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

Mohammad N. ElBsat
Johnson Controls, United States of America, mohammad.elbsat@jci.com

Matthew J. Ellis
Johnson Controls, United States of America, matthew.j.ellis@jci.com

Matthew J. Asmus
Johnson Controls, United States of America, matt.asmus@jci.com

Andrew J. Przybylski
Johnson Controls, United States of America, andrew.j.przybylski@jci.com

See next page for additional authors

Authors
Michael J. Wenzel, Mohammad N. ElBsat, Matthew J. Ellis, Matthew J. Asmus, Andrew J. Przybylski, Ryan Baumgartner, John H. Burroughs, Graeme Willmott, Kirk H. Drees, and Robert D. Turney

Large Scale Optimization Problems for Central Energy Facilities with Distributed Energy Storage

Michael J. WENZEL[1]*, Mohammad N. ELBSAT[1], Matthew J. ELLIS[1], Matthew J. ASMUS[1], Andrew J. PRZYBYLSKI[1], Ryan B. BAUMGARTNER[1], John H. BURROUGHS[1], Graeme WILLMOTT[1], Kirk H. DREES[1], Robert D. TURNEY[1]

[1]Johnson Controls Inc., Technology and Advanced Development, Milwaukee, WI, USA
mike.wenzel@jci.com*, mohammad.elbsat@jci.com, matthew.j.ellis@jci.com, matt.asmus@jci.com, andrew.j.przybylski@jci.com, ryan.baumgartner@jci.com, john.h.burroughs@jci.com, graeme.willmott@jci.com, kirk.h.drees@jci.com, robert.d.turney@jci.com

* Corresponding Author

ABSTRACT

On large campuses, energy facilities are used to serve the heating and cooling needs of all the buildings, while utilizing cost savings strategies to manage operational cost. Strategies range from shifting loads to participating in utility programs that offer payouts. Among available strategies are central plant optimization, electrical energy storage, participation in utility demand response programs, and manipulating the temperature setpoints in the campus buildings. However, simultaneously optimizing all of the central plant assets, temperature setpoints and participation in utility programs can be a daunting task even for a powerful computer if the desire is real time control. In this work, a hierarchal optimization system has been created to coordinate the optimization of the central plant, the battery, participation in demand response programs, and temperature setpoints. The required information shared by individual setpoint optimization from each program to the coordinating optimizer is given. Additionally, the common elements for any facility optimization problem are discussed. A great variety of facilities can be described with just a few components. Even without the dedicated solver, the problems can be solved in real time given this hierarchal scheme. However, the importance and wide applicability of these problems give reason to develop dedicated solvers.

1. INTRODUCTION

Buildings use a large fraction of the total energy consumption in the United States. In 2011, even before the economy had fully recovered, buildings were responsible for using 41 EJ (39 quad) of energy (U.S. D.O.E. 2011). It is for this reason that any savings in building energy consumption can have a large effect on the overall energy consumption if the method can be widely applied. At present, equipment has approached the theoretical maximum efficiency and increasing the efficiency further comes with a cost that is not economically viable. Researchers have moved to towards developing more efficient control; however, there is little efficiency to be gained from enhancements to local system control. Instead, one must consider the entire system in order to achieve the biggest impact on overall efficiency.

Building or facility control is a very complex problem. Even a medium sized commercial building may have hundreds of actuators that must be controlled. At a single instant in time, it may be possible to optimize all of these setpoints to achieve maximum energy efficiency. However, many facilities have energy storage (or their systems have dynamics of some kind) and energy rates may vary over time. To optimize cost, the entire system over a period of time at least as long as the dominant system dynamics must be considered. This quickly leads to an untenable problem; a problem that cannot be solved in real time in order to control the facility, completely eliminating the ability for the optimization to produce any cost savings.

Several engineering trade-offs must be made in order to solve these problems fast enough, such that the solution can be used to control equipment in real time. A hierarchal control scheme is necessary. In the proposed scheme, a multi-tiered approach is used. First, a coordinating controller containing an aggregate model of all the major components of the system is used to decompose the problem in space. Resource allocations are sent down to lower level controllers. The low level controllers convert the resource allocations into setpoints for the building automation system (BAS) to execute. The BAS system is capable of adjusting actuators at control rates in the seconds to achieve the requested setpoints. It is in this way that the computational burden is balanced. Optimizers with large scope calculate setpoints at rates on the order of several minutes and controllers with local scope are used to make short term adjustments to hit the setpoints.

