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Michael J. Wenzel
Johnson Controls Inc., United States of America, mike.wenzel@jci.com

Robert D. Turney
Johnson Controls Inc., United States of America, Robert.D.Turney@jci.com

Kirk H. Drees
Johnson Controls Inc., United States of America, Kirk.H.Drees@jci.com

Model Predictive Control for Central Plant Optimization with Thermal Energy Storage

Michael J. WENZEL[1]*, Robert D. TURNEY[1], Kirk H. DREES[1]

[1]Johnson Controls Inc.; Technology and Advanced Development, Building Efficiency;
Milwaukee, WI, United States of America
mike.wenzel@jci.com*, robert.d.turney@jci.com, kirk.h.drees@jci.com

* Corresponding Author

ABSTRACT

Linear Programming is used in order to determine how to distribute both hot and cold water loads across a central energy plant including heat pump chillers, conventional chillers, water heaters, and hot and cold water (thermal energy) storage. The objective of the optimization framework is to minimize cost in response to both real-time energy prices and demand charges. A planning tool that allows for the user to approximate a year's load distribution, and thus cost, in a few minutes is demonstrated. The optimization framework can also be used in real-time plant operation as a model predictive control (MPC) problem. In simulation, the system has demonstrated more than 10% savings over other schedule based control trajectories even when the sub-plants are assumed to be running optimally in both cases (i.e., optimal chiller staging, etc.) For large plants this can mean savings of more than US $1 million per year.

1. INTRODUCTION

Design and operation of central plants is becoming an increasingly difficult problem. Many high efficiency products are available; however, the effectiveness of these products in reducing the overall cost of operating a plant is highly dependent on the control technology that will be used to properly distribute the load across the many devices (Ma, 2011) (Yu, 2008).

Thermal energy storage can be used meet the design day load during the peak of the hotter summer days. Additionally, coupled with real-time pricing for electricity and demand charges, thermal energy storage (TES) offers another degree of freedom that can be used to greatly decrease energy costs by shifting production to low cost times or when other electrical loads are lower so that a new peak demand is not set. Of course, in order to get these benefits of thermal energy storage optimized control is necessary, a simple scheduled charge, hold, and discharge schedule will not suffice. In fact, to properly control the TES system one must predict the thermal loads on the building or campus, and determine the load distribution across all central plant assets that will result in the lowest cost. This optimization must be done over a receding horizon; the problem has most of the elements of a traditional model predictive control (MPC) problem.

This paper describes a model predictive control technique that is capable of running a plant with thermal energy storage optimally, while considering real-time electrical energy pricing, demand charges, as well as alternate methods of production which use different fuels. The optimal control is performed by splitting the optimization into two cascaded sub-problems that when solved produce a sub-optimal result, but under most conditions should be very near optimal. The lower level optimization determines, for each sub-plant (e.g., an assembly of heat pump chillers), the best devices to run, and the optimal operating setpoints for the chillers (e.g., flow, temperature, etc.) for any given load request and weather condition. This optimization can be done offline allowing for an optimal efficiency curve of the sub-plant to be given to the high level optimization. High level optimization is run using these efficiency curves, on-line, with a multiple day horizon over which the best distribution of load across the sub-plants and any thermal energy storage is found for each hour of the horizon using linear programming.

In simulation, the system has demonstrated more than 10% savings over other schedule based control trajectories even when the sub-plants are assumed to be running optimally in both cases (i.e., optimal chiller staging, etc.) For large plants this can mean savings of more than US $1 million per year.

2. PROBLEM DESCRIPTION

Central plant optimization is concerned with controlling any number of sub-plants feeding any number of loads in the most cost efficient manner possible. Figure 1 shows an illustrative view of the resource flow in a central plant that serves both hot and cold water loads of a building. The plant contains a chiller sub-plant, heater sub-plant, and a heat recovery chiller sub-plant and is served by electricity, natural gas, and water utilities. The goal is to serve the loads in a way that has the least economic cost. In real-time pricing scenarios or when there is an electrical demand charge.

To perform the optimization the thermal loads (and electrical loads) of the building must be predicted for some horizon (a number of days). For this reason the problem has all the elements of a model predictive control problem. It can be broken into two parts: prediction and optimization. The prediction problem is posed as: given weather forecast, $\hat{\phi}_w$, the day type, *day*, the time of day, *t*, and the past measured load data, Y_{k-1}, determine the best estimate of the future weather data. That is, find

$$\hat{\ell}_k\left(\hat{\phi}_w, day, t \mid Y_{k-1}\right), \tag{1}$$

the best estimate of the loads for length of the horizon.

The optimization problem is not as simple. If properly designed the thermal energy storage can have a very long time constant, energy can be stored for a fairly long time before it is lost to the environment or heat transfer across the thermocline makes the energy unusable. Because the dynamics of the tank are long, there may be some advantages in using a long horizon. However, the equipment performance curves (power used vs. equipment load) are, in general, non-convex and there are several device on/off decisions to be made. The optimization problem is a nonlinear, mixed integer program (NLMIP). This may be intractable in a short computational time. For this reason, the optimization problem is broken into subproblems.

