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Autonomous Optimization and Control for Central Plants with Energy Storage

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ABSTRACT

An economic model predictive control (MPC) framework is used to determine how to optimize the allocation of energy resources across a central energy facility including chillers, hot water generators, and thermal energy storage; present the results to an operator; and execute the plan. The objective of this MPC framework is to minimize cost in real-time in response to both real-time energy prices and demand charges as well as allow the operator to appropriately interact with the system. Operators must be given the correct intersection points in order to build trust before they are willing to turn the tool over and leave it in fully autonomous mode. Once in autonomous mode, operators need to be able to intervene and impute their knowledge of the facilities they are serving into the system without disengaging optimization.

1. INTRODUCTION

Design and operation of central energy facilities is becoming an increasingly difficult problem. High efficiency products are available; but it is necessary to plan for and control the products properly to realize the potential cost savings (Ma & Wang, 2011)(Yu et al., 2008). Recently, model predictive control for central energy facility was developed (Wenzel et al., 2014). It was established as a planning tool to help engineers choose a type of facility and the equipment types and capacities in that facility. Simulation showed the potential for savings of over 10%. In this paper, an operational tool is described that is capable of distributing the load across the various subplants, selecting the equipment to turn on, determining optimal setpoints, and most importantly communicating this information to the building automation system (BAS) for execution. In this way, the operational tool is capable of realizing this 10 to 15% savings estimated by the planning tool.

In order for any of the savings to be realized, the operational tool must remain in autonomous mode. A system with energy storage that is capable of supplying the campus load for as many as 10 hours has too many variables for any operator to efficiently manage. However, with the proper interface an operator is capable of augmenting the system with any knowledge that may be missing, and allowing the model predictive control algorithm to incorporate that additional knowledge into the algorithm's decisions.

Cascaded control logic is ubiquitous in building control systems. Typically, low level feedback controllers produce the actuator input for a system (e.g., drive speed), whereas supervisory controllers produce setpoints for these low level controllers. The reasons for this hierarchy are numerous: the low level requires feedback to respond to disturbances, the low level operates a much faster sample rate to keep control of the equipment, there is a decoupling of purpose to improve debugging capability when there is an issue, etc.

The operational tool presented in the present paper continues the idea of cascading the control algorithm. It describes how several cascaded sub-algorithms in a supervisory economic model predictive control algorithm provide a natural interface for the operators to interact with the system, thereby increasing the probability the system remains in autonomous mode. Of course, adding interfaces and cascading the control problem cannot improve optimal performance (as each level does not have all the information of the previous level). Cascaded control is still often used to convert a computationally unsolvable (in real-time) mixed-integer, non-linear optimization problem into several smaller, solvable, problems. With the current advances of computing technology and optimization techniques, it is possible to see a future where the hierarchy of control is not necessary and a single omniscient system can calculate all required system inputs for optimal control. There may still be debate as to whether this control would be "optimal" in a system where humans are still ultimately responsible for the facilities operations. Facility owners and operators of large facilities (where the most energy savings can be obtained) seem unmotivated to move to a system that gives them no control or only gives them the control to either "live with what the computer says" or "override the outputs". When posed with this type of system, operators may try to outthink the optimal control because there is no information as to why the controller made the decisions it did. Thus, the system will remain in manual override and no optimization will be performed. A cascaded system, however, decouples the purpose of each individual sub-algorithm, allowing the operator to understand purpose of each output, thus allowing him or her to comprehend the decisions made by the system. A system that the operator understands and has the ability to add knowledge to is more likely to be left in autonomous mode and capture the savings projected during planning.

A single omniscient control system has not only a problem with the user's ability to understand the output, but also the user's ability to change portions of the output. The operator of a large energy facility will likely still have more information about the plants operation than the control system, simply because it not possible to individually program all factors that could affect the optimal control decisions.. Furthermore, a control system that comes with a more general artificial intelligence where the inputs are essentially anything that it can be exposed to will fail in combinations of inputs that it has not yet seen. As long as there is an operator that has been on the job longer than the AI, the operator may have relevant information to improve the control systems information. Thus, it is necessary that contemporary central energy facility control systems provide an easy to understand interface for the operators to both gather information and to augment the system with their own knowledge.