In the present paper, a large facility, a university campus for example, is used to demonstrate the decomposition. It is shown how the entire system can be optimized. The decomposition consists of an asset allocation that determines the optimal allocations across all systems in a facility, a setpoint optimization that converts the allocation into optimal setpoints, and a BAS that continuously maintains these setpoints. It is noted that as one moves down in the hierarchy, the control problem is more specific to the type of equipment in the facility. On the other hand, asset allocation is a very general problem where it is possible to describe any facility, regardless of function, with only a few building blocks. The notation for facility optimization is described and a solver has been produced that converts the facility optimization problem into the matrices of a standard mixed-integer linear program (MILP). While it is possible to solve in real-time, no enhancements have been made to the MILP solver that take advantage of this class of problems. The task of building a dedicated solver for this type of problem is left to researchers in the optimization field.

2. DECOMPOSITION

Consider a facility that is responsible for providing heating, cooling, and electricity to a large campus. The facility has several chillers, steam turbines with heat recover steam generators, boilers, a large battery system, and several buildings, each with several hundred zones. The end goal is to set the chiller, pump, tower fan variable speed drive, damper positions, etc. in such a way that the overall cost of providing the energy services to the building is minimized for the time period of the optimization (the horizon). The cost function can be described by,

$$J = \sum_{utility} \sum_{horizon} cost\left(purchase_{resource,\,time}, time\right). \tag{1}$$

The large number of variables that affect the utility procurements and the length of the horizon ensure that this problem requires a decomposition to be able to solve it in any reasonable amount of time. Of course, setting the actuator positions is typically performed by the building automation system (BAS) so an assumption will be made that the first decomposition occurs at the setpoint level and the BAS is unchanged in its job of converting flow, temperature, etc. setpoints to actuator positions.

Assuming that the actuator control is left to the BAS, the remaining portion of the optimization problem takes predictions of the loads and rates and outputs setpoints to the BAS level control. A flow chart for the decomposed facility optimization system is shown in Figure 1. The decomposition includes, at the highest level, an asset allocation that performs resource balance on the system and allocates budgets/targets to all the underlying subproblems. The

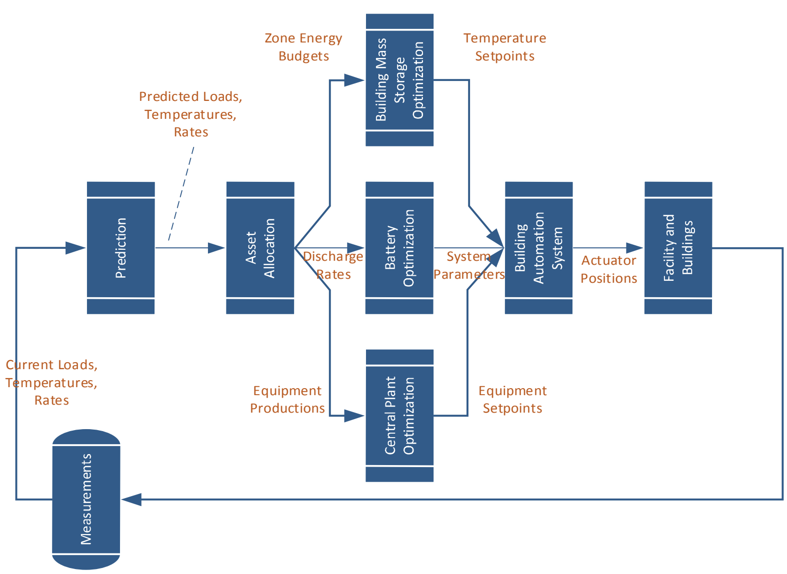

Figure 1: The decomposed facility optimization problem. The components of asset allocation, setpoint optimization, and building automation are shown.

subproblems must convert their budget/target into control parameters and setpoints. These subproblems are naturally split into categories based on major systems in the asset allocation. For the example problem, the setpoint optimization problems are central plant setpoint optimization (CPO), battery system optimization, and building mass storage optimization (BMSO). The remaining part of the paper is dedicated to describing the language of asset allocation and the three setpoint optimization problems.

3. ASSET ALLOCATION

Facilities share the same type of constraints and variables that may be present in their optimization problems. The most common variables are the productions or usages of resources. It is around these resources that a language (notation) for facility optimization is built. In a facility a resource can be purchased by a supplier, converted to another resource or stored by an asset, and used by a load. These three types of elements along with the nodes between them make up a facility optimization problem. The symbol for the facility optimization elements are shown in Figure 2 and a connected example of a facility asset allocation problem is shown in Figure 3.

The load is the request for a resource from the facility. In the typical example, the load is the chilled water, steam, electricity, etc. needed by the campus buildings. The load is the simplest of the three elements and leads to no decision variables in the optimization. It represents a use of the resource at a level equal to the predicted value.

