling power (i.e. the campus cooling load). The part load ratio is calculated by dividing the campus cooling load by the maximum available cooling capacity at that operational mode.

***Table 1.** Correlation Coefficient (R) of the Performance Curves*

Operating Conditions	*R*
1 Chiller (ice off)	0.71
2 Chiller (ice off)	0.64
3 Chiller (ice off)	0.61
4 Chiller (ice off)	0.84
1 Chiller (ice on)	0.80
2 Chiller (ice on)	0.85
3 Chiller (ice on)	0.93
4 Chiller (ice on)	No Data Available

Control logic is put in place to switch to the next operational mode if the PLR exceeds 0.95. A linear performance curve is also generated for the ice generation EIR as a function of Twb. The ice storage charge level is determined by assuming no thermal losses and estimating the energy lost due to discharge. With this model, the cooling plant electrical demand becomes a function of campus cooling load, Twb, and operational mode of the ice plant (i.e. charging, active, or idle). The model was validated using 2 months of data during the summer with a CVRMSE of 10.80%, an NMBE of 1.65%, and a correlation coefficient of 0.97. A comparison of the model output electrical demand and the actual electrical demand can be seen in Figure 2.

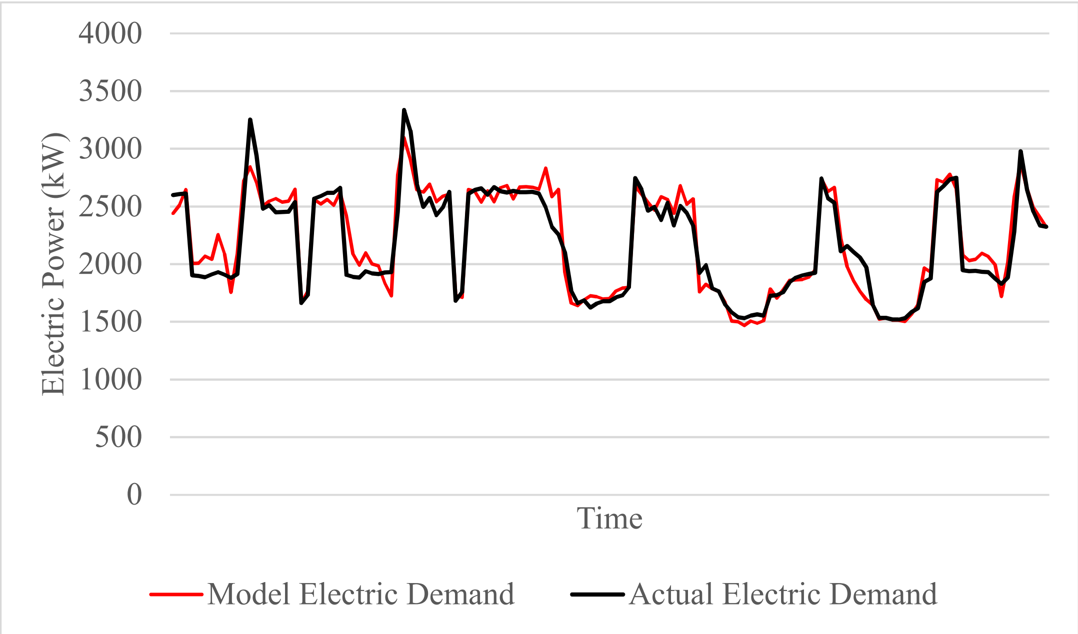

***Figure 2.** Comparison of Model Output and Actual Electric Demand*

The error statistics are well within ASHRAE guideline 14 Measurement of Energy and Demand Savings (ASHRAE 2002). To validate the model, the original static schedule of the ice storage was used.

Next, a neural network load prediction method is used to generate predicted campus load for 24 hours ahead, based on dry-bulb temperature, relative humidity, and global horizontal irradiation (GHI) (Yang et al. 2005). When integrating the neural network load prediction, the model solely becomes a function of dry-bulb temperature, relative humidity, and GHI, along with the operational state of the ice storage system.

OPTIMIZATION

The model can now be optimized based on an optimal charging and discharging schedule that minimizes the operational cost of the cooling plant. Also for comparison, the charge limit of the ice storage is optimized to investigate the savings potential. The utility company pricing structure, shown in Table 2, is used to calculate the energy costs of the cooling plant. There is also a demand charge for the electricity, but that is determined after the pay period is over. Since there is no startup penalty for the ice storage operation, it is assumed that once the ice storage is discharging, it will remain active until completely discharged. Similarly, the charging operation is turned on at a certain hour until charged to a set limit.

Table 2. *Electricity Pricing Structure*

Hours	*$/kWh*
0-5	0.01613
6-12	0.03530
12-16	0.07095
17-21	0.03530
22-24	0.01613

This reduces the optimization problem to a simple integer programming problem without considering the charging limit. With only 24 hour ahead cost being considered, 578 possible combinations are possible when including the ice storage being completely off for the day. This can be further reduced to ensure discharging during the daytime and charging during the night time. Although seemingly a large number, when considering the simple model, brute force searching can arrive at the optimal solution within a reasonable amount of time. When considering the ice charging limit as a parameter, the problem turns into a mixed integer nonlinear programming problem that can be solved by an evolutionary optimization method, although not guaranteed to arrive at the global optimum.