In the current paper, an operational tool is described which is capable of autonomous model predictive control and optimization of a central energy facility. The goal is not to provide a tool that runs the plant in the background with no potential for operator interaction, but to provide a tool the is capable of running a plant while providing for human-in-the-loop interactions where the operator can view future decisions of the control algorithm and easily provide additional information to the system as necessary. It is shown how the cascaded optimization problem provides a natural interface for the operators to make changes to the system. First the optimal control problem is described, the inputs and outputs of the system are enumerated and the optimization objective defined. Then a five layer cascaded model predictive control system is described. Finally, it is shown how this cascaded control problem is made into a tool for online plant operation with all the proper intersection points where the operators can interact with the system. Results from a live deployment of the operational tool are shown, illustrating that the operators are able to control the plant while leaving the system in autonomous mode. Thus, the majority of the potential savings are realized.

The first sub-algorithm is the prediction of the energy loads of the campus; i.e., the inputs to the optimization system. The predictions are made for a week in advance, giving the operator ample time to react to predictions they do not agree with and override the predictions if they feel it necessary. The predictions are inputs to the subplant energy distribution optimization. The energy distribution sub-algorithm determines the optimal distribution of energy across major equipment classes (subplants and storage) for the prediction horizon and sends the current distribution to the equipment selection and setpoint sub-algorithms. The operators are able to use the subplant-level optimization for "advisory" only and enter their own load distribution into the equipment level optimization. This could be done if they feel that they need to be conservative with the charge of the tank, etc. Finally, the equipment level optimization determines the devices to turn on and their setpoints in each subplant and sends those setpoints to the building automation system. These decisions can be overridden, but should be rare as the system takes device availability, accumulated runtime, etc. as inputs. The final tier is the low level control layer. To override this layer the operator has to put the building automation system (BAS) in "hand" mode and write specific outputs actuator inputs: valve positions, drive speeds, etc. This is likely to only be done during testing or maintenance of the system.

2. CASCADED CONTROL

As stated in the introduction the model predictive control and optimization of central energy facilities is broken into five distinct subalgorithms each with a specific purpose. By limiting the scope of any particular sub-algorithm of the control scheme, it is easier for an operator supervising the control to decide if intervention is necessary, and if necessary, how to intervene. The five sub-algorithms: prediction, energy distribution, equipment selection, system setpoints, and equipment control are described below. Much literature can be found for individual many of the sub-algorithms. It is the combination of these building blocks cascaded that makes possible a model predictive control scheme for the operational tool that gives the operator the ability to properly interact with the system. A flow chart of the control algorithm is shown in Figure 1 with the inputs and outputs of each of the five sub-algorithms clearly defined.

2.1 Prediction

Regardless of the method, to perform economic model predictive control, it is necessary to have the loads of each of the energy sinks and the pricing for purchasing energy from each of the energy sources for the length of the horizon. These predicted loads and rates then become the input to the economic model predictive control algorithm.

To perform prediction several factors contributing to the load/rate can be considered. For loads (and rates) it is typical to use the day-type (day of week, occurrence of special events), time of day, and weather conditions. Historical load data along with the independent factors used are collected and used to train a model. Model training can be done offline first to load the initial model. Subsequent model updates should be done automatically and online at regular intervals or continuously to account for changes in the model. However, the updates should be done in a separate process to avoid delaying the process performing the control.

