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ABSTRACT

This paper presents the development and evaluation of a rule-based control algorithm for minimizing energy costs in cooling plants with chilled water storage subject to dynamic electricity rates combined with demand charges. The control approach requires very little plant information, is relatively simple, and ensures that the storage will not be prematurely depleted. The control algorithm was evaluated using a model of an existing chiller plant with significant complexity built in a simulation testbed for different combinations of storage sizes, load profiles and RTP electricity rates. The performance of the near-optimal algorithm was compared with three different approaches: optimal control (baseline), and two heuristic control strategies commonly used for thermal energy storage: chiller priority and storage-priority load-limiting. The energy costs obtained with the near-optimal control algorithm were within 3.5% of the costs associated with optimal control. Comparison with other common heuristic control strategies shows that significant energy savings can be achieved with the proposed control method.

INTRODUCTION

Recently, many central cooling plants are incorporating some form of cool storage (commonly water or ice) aiming to reduce the electrical demand at peak hours by shifting the cooling load to times when electrical energy is less expensive. Optimal supervisory control of these systems requires determining a sequence of control commands for charging and discharging the storage media such that the total cost of supplying chilled water integrated over the billing period or storage cycle is minimized. Relatively few studies on this subject have been published in the last three decades. Henze et al. (1997) developed and evaluated a predictive optimal controller for ice storage systems subject to real-time-pricing (RTP) utility rates. Later, Henze and Krarty (1999) determined the effect of forecasting uncertainty on the cost savings performance of the predictive optimal controller for ice storage systems. Zhang et al. (2011) proposed a generic methodology for determining optimal operating strategies for a chilled-water storage system under time-of-use (TOU) electricity rates. Although these research efforts demonstrated the superior performance of optimal control compared to conventional strategies, especially for complex dynamic rate structures. the need for detailed information on the performance profiles of the cooling plant equipment and the computational processing effort required limits the implementation of these approaches.

Most of the practical work on control of thermal storage systems involves the development of heuristic strategies that are nearly optimal. Drees and Braun (1996) developed a control strategy for ice storage systems that combines elements of chiller-priority and storage-priority strategies, along with a demand-limiting algorithm and works well with TOU utility rates and demand charges. A simpler variant of this strategy that does not require the measurement of the total building electrical use is included in ASHRAE (2011). Later, Braun (2007a, b) extended the method to develop a simple control strategy for cool storage systems that works with RTP rates. These strategies are based on some combination of conventional control strategies such as chiller-priority, chiller-priority demand-limiting and storage-priority, and have demonstrated near-optimal performance when compared with optimal control in a simulation environment. The aforementioned strategies can be adapted, with some considerations, to develop a rule-based controller for chilled water systems. Nonetheless, to the authors knowledge, a solution for near-optimal control of storage subject to RTP rates combined with demand charges has not been developed. Consequently, this work will be dedicated to the development and evaluation of a near-optimal control approach for this case.

This paper presents the development and evaluation of a rule-based near-optimal control strategy for chilled water storage subject to RTP rates with demand charges. Most of the work on TES control has been made for ice-storage, probably because this storage media is much more compact than chilled-water storage. Ice making chillers, nonetheless, operate with lower efficiencies than conventional chillers, and consequently, the economic benefits obtainable with ice storage systems rely, to a greater extent, on the difference between on-peak and off-peak electricity rates. Further, since there is no need to add ice-making dedicated chillers it is much more straightforward and lower cost to retrofit an existing system with chilled water storage than with ice storage.

The work starts with the description of the problem of optimal control of a chilled-water storage system subject to electricity rates with demand charges. A simplified sensible storage device model that represents the upper limit for temperature stratification was utilized to reduce the number of control variables and make the dynamic optimization problem solvable for a whole billing period (i.e. a month) utilizing dynamic programming. Later on, previous research in control of ice-storage and the results obtained with this approach were utilized to develop and benchmark the ruled-based control strategy. The strategy is the result of a tradeoff between near-optimal performance and simplicity, and requires measurements of cooling load, building electrical usage and state-of-charge of storage at each decision time interval. Additionally, the strategy requires daily profiles of RTP rates, and daily forecasts of loads and building electrical usage. The Purdue Northwest Chiller Plant was utilized as the test facility to evaluate the performance of the ruled-based control approach over the whole cooling season. To this end a fully stratified chilled water tank was connected in parallel between the plant and the campus chilled water distribution system in a simulation testbed. Simulation results were compared with three benchmarks: (1) optimal control, (2) storage-priority load-limiting, and (3) chiller-priority.

1. OPTIMAL CONTROL OF CHILLED WATER STORAGE

1.1. The general optimization problem

Optimal supervisory control of storage involves minimizing the cost of electricity over a period of time. For a utility rate structure that includes demand charges, the optimization should cover the entire billing period (e.g. a month). In order to simplify the numerical solution, the general problem can be described as follows:

$$Minimize\ J = \sum_{k=1}^{N} E_k P_k \Delta t + TDC \tag{1}$$

with respect to the control variables $\boldsymbol{u}_1, \boldsymbol{u}_2, \dots \boldsymbol{u}_N$, and subject to the following constraints for each stage *k*:

$$\begin{gathered} \boldsymbol{x}_k = \varphi(\boldsymbol{x}_{k-1}, \boldsymbol{u}_{k-1}, \boldsymbol{w}_{k-1}) \\ \boldsymbol{x}_{min,k} \leq \boldsymbol{x}_k \leq \boldsymbol{x}_{max,k} \\ \boldsymbol{x}_N = \boldsymbol{x}_0 \\ \boldsymbol{u}_{min,k} \leq \boldsymbol{u}_k \leq \boldsymbol{u}_{max,k} \\ D_k P_k \leq TDC \end{gathered} \tag{2}$$

where J is the electricity cost over the billing period (e.g. a month), N is the number of time stages in a billing period, and for the stage k, Δt is the length of the time interval (typically equal to the time window over which demand charges are levied, e.g. 0.25h), E_k is the unit electricity cost ($/kWh), D_k is the demand charge rate ($/kW), P_k is the total electric power consumed by the building and the cooling plant averaged over the stage (kW), TDC is the target demand cost for the billing period ($), $\boldsymbol{u}_k$ is a vector of control variables that determine the rate of energy addition or removal to the storage over the stage, $\boldsymbol{x}_k$ is a vector of state variables, $\boldsymbol{w}_k$ is a vector of uncontrolled variables (i.e. ambient conditions), and φ is a state function. For a given value of TDC, the minimization of the operational cost with respect to the N control variables can be accomplished using dynamic programming or other direct search methods. The advantages of dynamic programming are that it can handle all the constraints in a straight forward manner and guarantees a global minimum. However, the computation becomes excessive if more than one state variable is needed to characterize the storage. The N variable optimization problem is solved at each iteration of an outer loop optimization for TDC.

1.2. Chilled Water Storage Model

A schematic of a chilled water storage tank connected in parallel between the chiller plant and the air handling equipment is shown in Figure 1. Cold water from the chillers is fed to the bottom of the storage during the charging cycle. During discharging the circulation is reversed: chilled water is pumped to the air handlers and warmer return water is added to the top of the tank.

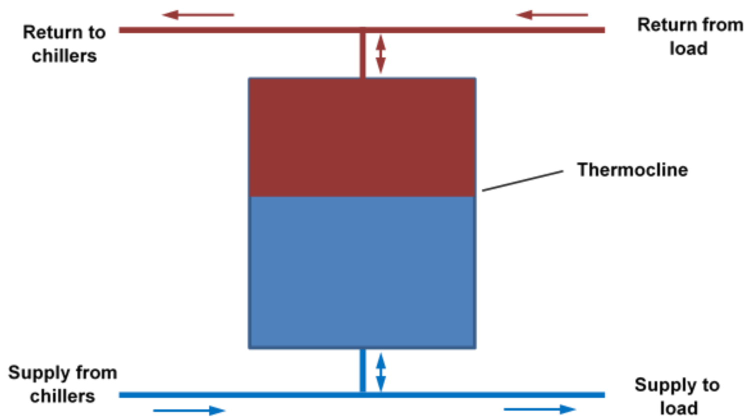

Figure 1. Fully stratified chilled water storage tank model

In order to simplify the numerical solution, a model of a fully stratified storage tank presented by Braun (1988) was utilized in this work. The performance of chilled water storage relies on stratification. A perfect sensible storage device would deliver water at the same temperature at which it was initially stored. This would require that the water returning to the storage neither mix, nor exchange heat with stored water in the tank or the surroundings of the tank. An additional simplification is obtained by using a constant inlet temperature for charging or discharging the storage, resulting in two distinct temperature zones separated by a boundary layer called the thermocline, as illustrated in Figure 1. Defining x as the distance of the thermocline above the bottom of the tank relative to the height of the tank, then a discrete equation for the position of the thermocline is given by:

$$x_{k+1} = x_k + u\Delta t \tag{3}$$

where u is the velocity of the fluid relative to the tank height, with positive directed upwards. The relative position of the thermocline x also represents the relative state of storage charge. When x takes a value of 0 the storage cannot provide any cooling, and when x takes a value of 1 the storage is fully charged. The rate of energy added to storage (i.e. storage discharge) can be expressed in terms of the control variable u as:

$$\dot{Q}_s = -Cap_s u \tag{4}$$

where Cap_s is the storage capacity or maximum possible change in internal energy of the storage. It follows that, for a given cooling requirement $\dot{Q}_{load}$, the chiller cooling rate is:

$$\dot{Q}_{ch} = \dot{Q}_{load} - \dot{Q}_s \tag{5}$$

Then, at any time, the total electric power consumption is given by

$$P = P_{plant} + P_{bd} \tag{6}$$

where P_{plant} is the electric power consumption of the cooling plant, and P_{bd} includes the building electricity that is not associated with cooling (i.e. lights, computers, etc.) and the electricity usage associated with the distribution of secondary fluid and air through the cooling coils. Since this last term can be considered independent of the storage control, the only term that can be minimized is plant power consumption. The plant power consumption depends on chiller load ($\dot{Q}_{ch}$) and ambient conditions, primary wet-bulb temperature for a plant with water-cooled chillers, and dry-bulb temperature for air-cooled chillers. Then, for a given cooling load, a stationary optimization of the cooling plant is performed outside of the routine for dynamic optimization of storage using any suitable method to find the minimum power consumption.

The fully stratified storage model described by Equations 3 through 5 requires only one state variable to characterize the storage (i.e. relative state-of-charge of storage) and one control variable (i.e. relative velocity of storage charge/discharge). This model is simple enough to be used in conjunction with dynamic programming to optimize the control of chilled water storage. This approach was described by Braun (1988) and was utilized here to obtain optimal control of chilled water storage for a given TDC. Then, the *N* variable optimization problem posed in Equations 1 and 2 was solved at each iteration of an outer loop optimization for TDC.