Figure 2: Components of facility optimization problems

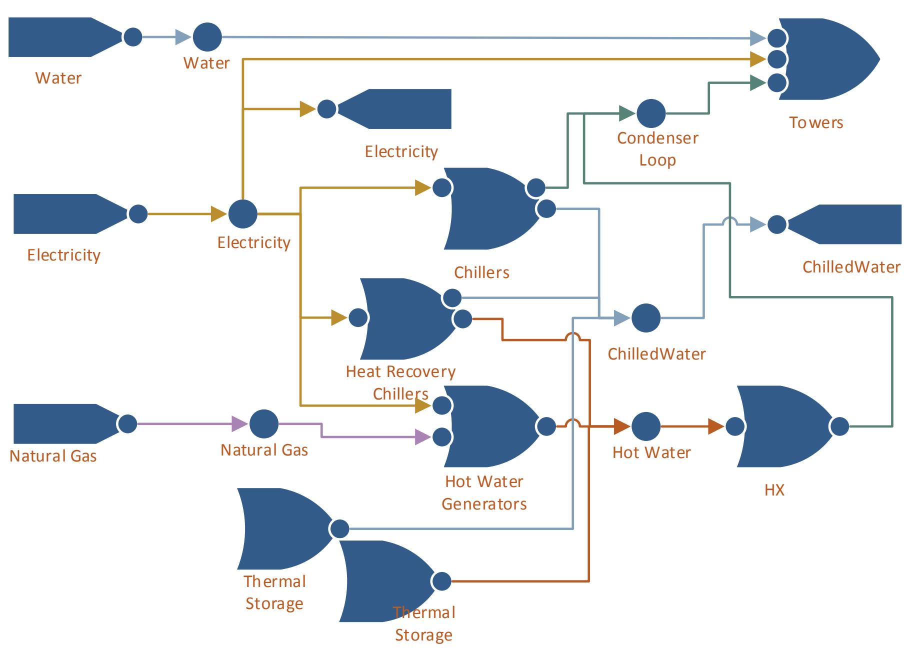

Figure 3: An example facility optimization problem that uses water, electric, and natural gas utilities to serve the electric, chilled water, and hot water needs of the campus. The facility has seven assets: a set of chillers, heat recovery chillers, hot water generators, towers, thermal energy storage tanks on both the hot and cold load and a heat exchanger allowing for excess hot water from the heat recovery chillers to be rejected by the towers.

3.1 Assets

Suppliers and assets are far more complicated components than the load. As stated above, an asset represents the ability to convert and/or store a resource. Assets have three components that characterize them: their resources, their operational domains, and their dynamics. The resources are simply the resources that the asset uses and the resources that it produces, represented by the bubbles on the asset symbol. The operational domains and dynamics represent constraints as to how the asset's use and production of resources are coupled.

Operational domains are regions in a subspace of the asset's resources. They state within which regions the asset can operate. An asset may contain several operational domains, each of which indicate the existence of several constraints on the variables in the subspace for which the operational domain is defined. An example of a set of operational domains is shown in Figure 4. Any operational domain can be described by a set of convex hulls, each defined by their vertices. Asset dynamics are state-space systems that describe how the inputs, outputs, and states of the asset must evolve over time. Dynamics represent equality constraints between time adjacent variables. An asset in the optimization problem must add at least one variable for every resource and internal variable, a set of constraints for each convex region in an operational domain, integer variables to allow for the optimization to choose between the convex regions within an operational domain, and equality constraints for the dynamics. It is noted that if a variable is known *a-priori*, i.e. it is a measureable and predictable disturbance (temperature is a common example), that portion of the operational domain can be collapsed before exposing it to the operational problem. It is not necessary to maintain convexity in this dimension and the solver can simply linearly interpolate between vertices in this region prior to creating the convex region that will be given to the optimizer.

The operational domains in Figure 4 represent an asset that contains a chiller and a tower. Operational domain (a) describes how much electricity is used as a function of chilled what production. The 0^{th} convex region represents the chiller off and convex region 1 represents the on region. The region in between the convex regions on the chilled water side represents the minimum turndown of the chiller. In most cases, optimization will keep the electrical usage on the lower boundary of convex region 1. However, if there were a reason for the optimizer to try to use more electricity than necessary (negative pricing for example), it might be necessary to break convex region 1 into two convex regions (one for each edge of the lower boundary). Operational domain (b) shows that water is directly proportional to the chilled water production. Note that chilled water is constrained to be greater than the minimum turndown in the first operational domain. Therefore, the minimum turndown will not be violated even though the second operational domain shows chilled water as a continuous range from zero to full capacity.