The equipment (low) level optimization determines which equipment, within a given subplant, to run given a load

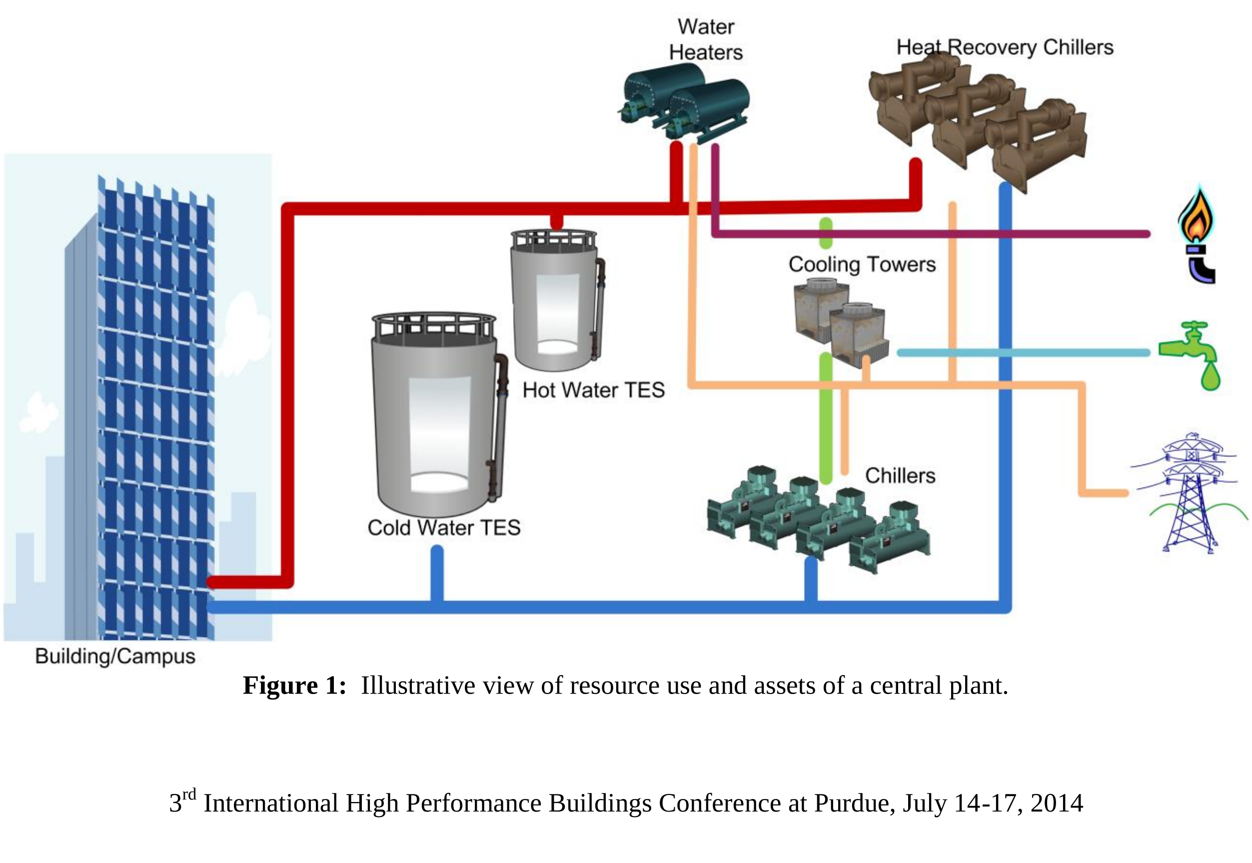

Figure 1: Illustrative view of resource use and assets of a central plant.

and environmental conditions. This is described in

$$\theta_{LL}^{*}\left(\dot{Q},\phi_{w}\right)=\underset{\theta_{LL}}{\arg\min}\, J_{LL}\left(\theta_{LL},\dot{Q},\phi_{w}\right), \tag{2}$$

where θ^{*}_{LL} contains the optimal low level decisions (i.e., binary equipment on/off decisions, flow setpoints, and temperature setpoints) based on the $\dot{Q}$, the subplant load, and ϕ_w, all pertinent weather conditions. To find the optimal set of low level decisions, the low level cost function J_{LL} is minimized. The low level cost function is the sum of the cost of all utility use per device summed over all equipment in the subplant. This is given by,

$$J_{LL}\left(\theta_{LL},\dot{Q},\phi_{w}\right)=\sum_{i=1}^{n_e}\left[\sum_{j=1}^{n_u} c_j u_{ji}\left(\theta_{LL},\dot{Q},\phi_{w}\right)\right], \tag{3}$$

where n_e and n_u are the number of devices in the subplant and the number of utilities serving the plant, respectively, c_j is the economic cost of utility j at the current time, and u_{ji} is the rate of use of utility j by device i. Similar problems have been solved, on optimal chiller selection (Deng, 2013). At the equipment level there is little in the form of system dynamics. The optimization is run slow enough that one can assume that the equipment control has reached its steady-state. Therefore, all the parameters and decisions need to be made only at an instance of time rather than over a long horizon.