In the present operational tool, finding an estimate of the future load, $\hat{l}_{k+h}$, prediction is done by adding a deterministic part, d_k, and a stochastic part, s_k, (ElBsat & Wenzel, 2016)

$$\hat{l}_{k+h} = d_{k+h}(m_{k+h};\theta) + s_{k+h}(e_k;\phi) \quad \forall h \in horizon = \{0,1,2,\ldots,N_h\}, \tag{1}$$

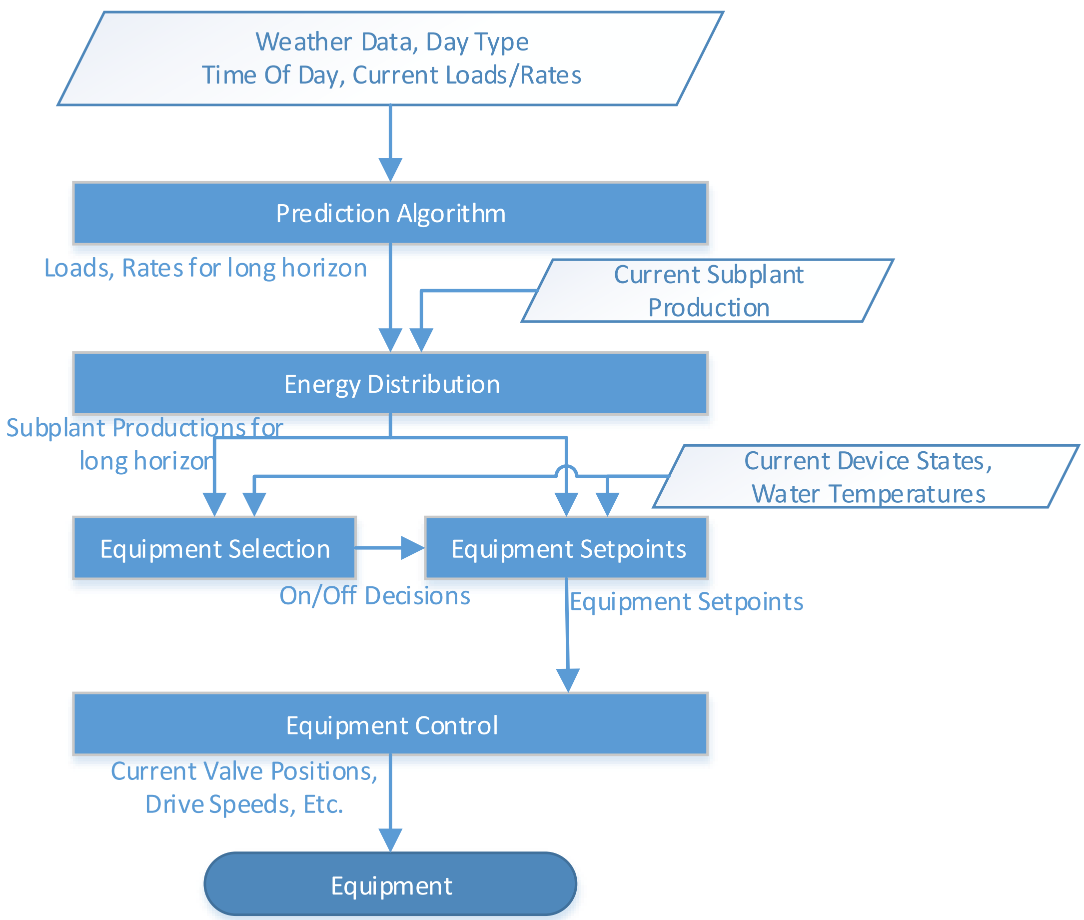

Figure 1: Flow chart of an operational tool using cascaded model predictive control.

where,

$$e_k = l_k - d_k(m_k;\theta). \quad (2)$$

The purpose of the deterministic model is to account for factors (m_k) that have a known relationship to the load. The relationship between the factors, such as weather, day type, and time-of-day, is a steady-state function. The parameters θ can be found by various curve fitting strategies. The purpose of the stochastic model is to update the prediction of the deterministic model base on its current error. Because it is impossible to account for every factor that can affect the load, it is necessary to update the prediction for short term prediction errors. To perform this an auto-regressive model is used. The difference between the predictions by the deterministic model is passed through an auto-regressive predictor and the output is added back to the prediction. Thus allowing for un-modeled disturbances to be accounted for in the overall prediction.