2. RULED-BASED CONTROL OF CHILLED WATER STORAGE

The starting point for this work is a ruled-based control strategy developed by Braun (2007a) for ice storage systems subject to RTP rates. The strategy switches between chiller-priority control and maximum-discharge storage-priority based on availability of storage and electricity price. Here the strategy was adapted to chilled-water storage and extended to provide near-optimal control for systems subject to RTP rates with demand charges through the development of a method for determining a near-optimal TDC. This TDC is updated at the beginning of each day. The rule-based controller requires measurements of building cooling load and state-of-charge of storage at each decision time interval (e.g. 0.25 h), and daily forecast of loads, RTP rates and building electrical usage for each time interval. Additionally, an estimate of the cooling plant COP is needed. For each day, the control strategy is divided into two parts: (1) determination of the near-optimal TDC, and (2) storage control aiming to minimize energy cost whilst preventing the demand cost to exceed the specified TDC. For clarity, the procedure for the second part will be described before the determination of the optimal TDC.

2.1. Storage control to minimize energy cost for a specified TDC

The storage is discharged during the occupancy period when the electricity rates and demand costs are high. The storage discharge strategy switches between two conventional strategies: maximum-discharge storage-priority control is applied over the period when the RTP rates are highest, if possible (i.e. if there is enough storage available), and chiller-priority demand-limiting control is used for all other times. The chiller load profile for this control strategy is shown in Figure 2. The maximum-discharge period is the maximum possible time period where the chillers can remain off and corresponds to the highest values of the RTP rates. The initial and final times for the maximum-discharge period, and the maximum load that can be applied on the chillers to prevent the demand cost from exceeding the specified TDC at all other times, are determined by applying the following procedure.

Let k_i and k_f be the initial and final time intervals of the occupied period, and k_{di} and k_{df} the initial and final intervals of the maximum-discharge period. Then, at the beginning of each decision interval k_c of the occupied period before the maximum-discharge period been initiated, the following steps are applied to determine k_{di} and k_{df}:

1. Obtain the electricity rates and updated forecasts of cooling loads and building electrical usage for each decision time interval of the remainder of the occupied period (i.e. for $k = k_c$ to k_f).
2. Determine a limiting value for the chiller load ($\dot{Q}_{chlim,k}$) that can be applied at each time interval k of the reminder of the occupied period to prevent the demand cost from exceeding the specified TDC, as follows:

$$\dot{Q}_{chlim,k} = \min\left[\dot{Q}_{max}, \left(\frac{TDC}{D_k} - \hat{P}_{bd,k}\right) \widehat{COP}\right] \tag{7}$$

   where $\dot{Q}_{max}$ is the maximum cooling capacity of the plant, $\hat{P}_{bd,k}$ is the forecast of building electricity usage for the k_{th} interval, and $\widehat{COP}$ is an estimate of the plant COP.

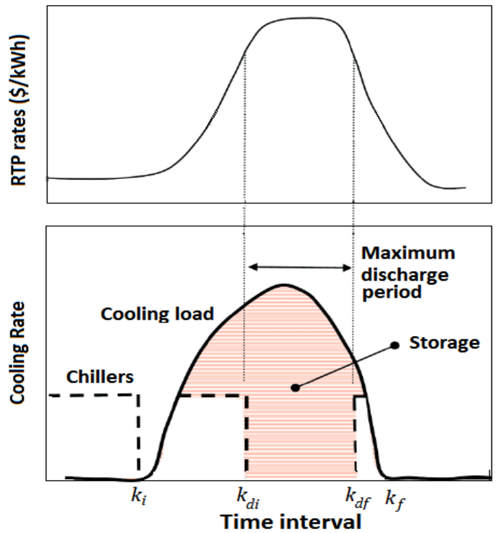

Figure 2. Ruled-based control strategy for chilled water storage and RTP rates

3. Use the state-of-charge of storage at the beginning of the current interval k_c, and forecasted loads to estimate the state-of-charge of storage at the end of the occupied period if only chiller-priority demand-limiting control were applied throughout the occupied period.

$$x_{k_f} = x_{k_c} - \sum_{k=k_c}^{k_f} \frac{max\left(0,\ \dot{Q}_{load,k} - \dot{Q}_{ch\_lim,k}\right)\Delta t}{Cap_s} \tag{8}$$

4. If $x_{k_f} \leq x_{min}$ then exit the algorithm, otherwise go to step 5.
5. Scan the electricity rates and find the time interval, m, having the highest electricity rate for the occupied period. Set the initial start and end stages for the maximum storage-discharge period as $k_{di} = m$ and $k_{df} = m$.
6. Estimate the state-of-charge of the storage at the end of the occupied period

$$x_{k_f} = x_{k_f} - \frac{min\left(\dot{Q}_{load,m}\ ,\ \dot{Q}_{ch\_lim,m}\right)\Delta t}{Cap_s} \tag{9}$$

7. If $x_{k_f} \leq x_{min}$ then exit the algorithm, otherwise go to step 8.
8. If $k_{df} + 1 \leq k_f$ and ($E_{k_{df}+1} > E_{k_{di}-1}$ or $k_{di} - 1 < k_c$), then set $k_{df} = k_{df} + 1$ and $m = k_{df}$, and go to step 6. Otherwise go to step 9.
9. If $k_{di} - 1 \geq k_c$, then set $k_{di} = k_{di} - 1$ and $m = k_{di}$, and go to step 6. Otherwise exit the algorithm.