The subplant (high) level optimization, on the other hand, requires a long horizon due to the time constant of the storage tanks. Its goal is to minimize the cost running meeting the load over the entire horizon by properly distributing the load across the subplants and storage tanks,

$$\theta_{HL}^{*}=\underset{\theta_{HL}}{\arg\min}\, J_{HL}\left(\theta_{HL}\right), \tag{4}$$

where θ_{HL}^{*} are the optimal high level decisions (i.e., what load should each of the subplants and storage tanks provide) for the entire horizon. J_{HL} is the high level cost function, the sum of the economic cost of each utility used by each subplant at every time in the horizon,

$$J_{HL}\left(\theta_{HL}\right)=\sum_{k=1}^{n_h}\sum_{i=1}^{n_s}\left[\sum_{j=1}^{n_u} c_{jk} u_{jik}\left(\theta_{HL}\right)\right], \tag{5}$$

where c_{jk} is the economic cost of utility j at time k into the horizon, and u_{jik} is the rate of use of utility j by subplant i, at time k into the horizon.

The solution should be designed in such a way that it provides for two distinct use cases. The optimization may either be used operationally to determine optimal plant operation (and either send the results directly to the building automation system or present the results to a building operator for implementation) or as a planning tool in order to determine the cost of running such an optimized system. The planning tool should allow for the user to change central plant configurations and recalculate cost for an entire year. The planning tool has much stricter computation time requirements as it must calculate an entire year of plant load distributions in a time frame that lends itself to interactive design.

3. SOLUTION DESIGN

3.1 Cascaded Subproblem Description

Figure 2 shows the cascaded approach to central plant optimization. The cascade has two advantages over solving the whole optimization problem:

1) Differences in the dynamics allow the equipment level optimization to be run with a very short or no horizon; whereas the subplant level optimization must look far into the future to properly make use of the thermal energy storage.

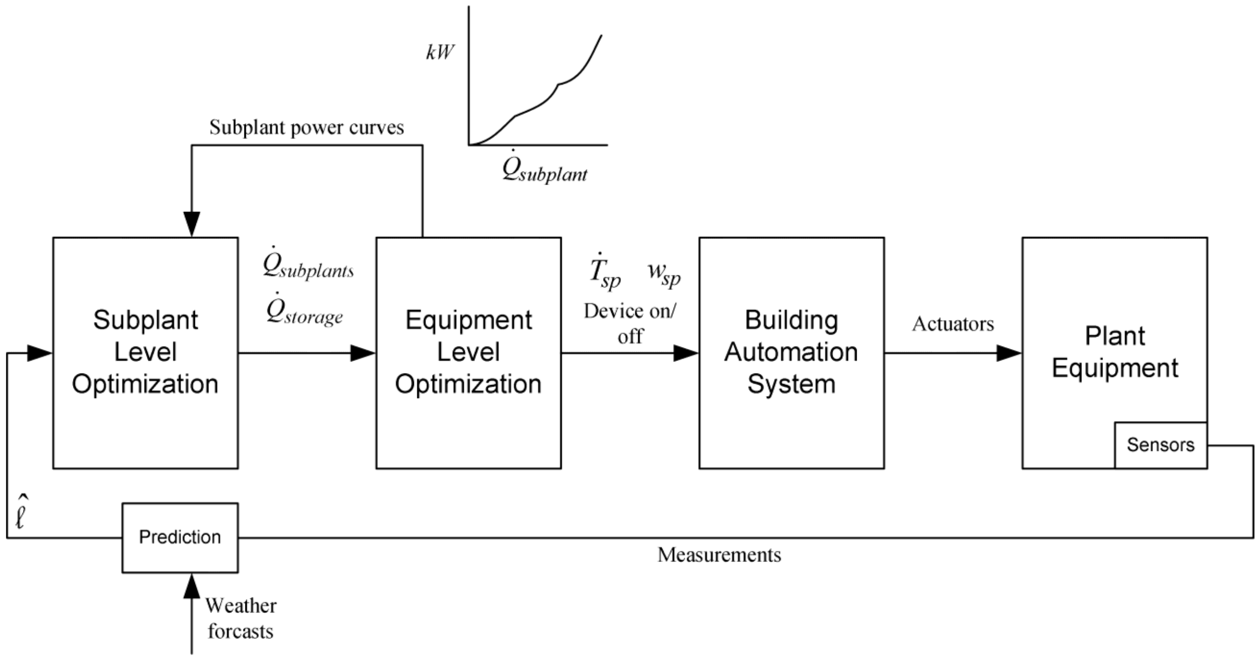

Figure 2: Illustrative view of resource use and assets of a central plant.