2.2 Energy Distribution

The predicted loads and rates from the prediction sub-algorithm are then directed to the energy distribution sub-algorithm where they are coupled the current subplant production in order to produce the optimal energy distribution over the entire horizon.

At a high-level, a central energy facility serving a large campus can be represented by the manner in which the energy can be distributed across the campus. An energy facility consists of subplants, formed of like equipment, that are capable serving campus by converting purchased energy (electricity, natural gas, etc.) into the energy required by the buildings (chilled water, steam, etc.). Mathematically, subplants describe a mapping from the space of independent decisions of that subplant to the space of the subplants productions and consumptions:

$$f:\Re^n \mapsto \Re^{n_p+n_c} \quad where \quad f_{subplant}(\theta)=\begin{bmatrix} p \\ c \end{bmatrix}. \quad (3)$$

An energy distribution diagram is shown in Figure 2. The energy facility pictured consists of five subplants capable converting utilities: electricity, natural gas, and water to chilled water and hot water. The job of the energy distribution sub-algorithm is to optimize the cost of purchasing energy, J, subject to constraints including: subplant capacities, equipment models, and energy balance equations at each resource:

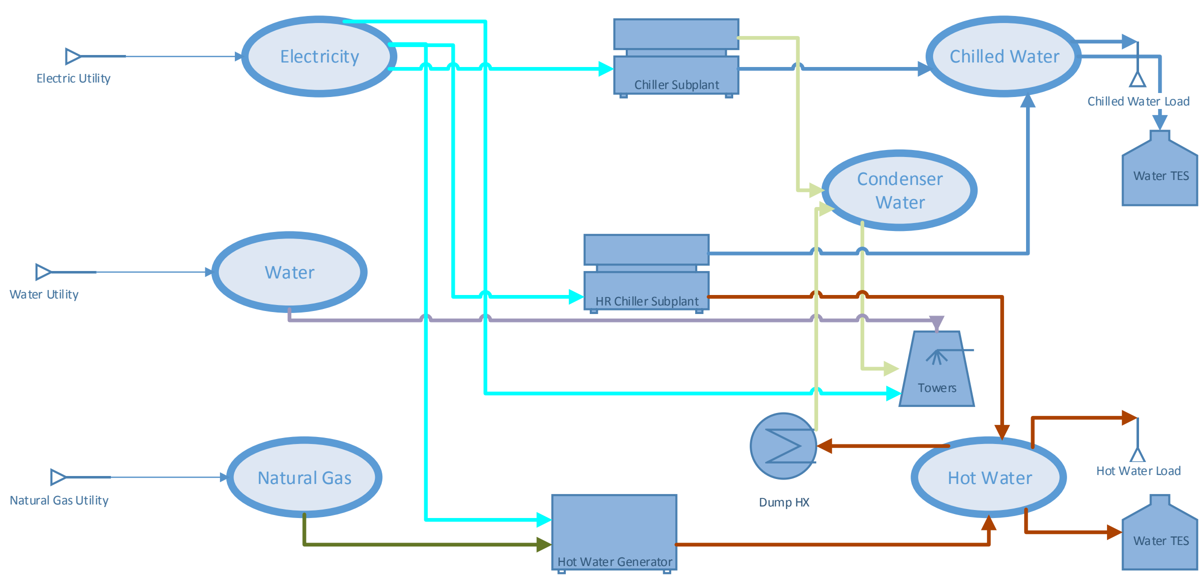

Figure 2: Energy distribution diagram for a plant with five subplants and two energy storage elements.

$$J = \sum_{utility} \sum_{horizon} cost\left(purchase_{resource,\,time}, time\right), \tag{4}$$

subject to,

$$\begin{gathered}\sum_{sources} purchase_{resource,\,time} + \sum_{subplants} production_{resource,time} - \sum_{subplants} consumption_{resource,time} + \cdots \\ \sum_{storages} disch\arg e_{resource,time} - \sum_{sinks} requests_{resource} = 0, \\ \forall resources, \forall time \in horizon.\end{gathered} \tag{5}$$

The formulation of this in a linear programming framework is described in (Wenzel et al., 2014). In general, the output of the energy distribution sub-algorithm is the amount of resource (typically energy, except in the case of water for the cooling towers) that is disturbed on the connections in energy distribution diagram of Figure 2.