The dynamics in an asset represent how the inputs and outputs from the asset change over time. They describe any constraints that do not operate on the same element of time in the horizon, but rather on time adjacent elements in the horizon. The dynamics take on the form of a set of state space models,

$$\begin{aligned} x_{k+1} &= f(x_k, u_k) \\ y_k &= h(x_k, u_k) \end{aligned}, \tag{2}$$

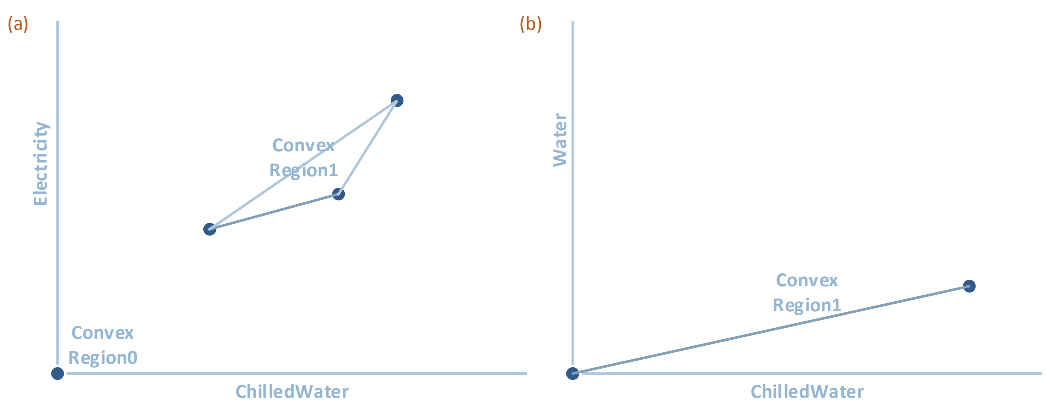

Figure 4: Operational Domains of a chiller group.

where the state space models, like the operational domains, act within a subspace of the usages, productions, and internal variables. Inputs and outputs of the state space system can be production, usages, or an externally predicted value. States are additional internal variables that are needed to represent the desired dynamics. Using generic nonlinear formulation will likely make the optimization problem computationally too expensive. Therefore, a linear state space model is also proposed.

One of the simplest assets that requires both an operational domain and dynamics is the battery system (or any type of simple storage). The dynamics of a battery are given by,

$$\phi_{k+1} = \phi_k - d_k. \tag{3}$$

Where ϕ_k is the state of charge of the battery (in kWh) and d_k is the discharge rate of the battery. The operational domain of the battery is given by the interior of the convex hexagon:

$$\begin{gathered}
\phi_k \geq \phi_{min} \\
\phi_k \leq \phi_{max} \\
d_k \geq -d_{max,charge} \\
d_k \leq d_{max,discharge} \\
\phi_k - \phi_{max} \leq \frac{\phi_{max} - \phi_{fullcharge}}{-d_{maxcharge\ fullSOC} + d_{max,charge}} \left(d_k - d_{maxcharge\ fullSOC}\right) \\
\phi_k - \phi_{min} > \frac{\phi_{fulldischarge} - \phi_{min}}{d_{max,discharge} - d_{max\ discharge\ minSOC}} \left(d_k - d_{maxdischarge\ minSOC}\right)
\end{gathered}. \tag{4}$$

This operational domain constrains the system such that the full discharge rate is reduced when the storage is nearly empty and the full charge rate is reduced when the storage is nearly full. These constraints are applicable to both battery and thermal storage. The variable definitions and the operational domain are shown in Figure 5. $d_{max,(dis)charge}$ is the maximum charge or discharge rate, $\phi_{full(dis)charge}$ is the state of charge at which the storage has access to full charge or discharge capability, and $d_{maxcharge\ fullSOC}$ and $d_{maxdischarge\ minSOC}$ are the charge rate at full SOC and the discharge rate at max SOC, respectively.

3.2 Suppliers

Suppliers represent the ability to purchase a resource from a utility. At the most basic level suppliers are simple; money is used to provide resources. In this way, suppliers add a single variable to the optimization problem per element of the horizon: the amount procured. This conversion is usually represented by a cost that is multiplied by the amount procured as shown in (1). This cost or rate changes with time to allow for time of use rates or real time pricing. The only requirement is that the rate can be predicted for the entirety of the optimization horizon. In summary, a supplier adds a term to the cost function, adds constraints for a maximum demand, and a minimum demand (may be non-zero for facilities with large electrical energy storage systems or cogeneration, which run the risk of putting power back on the grid), and adds a single variable to the optimization problem.