2) The subplant level optimization is performed without knowledge of the flow network. The equipment level optimization is communicating with BAS and needs to be tailored in some way to the plant. The subplant level optimization is more general and thus only has to depends on the subplants present.

In order to perform the optimization the subplant power curve (i.e., the rate of utility use by the subplant as a function of load produced) will be calculated. This is performed by running the equipment level optimization for several different loads and weather conditions. A curve is then fit to the data and the subplant curve is given to the subplant level optimization for its use. After obtaining the subplant power curve for each subplant the control is ready. A prediction is made and adjusted for feedback. With the predictions the subplant level optimization is able to use the power curves and utility rate data and find the distribution of the predicted loads across all subplants for the next n_h (horizon) samples.

The load distribution for the first time period of the horizon is given to the equipment level optimization. The equipment level optimization is then responsible for determining which devices to use, the temperature setpoints, and the flow setpoints that will optimally deliver the requested load from each subplant. The building automation system, through closed loop control, will then modulate the actuators in order to maintain the desired setpoints. The whole process of predicting and optimizing the subplant and equipment level is repeated every sample period.

3.2 Planning Tool Mode of Operation

The planning tool uses the same optimization algorithm; however, there is no need to predict the loads in real-time. The data entered into the planning tool will contain all loads for the year. A horizon of the given heating, cooling, and electrical loads along with utility pricing is taken, and the plant load distribution that results in the lowest economic cost is found using the subplant level optimization algorithm. A block of resultant load distribution is taken (a length of time that is less than or equal to the horizon) and accepted to be the true plant dispatch. The horizon is then shifted forward by the block size and the process is repeated as shown in Figure 3. This allows for the planning tool to be run in shorter periods of time and scale to yet scale to high fidelity overnight runs.

In the planning tool there is no reason that the optimization must be run for every sample period as is done in the operational tool. Because prediction is essentially perfect in the planning tool (data is just taken from the load time series), the only data that can change the optimization results is the new block of data that is obtained when the horizon is shifted. If the block size is a small percentage of the horizon this should have very little affect on conrol.

It can be seen in Figure 3 that hours 7 through 12 in the first optimization are nearly identical to hours 1 through 6 in the second optimization suggesting that even a 12 hour horizon would have had similar results in this case.

Once the optimal subplant load distribution is found for the extent of the planning tool run, the results of the equipment level optimization are used to calculate the production and utility use of each device within a subplant. The functions which perform this calculation are determined at the beginning of the planning tool run in the by sending various loads and weather conditions to the equipment level optimization and fitting the curves in the same way it is done in the operational tool.

4. OPTIMIZATION FRAMEWORK

4.1 Linear Programming

Linear programming was chosen as the optimization framework for the subplant level optimization. A linear programming problem has the form given by,