The energy distribution level is responsible for determining the energy distributed at every hour during a prediction horizon for several days. If the prediction horizon is one week, the prediction horizon contains 168 hours. It is this that causes the economic model predictive control to become difficult to solve. For a modest sized energy facility there may be around 25 pieces of equipment that can be turned on/off as well as a similar number of setpoints to control. While a mixed integer, non-linear program with 25 binaries and 25 continuous variables can be solved in a reasonable amount of time, when that it is multiplied by the 168 hours in the horizon there become 4200 binaries and 4200 continuous variables and problem becomes much more difficult. By limiting the problem to only the energy distribution, the problem can be posed as a linear program there by greatly reducing the computational time for the sub-algorithm that has the most decision variables due to the multiplicity of the long horizon.

2.3 Equipment Selection

Given the request for the subplant to produce a certain amount of energy for the entire length of the long horizon, it is possible to decide which equipment should be turned on/off. The purpose of the equipment selection sub-algorithm is to determine a method for mapping the independent decisions of a subplant to the on/off decisions of the equipment inside that subplant. There is not a need for a horizon at the equipment decision level. Its job is to minimize the energy use while producing the load request from the energy distribution level. However, it may be desired to display the expected device decisions for a short horizon. Assuming this is the case, then the equipment selection sub-algorithm can simply be called several times using the future values requested by the energy distribution level.

There are several approaches to decide which devices should be turned on (Deng et al., 2013). A dynamic programming version is to build the optimal decision points from a single device up. This done by taking two devices and generating the optimal performance of the subplant with these two. Combining the optimal performance of the first two devices with the next device and finding the optimal performance with these three devices. The process of adding one more device is continued until all devices have been added. An example of the process for 3 chillers is shown in Figure 3. First chillers 1 and 2 are combined by comparing the electricity used for all each chiller and both chillers (it was assumed that each chiller must run at the same part load ratio). The minimum electricity used is found for each amount of production and the device selection that produces this is stored, Figure 3b. The optimal place to on chiller 2 is at approximately 3150 kW. Now the third chiller is combined by comparing the energy use of the result from combining chillers 1 and 2 with chiller 3 and the sum of the two of them, Figure 3c. Now it is possible to see that it optimal selection strategy is to run chiller 1 up to 3150 kW then run chillers 1 and 3 to 4000 kW, chillers 1 and 2 from 4000 to 5250, and all chillers above that load.

2.4 Equipment/System Setpoints

The purpose of the setpoint sub-algorithm is to output the setpoints that are used in order to obtain the loads specified by the energy distribution algorithm with the equipment determined by the device selection. Again, in this sub-algorithm, there is not a need for a horizon. If a display horizon is required then the setpoint sub-algorithm can be called several times using the future values requested by the energy distribution level. This layer requires a plant model and needs to optimize the setpoints given the constraints representing the optimal energy distribution and equipment selection. Conceptually, this may be one of the simpler sub-algorithms, as it is a call to a nonlinear optimization routine where the cost function, $J(x_{SP})$, is the cost calculated by a steady-state simulation of the plant model given the current setpoints being evaluated. While conceptually simple, expressing the steady-state cost of the energy facility given several setpoints and device selections in a manner that can solved quickly enough for the nonlinear optimizer to converge in short amount of time is difficult. The equipment/system setpoints that produce the lowest cost are computed and set to the equipment control sub-algorithm for final execution of the plan.