In practice, suppliers become significantly more complex due to the variety of programs and cost structures offered by the utilities. Rates may be progressive (or regressive) based on the total consumption at the end of the billing period.

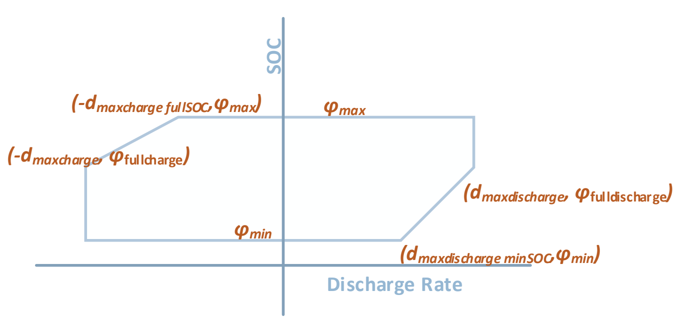

Figure 5: Operational domain of a simple storage system

Demand charges produce costs based on the peak amount procured during a time period. The time period of a demand charge could be a month or it could even be a year due to ratcheting. Incentive programs cause adjustments to the rates during participation in demand reduction programs or offer payments for using an asset for an ancillary service. The following sections talk about the three types of common programs that are part of the facility optimization language.

3.3 Node

The node represents a balance point in the asset allocation problem. When a node is added to the allocation problem a variable is added to the optimization to account for the possibility of any unmet load (this is slack variable to ensure constraint feasibility) and constraints are added that force resource balance. The constraints are given by,

$$s_k + \sum_{p\epsilon Rp} \eta_p r_{p,k} = \sum_{u\epsilon Ru} \frac{1}{\eta_u} r_{u,k}, \tag{5}$$

where η_p and η_u represent the transport efficiency from the p^{th} connected resource and the transport efficiency to the u^{th} connected resource, respectively, r represents the production/usage of a connected resource, and s_k is the slack variable. The output of asset allocation can be conveniently displayed for every node in the system in the form of a dispatch chart (an example is shown in Figure 6). The dispatch chart shows the slack variable and the resources allocations for any supplier, asset, or load connected to the node. Components supplying resource to the node are shown on the positive side and components using resource from the node are shown on the negative side. The dispatch chart must balance and therefore there is a mirroring across the time access on all dispatches.

3.4 Demand Charges

Demand charges are common for electrical tariffs. When a demand charge exists, the customer is typically charged a rate times the peak demand during the active hours of a period. A demand charge can be added to the system by adding a single variable and several constraints. First the cost function is augmented by:

$$J = \cdots + \max_{k \in P}\left(r_{d,k} p_k\right) \tag{6}$$

where r_k is the demand rate, p_k is the amount procured from the supplier, and P is the period over which the demand charge is active. This is the most general form of the demand charge. For common demand charges, that are active anytime during the period, the rate is a constant value. Other demand charges have times when the demand charge is not active (off-peak periods, for example), in this case the rate will switch between the demand rate and zero. The general form shown also allows for the hours to be weighted rather than on and off. To cast this problem into the linear programming framework, an auxillary variable is added (as single variable for the entire period), the cost function is augmented with the demand charge itself,

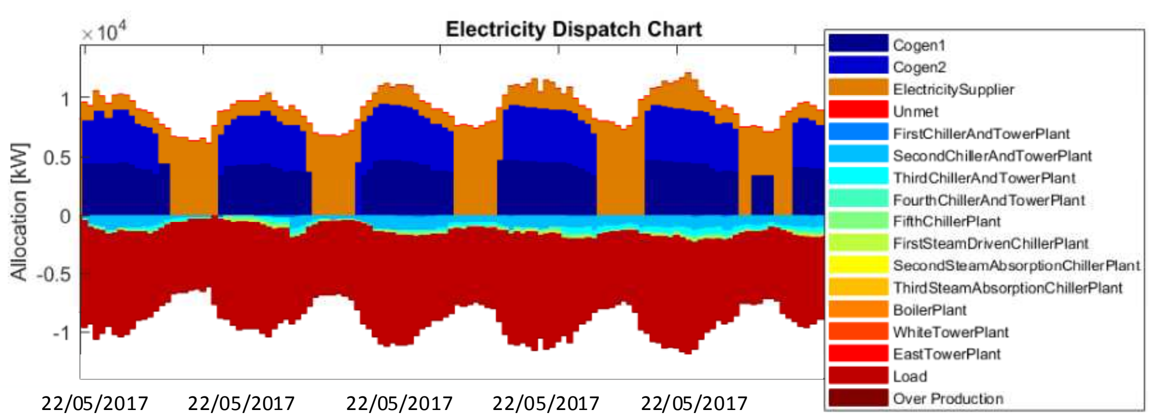

Figure 6: Dispatch chart for electricity. Productions into the node are shown as positive and usages from the node negative. The image is always mirrored about the time axis.