$$\arg\min_{x} c^T x; \ \ subject \ \ to \ \ Ax \le b, \ \ Hx = g, \tag{6}$$

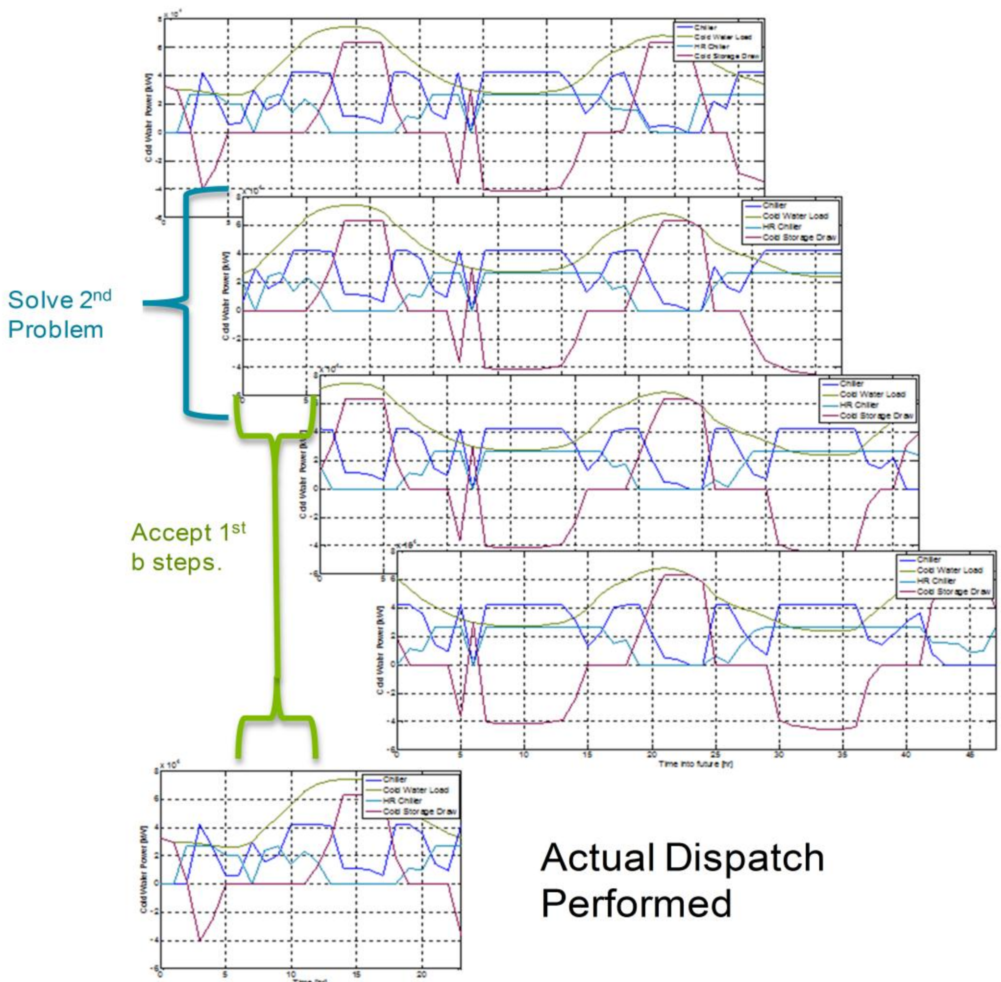

Figure 3: In planning mode the algorithm will optimize load distribution over a horizon and then accept a block of those (b) as the actual plant dispatch. This is repeated as the horizon is slid forward in time.

where c is the cost vector, x is the decision matrix, A and b are the matrix and vector which describe the inequality constraints, and H and g are the matrix and vector which describe the equality constraints. This framework appears highly restrictive; however within this framework it is possible to determine the subplant load distribution for a long horizon in a very short time frame complete with load change penalties, demand charges, and plant performance curves.

4.2 Central Plant Optimization as a Linear Programming Problem

First the problem is formulated for the simple case, where only energy cost and equipment constraints are considered. Take the example plant given in section 2. The plant assets across which the loads are to be distributed are a chiller subplant, a heat recovery chiller subplant, a heater subplant, cold water storage and hot water storage. The loads across each one of these subplants are the 5 decision variables that the optimization must determine for each sample period of the horizon, i.e.,

$$x = \left[\dot{Q}_{chiller,1..n}, \dot{Q}_{hrChiller,1..n}, \dot{Q}_{heater,1..n}, \dot{Q}_{hotStorage,1..n}, \dot{Q}_{coldStorage,1..n}\right]^T . \tag{7}$$

In the simplest form it is possible to assume that each subplant has a specific cost per load. This constant COP (efficiency) can change for any given element of the horizon, but for this simple case is not a function of the loading. c is given by,

$$c = \left[\left[\sum_{j=1}^{n_u} c_j u_{j,chiller}\right]_{1..h}, \left[\sum_{j=1}^{n_u} c_j u_{j,hrChiller}\right]_{1..h}, \left[\sum_{j=1}^{n_u} c_j u_{j,heater}\right]_{1..h}, 0_h, 0_h\right]^T , \tag{8}$$

where $\left[\sum_{j=1}^{n_u} c_j u_{j,hrChiller}\right]_{1..h}$ is used to represent a vector of h sums, one for every element of the horizon. The last $2h$ elements are *0* to indicate that charging or discharging the storage tank has no cost (pumping power is neglected).

It is also necessary to define the constraints on the decision variables. Each subplant has two capacity constraints,

$$\begin{aligned} &\dot{Q}_{chiller,k} \le \dot{Q}_{chiller,\max} \quad \forall k \in horizon, \\ &\dot{Q}_{chiller,k} \ge 0 \quad \forall k \in horizon. \end{aligned} \tag{9}$$

These inequality constraints can be placed in the form of (6) by entering,

$$A = \begin{bmatrix} [I_h] & [0_h] & [0_h] & [0_h] & [0_h] \\ [-I_h] & [0_h] & [0_h] & [0_h] & [0_h] \end{bmatrix}, \ b = \begin{bmatrix} \dot{Q}_{chiller,\max}[1_h] \\ [0_h] \end{bmatrix}, \tag{10}$$

into the rows of the inequality constraint matrix and vector. Here $[I_h]$ used as the h by h identity matrix, $[0_h]$ is used as either an h by h zero matrix or h by 1 zero vector, and $[1_h]$ is the h by 1 ones vector. The storage tanks have similar constraints for their maximum charge and discharge rate (in this case we consider discharging as a positive load in the vector x). The constraints are given by,

$$A = \begin{bmatrix} [0_h] & [0_h] & [0_h] & [I_h] & [0_h] \\ [0_h] & [0_h] & [0_h] & [-I_h] & [0_h] \end{bmatrix}, \ b = \begin{bmatrix} \dot{Q}_{discharge,\max}[1_h] \\ \dot{Q}_{charge,\max}[1_h] \end{bmatrix}, \tag{11}$$