If the maximum storage-discharge period has not started, then chiller-priority demand-limiting control is applied and the chiller load for the current interval is given by

$$\dot{Q}_{ch,k_c} = \min\left(\dot{Q}_{load,k_c}, \dot{Q}_{chlim,k_c}\right) \tag{10}$$

Once the maximum storage-discharge period begins, it is necessary to continually update the estimate of the final time interval for this period (k_{df}) in order to utilize more up-to-date forecasts and prevent depletion of storage.

For charging the storage, a simple strategy is to operate the chillers at $\dot{Q}_{ch\_lim}$ over the period when the electricity rates are lowest and the building is unoccupied (or has the lowest occupancy). The charging period ends when the storage is fully charged or the building occupancy period begins.

Notice that, if an artificially high TDC is set, then the routine described above will minimize energy costs without any limit on peak power consumption, and the resulting demand cost can be used to establish an upper limit for the TDC. On the other hand, if the value of the TDC is progressively reduced, the duration of the resulting maximum-discharge period will be shorter, until reaching zero. The demand cost that makes the maximum-discharge period zero establishes a lower limit for TDC. Any attempt to meet a TDC lower than this value would cause premature depletion of storage.

2.2. Determination of the near-optimal TDC

For a given month the TDC that results in the minimum operational costs is a trade-off between energy and demand costs. The proposed routine attempts to minimize the total operational costs by assigning an estimate of the optimal TDC at the beginning of the first day of the month. This estimate is updated, if necessary, at the beginning of each day according to the procedure described below.

1. If the current day is the first day of the month, then set TDC = 0.
2. Obtain the electricity rates and forecasts of cooling loads and building electrical usage for each decision time interval of the day (i.e. for *k* = 1 to *N*).
3. Define the initial and final time intervals of the occupied period, k_i and k_f.
4. Assign an artificially high TDC and apply the procedure described in the previous section to determine the initial and final times for the maximum-discharge period, and the chiller loading profile for all the day.
5. Use the resulting chiller load profile to determine an upper bound for TDC:

$$TDC_{max} = Max_{1\leq k\leq N}\left[D_k\left(\hat{P}_{bd,k} + \frac{\dot{Q}_{ch,k}}{\widehat{COP}}\right)\right] \tag{11}$$

6. If $TDC_{max} \leq TDC$ then keep the current TDC and exit the algorithm. Otherwise go to step 7.
7. Find a lower bound for the demand target (i.e. TDC_{min}). This value corresponds to the TDC that would deplete the storage at the end of the occupied period without any chance to turn the chillers off (i.e. zero duration of maximum-discharge discharge period). This condition is expressed by Equation 12.

$$x_{k_i} - \sum_{k=k_i}^{k_f} \frac{max\left(0,\ \dot{Q}_{load,k} - \dot{Q}_{ch\_lim,k}\right)\Delta t}{Cap_s} - x_{min} = 0 \tag{12}$$

   where x_{k_i} is the state-of-charge of storage at the beginning of the occupied period and $\dot{Q}_{chlim,k}$ is a function of TDC, given by Equation 7. Equations 7 and 12 can be solved iteratively by the bisection method to find TDC_{min}.

8. Use a search method or any suitable optimization method to find the value of TDC that minimizes the electricity costs (TDC_{opt}). The problem is stated as follows:

$$Minimize\ \hat{J} = N_{days}\sum_{k=0}^{N}\left[E_k\left(\hat{P}_{bd,k} + \frac{\dot{Q}_{ch,k}}{\widehat{COP}}\right)\Delta t\right] + TDC \tag{13}$$

   and subject to $$TDC_{min} \leq TDC \leq TDC_{max}$$

   where N_{days} is a weighting factor that takes the value of the number of days of the month if the day in question is the first day of the month, and one otherwise. In this way, for the first day of the month $\hat{J}$ represents an estimate of the electricity costs of the whole billing period. The chiller load for each time interval of the day $\dot{Q}_{ch,k}$ is obtained by applying the heuristic control strategy for minimizing energy costs for a given TDC described in the previous section.

9. Set $TDC = max\left(TDC,\ TDC_{opt}\right)$

3. EVALUATION OF THE CONTROL STRATEGY

3.1. Case Study: Purdue Northwest Plant

The Northwest Plant at Purdue Campus was utilized as the test facility to evaluate the performance of the different storage control strategies. A schematic of the plant is illustrated in Figure 3. The plant delivers chilled water through 37 km of underground piping to partially meet the cooling requirements of more than 150 buildings on the campus. The plant consists mainly of six duplex centrifugal chillers (i.e. chillers with two separate compressors with independent refrigerant circuits in a series counter-flow arrangement), variable-speed condenser and chilled water pumps, and four evaporative cooling towers: one concrete counter-flow structure and three metal cross-flow cooling towers. Each cooling tower has three cells with variable-speed fans giving a total of 12 tower cells.