$$J = \cdots + c_d, \tag{7}$$

and the constraints,

$$\begin{gathered} c_d \geq r_{d,k} p_k \\ c_d \geq c_{d0} \end{gathered}, \tag{8}$$

are added to guarantee that the cost added satisfies the max function. Here, c_{d0} is added to ensure that the demand charge is also at least equal to the carried over demand charge for the same period in this month. It is possible that a single facility is subject to several demand charges. For example, a facility may have an off-peak, on-peak, and anytime demand charge. In this case, three terms would be added to (6) and three variables to (7) and three sets of constraints as in (8). The anytime demand charge would have a constant rate, whereas the on-peak and off-peak demand charge would have a rate that is constant and equal to the corresponding demand rate during the active hours and zero otherwise. This is different from the case of a weighted demand charge, consisting of a single charge as in (6) where the maximum (and thus the charge) is weighted by the rate.

Demand charges have the additional complication of being charged for a period that is typically much longer than the optimization horizon (typically a month compared to a horizon of a week or less). Thus, the demand charge must be weighted in order to give it the same weight as the other hourly charges of the horizon. This weighting is added to the demand term in the augmented cost function (7). One proposal for the weight w is the ratio of the hours remaining in the horizon to the hours remaining in the demand charge period (Wenzel *et. al.* 2014).

3.5 Rate Adjustment Programs

Certain programs offered by utilities manifest as an adjustment to their rate. This adjustment occurs in response to the occurrence of an event (coincident peak charges) or the participation in a program (economic demand response curtailment programs) (ElBsat and Wenzel). A rate adjustment is easily visualized in the cost function,

$$J = \cdots + (r_k + a_k) p_k + \cdots, \tag{9}$$

where a_k is the adjustment. The beauty of the rate adjustment is that several programs can fall within this simple approach; an approach that adds no computational burden to the optimization algorithm. Each program simply must define its way for adjusting the rate.

3.6 Reservation Programs

Other programs require the reservation of an asset in order to participate. The commonality in these types of programs is that the cost function is given a revenue term for the tightening of a constraint (the reservation). The reservation program requires the addition of a variable (amount of reservation) and a set of constraints (the reservation). The cost function is augmented with the revenue term for making the reservation:

$$J = \cdots - r_{i,k} p_{res,k}, \tag{10}$$

where $r_{i,k}$is the incentive rate for participation, $p_{res,k}$is the amount of participation in the reservation program and the negative sign represents that a revenue is being generated. The reservation removes some slack from a different constraint,

$$A_{ineq,(p,:)} x \leq b_{ineq,p} - f_p p_{res,k}, \tag{11}$$

which shows that existing constraint in row p is modified by an amount equal to a fraction of the reservation program participation. A reservation program may affect one or more constraints. Reservation programs can be thought of as the dual to the rate adjustment program or a “constraint adjustment program”.

3.7 Summary of Asset Allocation

Asset allocation is a special class of optimization problem consisting of suppliers, assets, and loads as described previously. This class of optimization problems is very general in its application to facility optimization problems, but yet only contains a small number of fundamental components to describe any problem. To date, a specialized solvers does not exist that can take advantage of the features in this class of problems. The results shown in Figure 6 use a computer routine that converts the asset allocation problem structure into a standard commercially available Mixed-

Integer Linear Program (MILP) solver. Significant advancements to the computational time for this type of problem are likely possible if the inherent structure of the problem is taken into account.

4. THE SETPOINT OPTIMIZATION LAYER

As shown in Figure 1, the setpoint optimization layer converts the resource allocation targets into setpoints for the building automation system to target. For the example problem, the setpoint optimization layer consists of three components:

- Central Plant Optimization takes equipment resource allocation and converts them into flow and temperature setpoints to be executed by the BAS or PLC controlling the central plant.
- Battery Optimization takes the (dis)charge rates and participation in any reservation programs that affect the battery and convert them into the parameters and setpoints used by the battery controller.
- Building Mass Storage Optimization takes the airside HVAC equipment load targets and converts them into a trajectory of temperature setpoints.