2.5 Equipment Control

The equipment control layer exists in the BAS and is typically implemented by PID controllers. Its job is to manipulate the actuation points so that the measured values are at the setpoints calculated by the equipment/system setpoints sub-algorithm. This layer of control is likely to exist at any existing central energy plant.

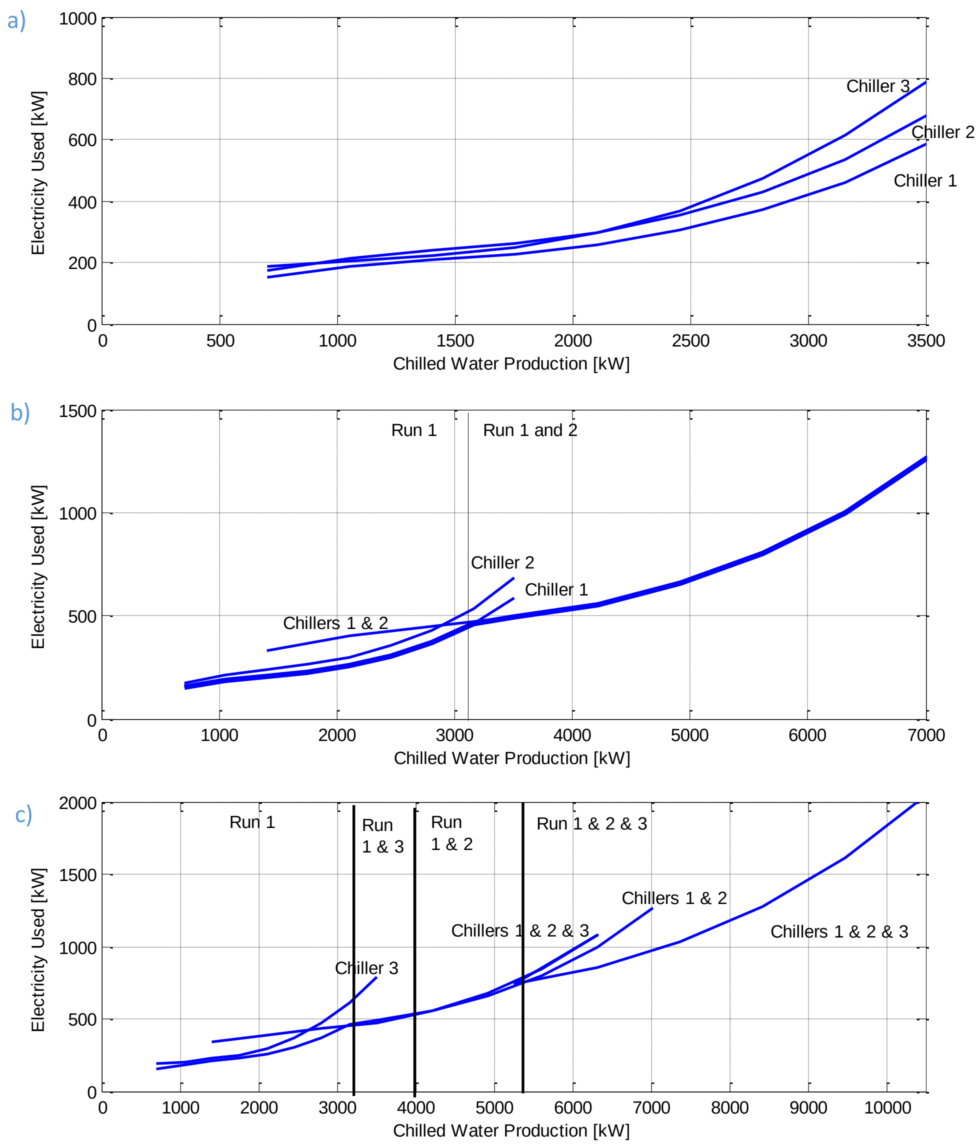

Figure 3: Determining the optimal equipment selection using the principle of optimality. a) The performance of chillers 1, 2, and 3 each with a 3510 kW (1000 ton) capacity. b) locus of possible chiller production and useage using only chillers 1 and 2. c) locus of possible chiller productoion and useage when chiller 3 is combined with the minimal use of chillers 1 and 2