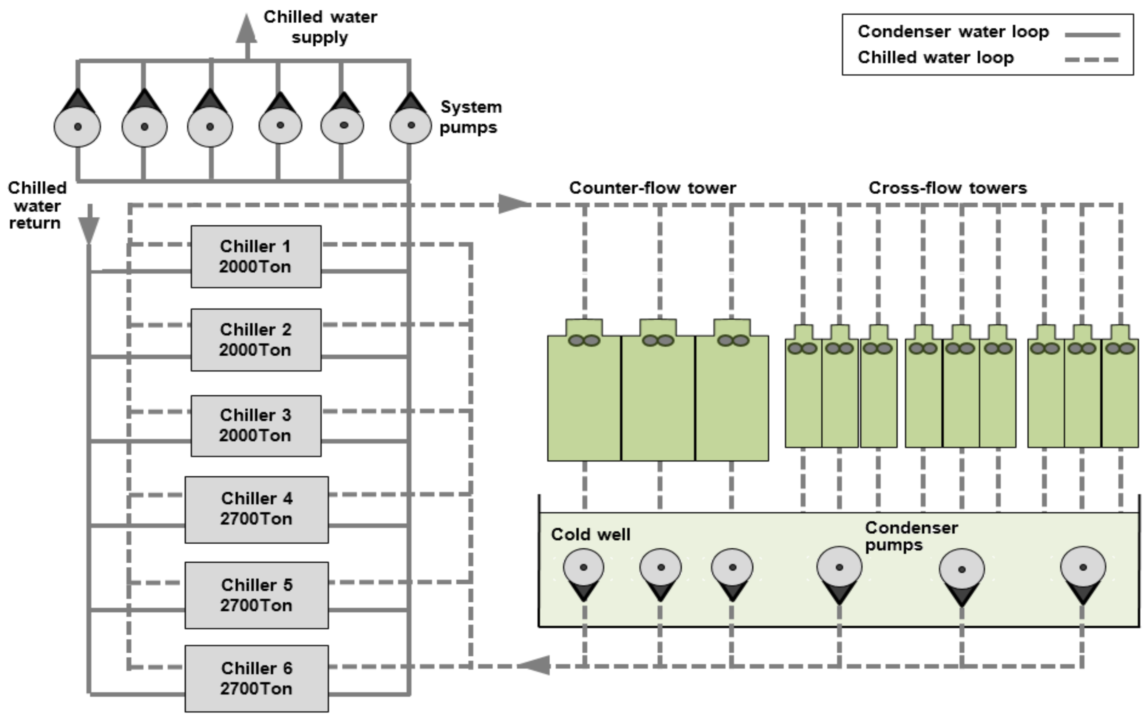

Figure 3. Northwest Chiller Plant schematic

Previous work by Jaramillo et al. (2014) presented the development of a mathematical model of a cooling plant using MATLAB software. In this setting, each hardware component of the plant (i.e. chillers, cooling towers and pumps) was represented using semi-empirical models as a separate set of mathematical relationships with its own parameters, inputs and output variables. The parameters of the models were determined from regression of performance data. These models were interconnected through flow variables (i.e. flow rates and temperatures) according to the arrangement of the physical plant. Heuristic rules for loading chillers and sequencing pumps and tower cells were also included in the model to reduce the number of control variables. For a fixed chilled water supply temperature set-point, the plant model computes the power consumption for given load, ambient conditions and two control variables: condenser water flow and tower air flow.

In order to reduce the computational processing effort required by the dynamic optimization of storage, an optimum performance map of the Northwest plant was elaborated using a genetic algorithm. Values of minimum power consumption of the plant were tabulated as a function of discrete values of two variables: cooling load and wet-bulb temperature. Then, an interpolation routine was used to obtain the minimum power consumption as a function of these two variables. This optimum map was also utilized to compute the plant power consumption corresponding to the control settings (i.e. storage discharge rate and chiller loading) established with the heuristic control strategies.

For the purposes of this study, a chilled water storage tank was connected in parallel between the plant and the air handling equipment, according to the configuration shown in Figure 1. The base storage size used in this simulation was 33,500 ton-h and was taken from a feasibility study for chilled water storage implementation at the Northwest Plant. The chilled water supply temperature set-point was 40°F, and the temperature of the water returning from campus was assumed to remain constant at 55°F.

3.2. Simulation Assessment of Storage Control

The performance of the rule-based control was compared with three benchmarks: (1) optimal control, (2) storage-priority load-limiting control, and (3) chiller priority. All the control approaches were implemented in the simulation testbed with the assumption of perfect forecasts of cooling loads, campus electrical usage and electricity rates. Purdue campus hourly-averaged historical data from April 1 to October 31, 2017 consisting of wet-bulb and dry-bulb temperatures, Northwest Plant cooling load, campus electricity consumption (excluding the plant), and electricity rates were analyzed. The months with the lowest and the highest average dry-bulb temperature were selected to simulate the performance of the different control strategies: April and July. These two months also have the lowest and the highest integrated cooling loads, respectively. The performance of the strategies was simulated for three storage sizes: 75%, 100% and 125% of the base storage size. Three utility rate structures were considered: the Purdue campus hourly RTP electricity rates, and two utility rates generated using a model described by Sun et al. (2006). The model produces a time-varying price for the cost of electricity that depends on season (summer or winter), type of day (week day or weekend), time of day, and maximum temperature of the day. The rate model for summer periods and Purdue temperature data were used to generate the RTP rates for two different utilities defined by Braun (2006). Figure 4 shows outputs from these models for a week day and different temperatures. Utility 2 generally has higher rates with peaks that occur earlier in the afternoon compared to Utility 3. The peak rates increase dramatically with day peak temperature for both utilities. A fixed unit demand cost of 40 times the RTP rate base value ($/kW) was applied to both utilities. This relation approximately corresponds to the unit demand costs applied at Purdue. Then, these unit demand costs were multiplied by a factor of 10 to assess the effect of the relative magnitude of the demand cost on the performance of the control strategy. The range of storage sizes, RTP rates and demand costs are shown in Table 1. All combinations of these variables were considered, giving a total of 36 monthly simulations for each of the four control strategies.