and similarily for the cold water tank. A total demand constraint, $P_{elec,max}$ can be implemented by adding the electrical usage of all the subplants and the building/campus itself, $P_{elec,campus}$. The rows of constraints are,

$$A = \left[u_{electrical,chiller}[I_h], u_{electrical,hrChiller}[I_h], u_{electrical,heater}[I_h], 0_n, 0_n\right], \ b = P_{elec,\max}[1_h] - P_{elec,campus,k}, \tag{12}$$

to implement a demand constraint. The final inequality constraints deal with tank capacities. The tank must never charge above its capacity or be discharged below zero. This leads to a series of constraints that ensure that the tank level at the beginning of the horizon, $Q_{0,Hot}$, plus all the charging from 1 to k elements into the horizon (with discharge from the tank taken as positive this will be a subtraction) is less than the capacity, $Q_{\max,Hot}$. A similar constraint prevents over discharging the tank. These entries into the constraint matrix have triangular matrices. For the hot storage tank,

$$A = \begin{bmatrix} [0_h] & [0_h] & [0_h] & T_s[\Delta_h] & [0_h] \\ [0_h] & [0_h] & [0_h] & T_s[-\Delta_h] & [0_h] \end{bmatrix}, \; b = \begin{bmatrix} Q_{0,Hot}[1_h] \\ Q_{\max,Hot} - Q_{0,Hot}[1_h] \end{bmatrix}, \tag{13}$$

where Δ_h is a lower triangular matrix of ones and T_s is the length of time of a element of the horizon. Finally the loads must be satisfied, which leads to two sets of equality constraints, one for the hot water load and one for the cold water load. To implement the load constraints,

$$H = \begin{bmatrix} [I_h] & [I_h] & [0_h] & [0_h] & [I_h] \\ [0_h] & (1+u_{electrical,hrChiller})[I_h] & [I_h] & [I_h] & [0_h] \end{bmatrix}, \; g = \begin{bmatrix} \hat{\ell}_{Cold,1..k} \\ \hat{\ell}_{Hot,1..k} \end{bmatrix}. \tag{14}$$

For this example problem (assuming a horizon of 72 one hour samples) the linear program has 360 decision variables, and 1224 constraints. However, in the linear programming framework this can be solved in less than 200ms so a planning problem with 12 hour blocks can be solved in only 2 minutes.

4.3 Demand Charge Optimization

Proper inclusion of the demand charge into the optimization framework is one way to greatly improve the performance of central plant optimization. Inclusion of demand optimization has been shown to save as much as 5% of plant operation cost on top of the already 8 – 10% energy optimization alone will save. To include the demand charge it is necessary to modify the cost function. The first equation in (6) must be changed to,

$$\arg\min_{x} \left[c^T x + c_{demand} \max\left(P_{elec,k}(x)\right) \right], \tag{15}$$

where c_{demand} is the period's demand charge. Two things make the inclusion of the demand charge complicated: first, the cost function is no longer linear due to the inclusion of the max function; second, the $c^T x$ is the energy cost over the horizon, whereas the demand charge is over the demand period. These two periods might not be the same.

To cast the new cost function into the linear frame work a new decision variable, x_{peak} (the peak demand), is required. Then c can simply be augmented with c_{demand} and x with x_{peak},

$$c_{new}^{\;T} = \left[c^T, c_{demand}\right]^T, \;\; x_{new} = \left[x^T, x_{peak}\right]. \tag{16}$$

Constraints are used to insure that x_{peak} is greater than the greatest of all the demands over the horizon. x_{peak} would never be greater than this as it would be suboptimal. The constraints required are given by,

$$A = \left[u_{electrical,chiller}[I_h], u_{electrical,hrChiller}[I_h], u_{electrical,heater}[I_h], 0_n, 0_n, -1_h\right], \; b = -P_{elec,campus,k}, \tag{17}$$

Additionally the peak decision variable must be greater than it has been at anytime in the past during this demand period.

To properly make the trade-off between increasing the demand charge versus increasing energy cost it is necessary to weight the demand charge. The cost function in (16) has components that are over different periods and cannot be directly compared. The energy cost is over the horizon whereas the demand charge is over the demand period. To reweight the objective function it is necessary to find the average energy cost per day over the horizon this can then be multiplied by the number of days left in the demand period (d_{demand}) so that the entire cost function is over the demand period. The new optimization function would be given by,

$$\arg\min_{x}\left[\frac{d_{demand}}{h}c^{T}x+c_{demand}x_{peak}\right], \tag{18}$$

which is equivalent to,

$$\arg\min_{x}\left[c^{T}x+\frac{h}{d_{demand}}c_{demand}x_{peak}\right]. \tag{19}$$

Eqn. (19) simply has the advantage of adjusting only one element of the cost vector rather than several.