3. OPERATOR INTERACTION

Empowering the operators to impart their knowledge through human-in-the-loop decisions while remaining in autonomous mode is likely the most powerful tool the engineer design the optimization system has in maximizing the time that the system spends in automatic mode. It is likely impossible for the optimization algorithm to take into account explicitly all factors that can influence the optimal control sequence. In the near term, it is equally unlikely that an AI could be placed on the site and learn all the factors that operators already know.

3.1 Predictor Overrides

Periodically, the prediction algorithm will not take into account a factor that has a significant effect on the load. A common example is special events. When this occurs, the operator would have to take the system out of autonomous mode if no interface was given to allow the user to override the prediction. Instead, the current system allows the operator to view the prediction and add an override that will be used during optimization.

For the optimization and control algorithm to be autonomous, the system must produce outputs on a regular interval. It is impossible to allow the system to wait for an operator to override any predictions. Instead, the system must output load and rate predictions for several hours (days) into the future. The operator then has the ability to make a decision about the load and override it if necessary. If the override is far enough in the future it should have little effect on the current decisions and the system will have the time to optimally respond to the new information.

Figure 4 shows a capture of the operational tool. The cooling load has been predicted for the next 7 days of operations. Here an operator decided that the load in the morning of June 23rd was too small, and decided to override the load to be larger. Overridden predictions are shown in yellow in the figure. The knowledge of the increased loads provided by the operator is already being used to optimally distribute energy across the subplants and the storage, shown in Figure 5. By giving the operator the time to decide if an override is required for a future dispatch it is also possible to give the model predictive control algorithm time to blend the new information into the dispatch between the current time and the override without having a large change or disturbance in current operations when the override is added.

3.2 Energy Distribution Overrides

In the case that the operator is not satisfied with the high level load distribution created by the energy distribution sub-algorithm, constraints can be entered in order to force the energy distribution sub-algorithm to allocate a specific load to a specific subplant. Again, optimization can continue as expected subject to the additional constraints,