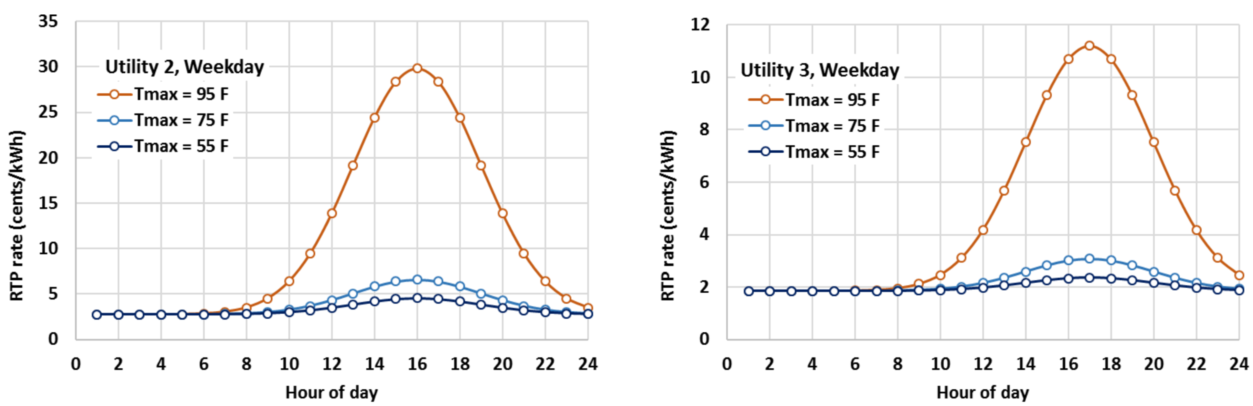

Figure 4. RTP rates obtained from model for weekdays

Table 1. Control strategy evaluation matrix.

Parameter	Values
Storage size	75%, 100%, and 125% of recommended storage size
RTP rates	Purdue, Utility 2, Utility 3
Demand cost factor	1, 10
Months	April, July

As a first step in illustrating the behavior of the optimal and rule-based control strategies, a single day was simulated. Figure 5a shows hourly-averaged building electricity usage and unit cost of electricity for July 15, 2017. Figures 5b and 5c present comparisons of chiller loading and state-of-charge of storage obtained with both control strategies for a target demand defined as the average between the minimum and maximum possible demand costs for this day. In these figures, time zero corresponds to the time where the occupancy period begins, which is 8am. The rule-based control strategy closely reproduces the optimal storage discharge control path and makes complete use of the storage during the period with the highest value of the electricity unit cost. Nonetheless, the rule-based strategy starts charging the storage later than the optimal control and aims to maintain a constant load on the chillers until the storage is fully charged. These differences stem from the fact that the optimal control trajectory accounts for the different efficiencies of the operating chillers and, consequently, attempts to operate the minimum number of chillers at the highest possible efficiency, which occurs when they are fully loaded. The rule-based control trajectory, on the other hand, is based on a constant estimate of the plant COP and is indifferent to the number of operating chillers. However, the deviation of the daily energy cost obtained with the rule-based strategy from the optimal was only 0.31%.