It is noted that this is not an extensive list of the possible components of the setpoint optimization layer. The number of components is dependent on the variety of systems in the facility. The commonality between these layers is simply that they take resource allocations and convert them into setpoints for the automation system to execute. Consider a pharmaceuticals manufacturing plant. Asset allocation could certainly determine the optimal production rates, but it does not have any idea as to how those productions can be executed. A setpoint optimization layer for the plant would have to be created to convert production rates into setpoints in the PLCs controlling the production.

The setpoints optimization layer must communicate back to the asset allocation. This is done by building operational domains for the asset allocation. Consider two chillers represented as separate assets in the allocation problem. The chillers have headered pumps and isolation valves that open to allow flow when the chiller is running. The assets in this case are coupled by the hydronic system, however there is nothing in the asset allocation problem that shows this coupling. Central plant optimization, however, must know of this coupling to properly send setpoints to the BAS. In this case, it is not possible control flow independently and thus it is impossible to set the chillers' production independently when they are both running. However, by controlling the chilled water setpoint and performing mixing there is a little bit of variation possible. CPO is polled using a meshgrid at various chilled water productions from each of the chillers. In some cases, the optimization will indicate that the system cannot be operated in this area. An algorithm can then be used to produce an operational domain from the resulting samples of CPO. This process is illustrated in Figure 7. The actual development of a CPO algorithm is discussed in several sources (Asmus 2017) (Ma and Wang 2011) (Yu and Chan 2008).

The building side of a facility has potentially thousands of individual temperature setpoints to control. It would be impossible to include all these setpoints and dynamics in a single optimization problem. The solution is again a decomposition. Zones are aggregated into zone groups. All the zones of a zone group are controlled synchronously. That is, the same value for the "state of charge" setpoint is sent to each of the zones in a zone group. For this reason, zone groups should be chosen carefully so aggregated zones share similar dynamics. The state of charge setpoint can

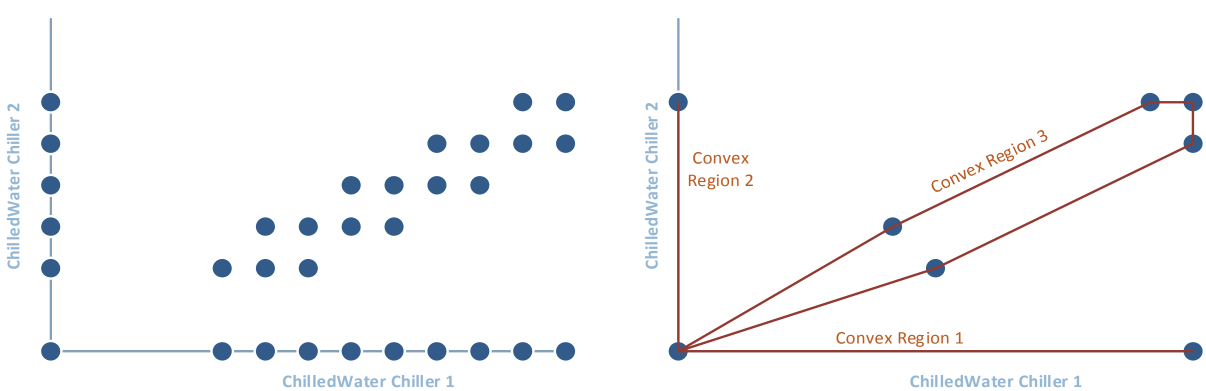

Figure 7: (left) locations on a meshgrid for which central plant optimization returned a consumption value, (right) resultant operational domain that defines the constraints.

in the simplest case be the zone temperature setpoint or, if zones have different comfort bands, a zero to one value that maps to a temperature setpoint for each zone as shown for the i^{th} zone in,

$$T_{sp,i} = T_{SOC}\left(T_{max,k} - T_{min,k}\right) + T_{min,k} \tag{12}$$

The dynamics of several zone groups are aggregated together in order to produce a building mass storage asset. In order to aggregate the dynamics, a similar procedure is performed as was performed to find the asset level models from CPO. A trajectory of energy budgets are passed to the BMS optimization, optimization is performed and the dynamics of all the zone groups are simulated. System identification is performed using the load targets and aggregated temperatures of the aggregate system as the input/output data of the experiment. For information on system identification for building mass storage systems as well as potential dynamic models for these systems refer to (Ellis *et. al.* 2016) or (Patel, *et. al*. 2016)

The final piece of the setpoint optimization layer is the battery optimizer. The optimizer takes the discharge rates and the participation in the frequency response reservation program to create setpoints as well as the parameters that battery controller uses to determine the system (dis)charge rates at a two second frequency.