4.4 Performance Curves and Change of Load Penalty

Performance curve can be easily added in a manner similar to the method demonstrated in adding the demand charge. Any convex performance curve can be added by the addition of a decision variable for each utility for which its usage vs. production curve is nonlinear, but convex. In this case, the cost associated with the variables actual production is zero, while the new variable for each utility is a given a cost equal to the utility's cost at that time. Linear inequality constraints are then used to constrain the utility use state to be in a piecewise linear approximation of the epigraph of the performance curve. Of course the utility use will lie on the curve (boundary of the epigraph), because to move above the curve would be suboptimal.

Often times the optimization algorithm will take a subplant from off to full load and back to off again in a matter of 3 elements of the horizon. The optimization is finding areas where there are small fluctuations in the utility cost cause this behavior to have the least economic cost. This behavior is certainly not optimal especially if the cost saved is on the order of few cents or dollars. This problem can also be attacked by augmenting x with additional decision variables. In this case a "load change" amount is added at every step in the horizon. The cost of this decision variable is given an adjustable penalty (which can be specified in dollars per percent change). The load change decision is then constrained to the epigraph of the absolute value of difference between the two previous load decisions using the inequality constraints.

5. PRELIMINARY SIMULATION RESULTS

To demonstrate the central plant optimization algorithm an example plant was constructed using 42.1 MW (12000 ton) of chiller capacity 26.3 MW (7500 ton) of heat pump chiller capacity, and 53.2 MW (162 mmBTU/hr) of water heater capacity. The cold thermal energy storage had 316 MWh (90000 ton hr) of capacity and could charge or discharge at a maximum rate of 20% per hour. The hot thermal energy storage had 176 MWh (600 mmBTU) of capacity and could also charge and discharge at a rate of 20% per hour. All chiller were assumed identical with a COP that depended on the wetbulb temperature, all water heaters were assumed identical with an efficiency of 0.85, and each of the three heat pump chillers had a capacity of 8.78 MW (2500 ton) and COP (defined as cooling output over electrical input) of 1.95, 1.94, and 1.93. To perform a simulation the data was run in "planning mode" with the expected hot, cold, and electrical loads of the campus served by the central plant.

The simulation results for various horizons and block sizes are shown in table 1. These results include the electricity, gas, and water required to run the central plant along with the corresponding costs (demand is shown for the entire building). As shown in the table the cost decreases as the horizon increases and block size decreases. However, the increase in savings from a horizon above 72 hours is less than $10k. The optimization provides approximately $910k in savings compared to a scheduled thermal energy storage solution. Inclusion of the demand optimization is worth another $400k in savings.

hrzn	blck	elec. energy (GWh)	elec. energy cost (M$)	elec. demand (MW)	elec. demand cost (M$)	natural gas energy (GWh)	natural gas cost (M$)	water (km^3)	water cost (M$)	Total Cost (M$)	Comp. Time (s)
24	24	96.3	5.51	5.35	2.69	72.2	1.33	98.5	0.25	9.78	32.9
24	12	96.4	5.50	5.27	2.69	71.7	1.32	98.1	0.25	9.76	62.3
48	12	97.0	5.54	52.6	2.68	69.0	1.27	96.3	0.24	9.75	162
72	12	97.2	5.55	52.6	2.70	67.9	1.25	95.6	0.24	9.74	431
96	8	97.3	5.56	52.6	2.70	67.4	1.24	95.3	0.24	9.74	1199
168	1	97.4	5.56	52.6	2.70	67.2	1.24	95.1	0.24	9.74	25937
INCLUDE DEMAND CHARGE OPTIMIZATION---											
96	8	97.1	5.60	42.5	2.23	68.7	1.27	96.1	0.24	9.34	1236
INCLUDE LOAD CHANGE PENALTY $1 PER PERCENT PER HOUR--											
96	8	97.4	5.60	48.9	2.60	67.3	1.24	95.1	0.24	9.68	1430
NO OPTIMIZATION--											
N/A	N/A	75.3	4.44	56.1	2.63	171	3.15	170	0.43	10.65	N/A

Table 1: Simulation results

It should be noted that when incorporating the demand charge there are significant gains to be made by extending the horizon to 96 hours. When including the demand charge optimization the energy cost is averaged to a per day basis and then extrapolated to fit the whole demand period. This extrapolation gets increasingly better as the length of the horizon is increased. Also, the results show that including the change penalty decreases cost. In general this would not be the case. Here, the load change penalty had a secondary effect of reducing the demand. If the load change were run with demand optimization, the solution with the load change penalty would definately be greater than the US $9.34 million cost without the change of load penalty.

Figure 4 shows the results of the simulation. The top two plots are zoomed in to show the effect of the load change penalty on the cold water load. With the load change penalty it can be clearly seen that the chiller load is significantly smoother. The second two plots show the effect of demand optimization. On the first plot demand peaks are clearly over 50 MW in several locations. However, demand optimization effectively trims those peaks to a target that is established each month.