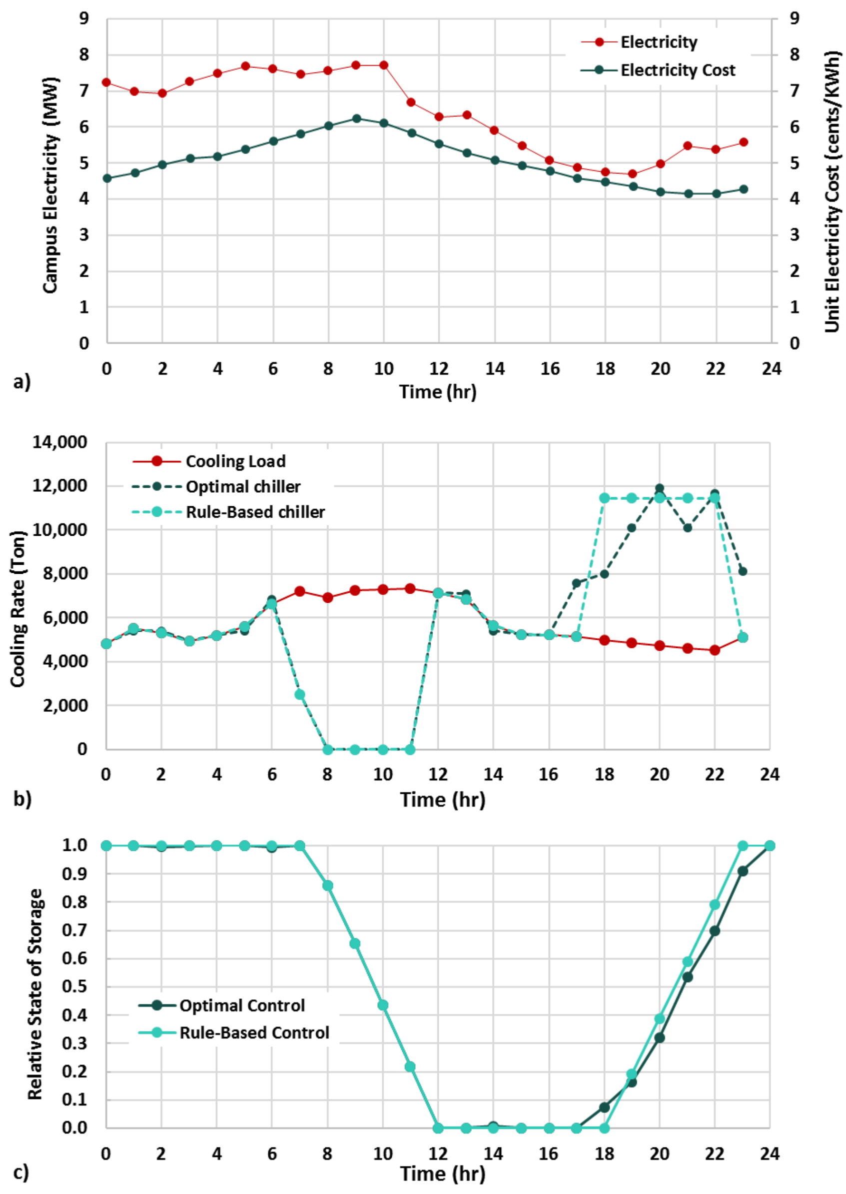

Figure 5. Comparison of optimal and rule-based control for 100% storage size, Purdue RTP rates and an average TDC in July 15: a) RTP rates and campus electricity, b) chiller loading, and c) state-of-charge of storage

Figure 6 presents a comparison of monthly electricity costs (combined plant energy consumption and total demand) obtained with rule-based control, storage-priority load-limiting, and chiller priority to optimal control, for all the combinations of variables listed in Table 1. The costs associated with the rule-based control are the closest to the optimal with a maximum deviation of 3.4%. Although the load-limiting strategy also performed relatively well, the costs obtained were between 3% and 15% greater than the optimal. The storage-priority load-limiting strategy is simpler to implement and does not require measurements of electricity usage, and might be considered as an alternative in absence of power measurements. The performance of chiller priority was much worse with costs between 10% and 32% greater than the optimal. Further, it can be observed that the cost deviation from optimal for both storage-priority and chiller-priority control increases when the demand charges are higher (the higher costs in the plot correspond to the unit demand cost multiplied by 10), whereas the rule-based control is almost insensitive to the increase in the unit demand cost. The cost deviation from optimal for the different strategies can be better appreciated in the histogram shown in Figure 7.

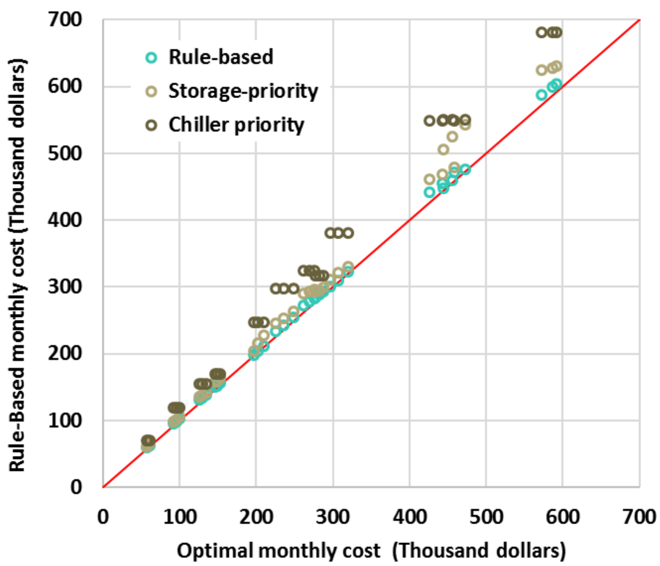

Figure 6. Optimal vs. heuristic control monthly electricity costs

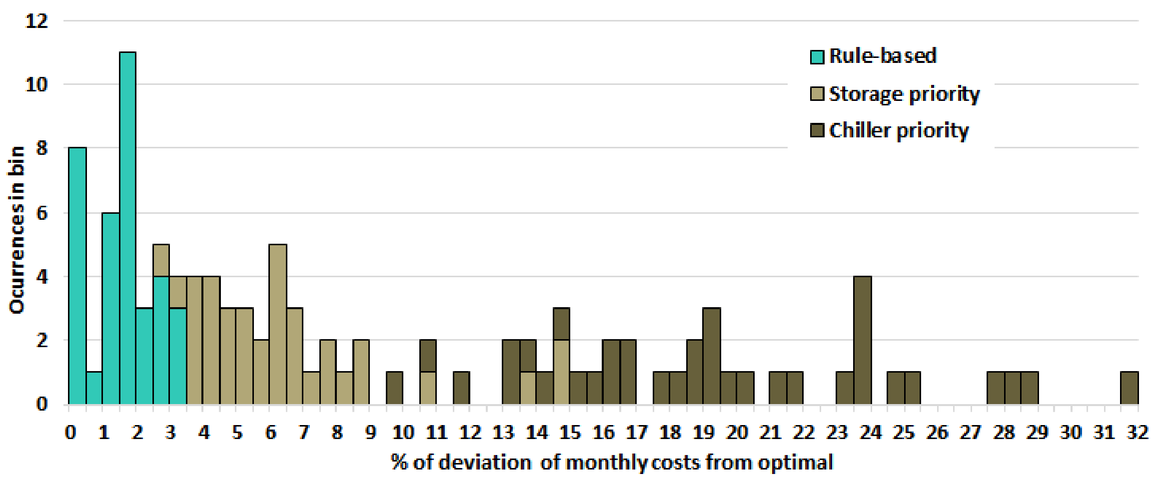

Figure 7. Frequency distribution of deviation of monthly electricity costs from optimal

Finally, a comparison of monthly savings obtained with the different control strategies with respect to chiller-priority control is shown in Figure 9. The savings presented here were evaluated with the original RTP rates applied at Purdue and different combinations of unit demand costs and storage sizes. It can be observed that the savings obtained with the rule-based control are much closer to the optimal than the ones obtained with storage-priority load-limiting control.