To understand how battery optimization works, it is necessary to first understand a little bit about how the two second battery controller works. The battery controller is responsible for maintaining the (dis)charge rate of the battery, managing the total demand, and reacting to the frequency response signal if the battery has been reserved for that program. In the simplest form, the battery storage controller would simply continuously send the (dis)charge rate asset allocation to the battery system's inverter. However, it is necessary to consider that asset allocation occurs at a very course granularity in time (every 15 minutes for example). A lot can change on the electric load in 15 minutes. Assuming asset allocation had set the battery to discharge at a certain rate to keep the electrical amount procured at a demand target, any increase in the building load would cause a corresponding increase in the demand if not compensated by the battery. This could lead to poor demand management with the slow sampling time of asset allocation. An example of the electrical amount procured with and without 2 second demand management is shown in Figure 8. This demonstrates the need for this type of controller.

Participation in frequency response also requires 2 second battery control. In frequency response, it is necessary to reserve a portion of the battery system's power and energy (a reservation program) to rapidly respond to the utility's request to add power to or remove load from the grid. Information on the frequency response program can be found in PJM manual 11 (PJM, 2018). When performing frequency response, the 2 second battery controller also quickly updates the (dis)charge rate in order to match the desired frequency response signal. In this case, the battery must make up for changes in both the electrical load of the campus buildings and the frequency response signal itself.

Making constant 2 second adjustments to the battery charge/discharge can be deleterious to the life of the battery. Battery optimization must determine parameters that regularize the operation of the battery system while still maintaining demand management and frequency response. Using a battery life model, the battery optimization routine determines optimal parameters for the maximum charge/discharge rate and the maximum rate of change in charge/discharge by considering the tradeoff between the revenue from frequency response, the cost of not performing demand management, and the effective cost of permanent damage to the battery. This is in addition to calculating the proper midpoint while accounting for losses that were not taken into account during asset allocation. These parameters are found and sent to the 2 second battery controller. Figure 8 was generated by simulating the 2 second battery controller using (dis)charge rates found from asset allocation and parameters generated by battery optimization.

5. SUMMARY AND CONCLUSIONS

The focus of this paper has been on three things. First, a natural decomposition of the facility control problem was given. The decomposition broke the control into asset allocation, setpoint optimization, and automatic control. Asset allocation was used to determine the resource use/production targets of each asset of the facility. Setpoint optimization then converted the asset allocations into setpoints for the building automation system to execute. Asset allocation and setpoint optimization have been shown to be able to complete in less than four minutes. This is fast enough to perform online control given that the BAS is keeping the system under control to the setpoints at a much faster speed. It is also possible to run all setpoint optimizations in parallel if necessary. These optimizations are independent of each other.

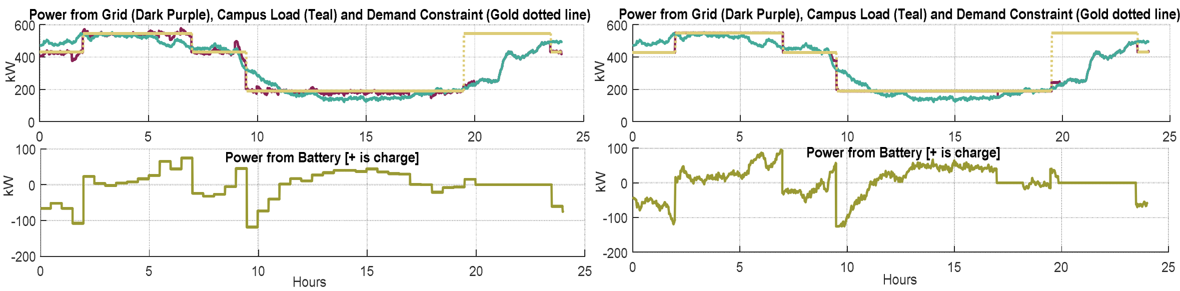

Figure 8: (left) battery control without 2 second controller. The demand peak is elevated due to changes in campus load. (right) demand management.

Additionally, a nomenclature for facility asset allocation was presented. The nomenclature included a supplier to provide resources, an asset to convert/store resources, a load to use resources, and nodes that connect the components together. A solver was created to solve this class of problems. The solver developed was capable of solving the system in the required amount of time. However, for even more complex problems, it is possible that there will not be enough time to solve or that more equipment will have to be aggregated so that computational time is reduced at the expense of optimality if poor aggregations are chosen. The solver does not make use of the specific structure inherent in the facility optimization problem. Instead, it converts the asset allocation problem into a set of A, b, etc. matrices to be solved by a standard commercially available mixed-integer linear program solver. Given this broad applicability to facility optimization with a very small number of components, it is likely that future work in the form of a dedicated solver for this class of problems would yield improvement in computational time.

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