6. CONCLUSION

A cascaded approach to central plant optimization has been shown. The subplant level determines how to distribute the loads between different asset classes within a central plant, whereas the equipment level determines how to best run the subplant at that load. Additionally linear programming was shown to optimize subplant level distribution, and able to incorporate demand charge, load change penalty, and performance curves.

The cascaded approach allows one make optimal use of computational time. The cascaded approach uses no horizon at the equipment level, when dynamics are fast compared to the time to re-optimize plant loads, and use a long horizon when the dynamics and capacity of the thermal energy storage allow one to defer loads for long time periods. Additionally, linear programming appears to be a good optimization framework for the subplant level optimization. It is capable of incorporating real-world problems like demand charges, load change penalties, and performance curves into its framework. The linear program can be solved in a time frame that makes possible a planning tool capable of running all the hours of a year in a time that facilitates interactive plant design, possibly plant design optimization. Simulations have shown that the optimization framework is capable of saving over 10% of plant operation cost over a scheduled thermal energy storage system.

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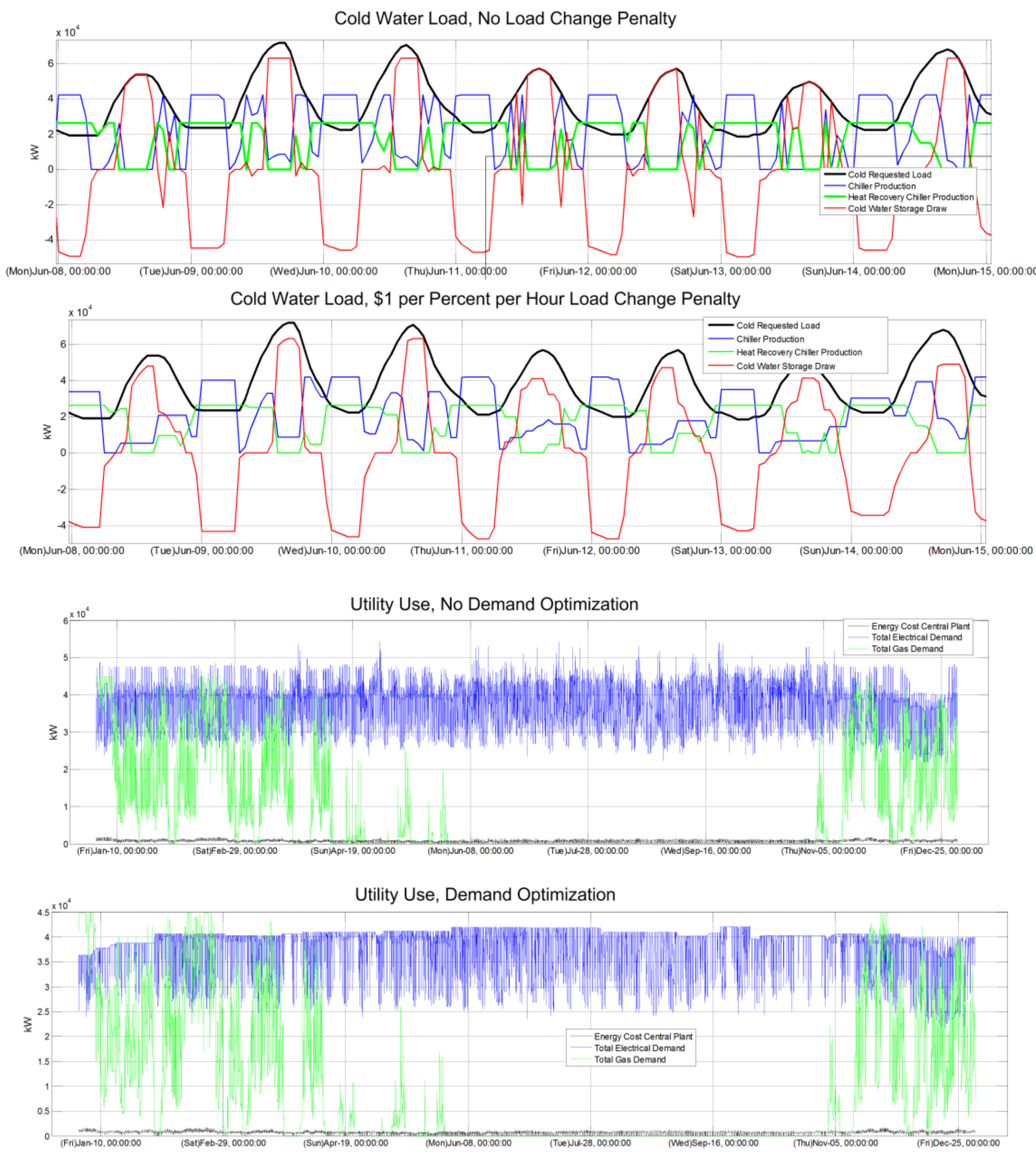

Figure 4: Simulation results

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