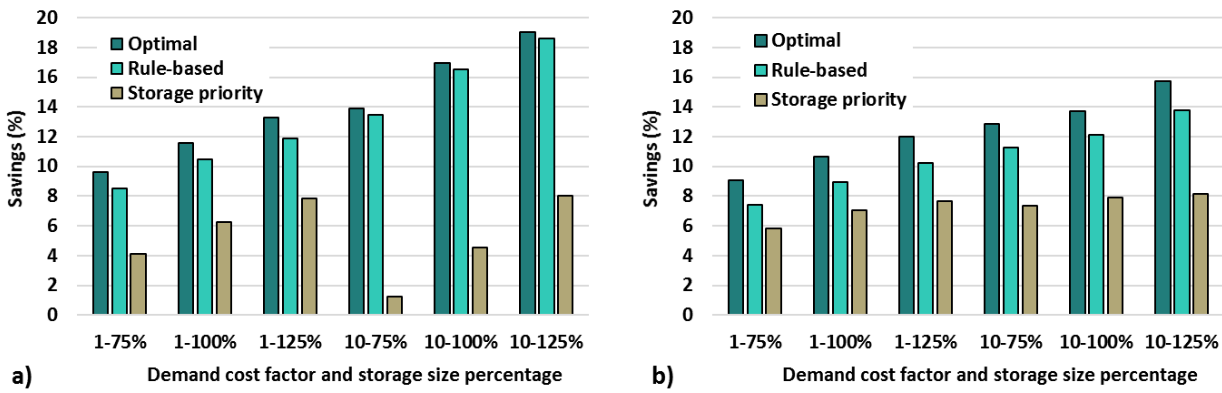

Figure 8. % of savings obtained with different storage control strategies with respect to chiller priority for Purdue RTP rates in two months: a) April and, b) July

CONCLUSIONS

This paper presented the results of the evaluation of a rule-based control strategy for chilled water storage subject to RTP electricity rates. The strategy requires measurements of cooling load, building electrical usage and state-of-charge of storage at each decision time interval. Additionally, daily profiles of RTP rates, and daily forecasts of loads and building electrical usage should be supplied at the beginning of each day and updated at each decision time interval. The strategy requires very little plant information (only an estimate of the plant COP) and ensures that the storage will not be prematurely depleted.

Monthly simulations of performance of the rule-based control strategy for a combination of storage sizes, load profiles and RTP electricity rates showed that the monthly costs obtained were within 3.5% of the optimal cost. Comparison with conventional strategies such as load-liming control and chiller priority showed the superior performance of the rule-based strategy. These results, nonetheless, were obtained using a perfectly stratified chilled water storage model and perfect predictions of cooling loads and building electricity usage, which make them useful only for benchmarking the rule-based control strategy, not for economic assessment of chilled water storage.

The rule-based control algorithm is the result of a trade-off between performance and simplicity; consequently, its ability to produce near-optimal results is subject to certain conditions. One of the factors that affect the performance of the strategy is the location of the day that establishes the target demand cost (TDC) for the month. The closest this day is to the beginning of the month, the better the strategy does at minimizing the energy costs. The occurrence of a day with an unusually high electrical and thermal load close to the end of the month would cause a significant deviation of the monthly costs from the optimal. Further, the control strategy works well if the RTP rates are lowest during the period of lowest occupancy (which is generally the case), and for systems sized such that the unoccupied period is sufficient to recharge a large portion of the storage capacity.

NOMENCLATURE

Symbols

Cap_s	storage capacity or maximum possible change in internal energy of the storage
COP	cooling plant coefficient of performance (i.e. ratio of plant cooling load to power consumption)
D	demand charge rate
E	unit electricity cost
J	electricity cost over the billing period (e.g. a month)
k_{di}	initial stage of maximum storage-discharge period
k_{df}	final stage of maximum storage-discharge period

N number of time stages in a billing period
P total electric power consumed by the building and the cooling plant
P_{bd} buildings electric power consumption
P_{plant} electric power consumption of the cooling plant
$\dot{Q}_{ch}$ chiller cooling rate
$\dot{Q}_{chlim}$ limiting value for chiller load so the demand cost does not exceed the specified TDC
$\dot{Q}_{load}$ cooling load
$\dot{Q}_{max}$ maximum plant cooling capacity
$\dot{Q}_{s}$ rate of energy added to storage (positive for discharging, and negative for charging)
RTP real-time-pricing utility rates
TDC target demand cost for the billing period ($)
u velocity of the fluid relative to storage tank height, positive upwards.
w uncontrolled variable (i.e. ambient conditions)
x relative state-of-charge of storage (0 for discharged, 1 for completely charged)
Δt length of the decision time interval
φ state function

Subscripts/Superscripts
i initial
f final
k stage

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