RESULTS AND DISCUSSION

One week in June is considered for the test week. To ensure the pricing structure has not introduced a bias into the savings amount, the normal operation schedule cost from the model is compared with the actual electrical load cost. The results indicate 0.017% savings, indicating minimal bias. Next, the cost of the cooling plant is calculated when using no ice storage for the entire week. This result is compared with ice storage savings under normal operation and under optimized operation using "perfect load forecasting" and neural network load forecasting. Table 3 summarizes the results of these comparisons, when considering no ice charging limit.

Table 3. *Optimal Scheduling Results with No Ice Charging Limit*

Operational mode	*Cost ($)*	*Savings*
No Ice Storage	11,614.54	-
Ice Storage with Static Scheduling	10,498.29	9.16%
Ice Storage with Optimized Scheduling (perfect forecasting)	10,158.05	12.52%
Ice Storage with Optimal Scheduling (NN forecasting)	10,216.29	12.04%

The ice storage with static scheduling offers significant savings for the week in question, even when not including demand charges. By adding an optimal scheduler, the savings are increased by 3.2% to a total of 12.52% cost savings from the system with no storage. Figure 3 shows the resulting electrical load with no ice storage and optimal schedule. It shows that the electricity consumptions during the peak hours (i.e., 12-16 hours) can be significantly reduced using an optimal schedule strategy.

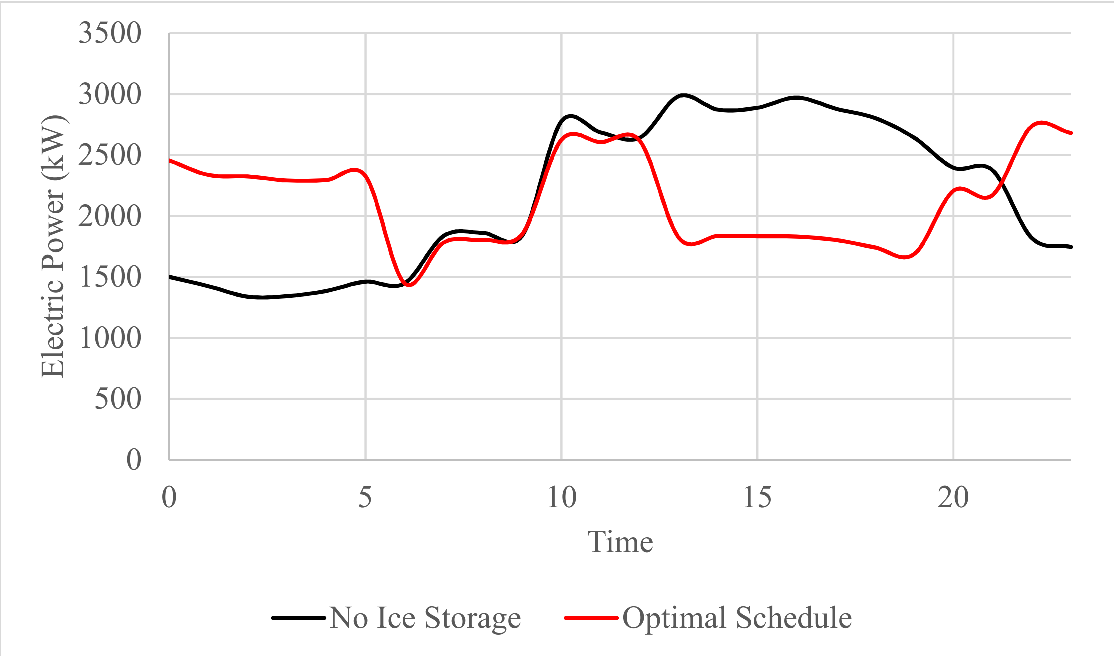

Figure 3. *Comparison of the Cooling Plant with Ice Storage and Without*

Next, the same comparison is made but with the ice charging limit as a parameter of the optimization problem. The results are shown in Table 4. The biggest savings result from the optimal scheduling of the charging and discharging start time. In addition, this method is much simpler and can be solved by simple brute force searching, due to the small number of combinations. Adding in the ice charging limit results in a negligible amount of savings but will most likely be more influential during the transition seasons.

Table 4. *Optimal Scheduling Results with Ice Charging Limit*

Operational mode	*Cost ($)*	*Savings*
No Ice Storage	11,614.54	-
Ice Storage with Static Scheduling	10,446.92	10.06%
Ice Storage with Optimized Scheduling (perfect forecasting)	10,136.46	12.73%
Ice Storage with Optimal Scheduling (NN forecasting)	10,143.84	12.66%

CONCLUSION

Ice storage is an effective way to reduce the peak electrical load in a district cooling system. By using an optimal control strategy based on 24 hour ahead load prediction, the cost savings compared to a static schedule can be increased by around 3%. As this study does not include a demand charge, the savings will likely be even greater. In addition, the energy consumption is only increased by around 1% when compared to cooling plant with no ice storage energy consumption. The method proposed in this study can be easily implemented into a common building energy management system, especially those lacking sufficient data for more complicated methods. Future work will include adding in a pricing structure for demand charge along with lengthening the study period.

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