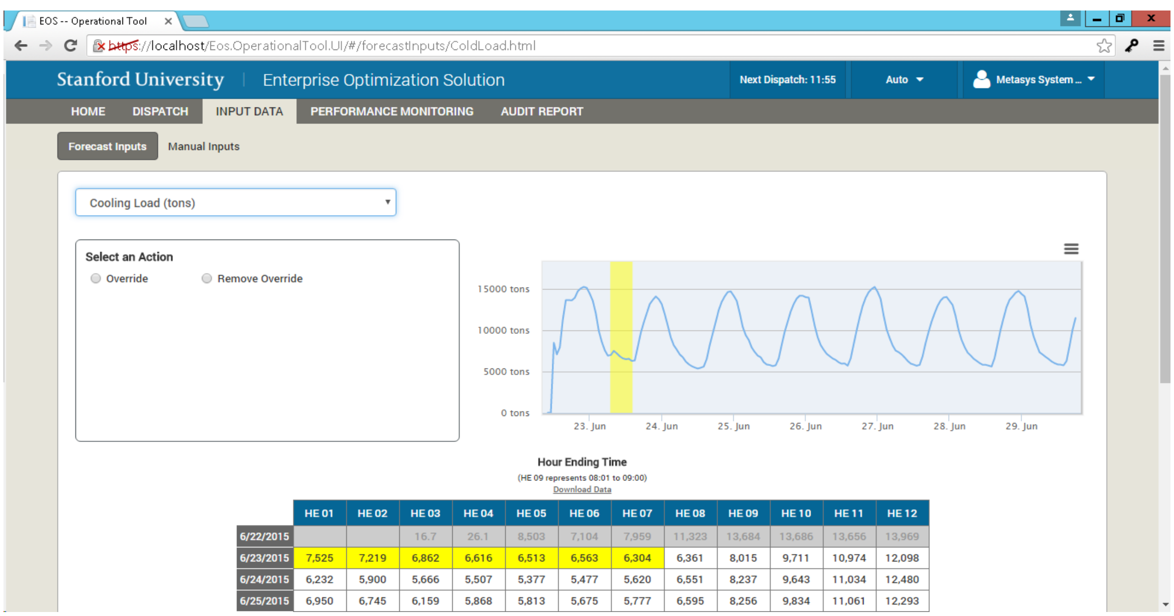

Figure 4: Screen capture of an operational tool while the operator is using the predictor override interface.

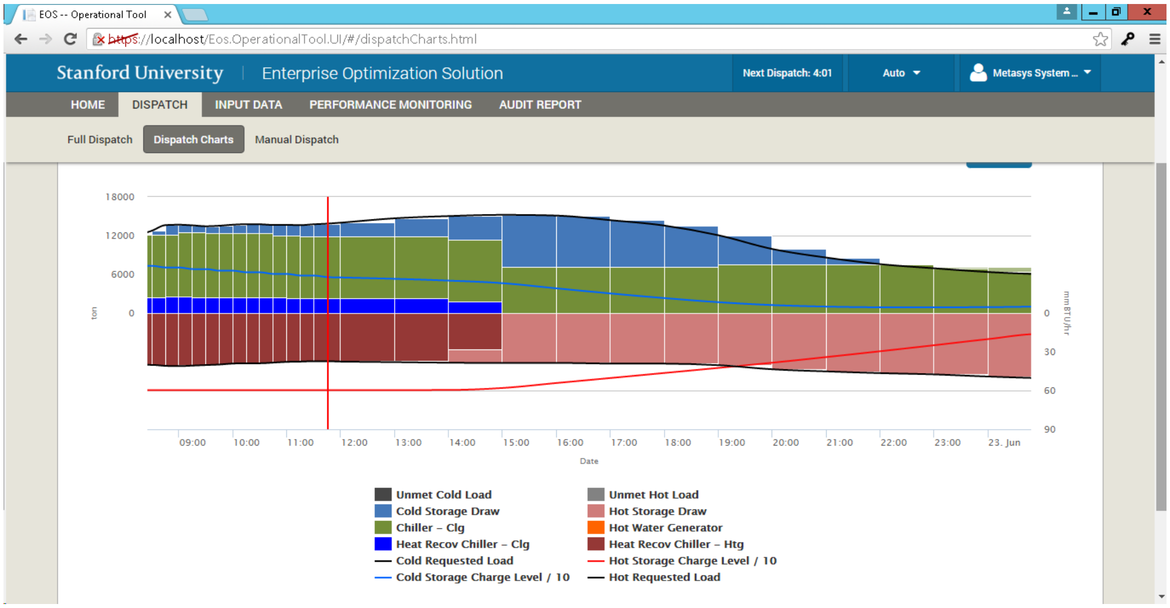

Figure 5: Operational tool dispatch zoomed to show the next 12 hours of energy distributions.

thereby allowing the operator to augment the system with his knowledge rather than simply taking command of control. If the constraint is added with ample time before it occurs, the model predictive control algorithm should have the time to blend the new information into the dispatch without creating a disturbance in current operations.

Additionally, the operators are able to use "manual mode" in which they are capable of specifying the production they want performed by each subplant. In manual mode, equipment selections, setpoints, and equipment control still follow their normal path. However, the dispatch is only updated on the operator's request. The allocation developed by the energy distribution sub-algorithm is used as advisory information.

3.3 Equipment Selection Overrides

In most cases, operators should not have a preference of which equipment runs to produce the desired load. The exception to this rule is when a device needs to be removed from service for maintenance. Again, it is undesirable to force the operator to remove the system from autonomous mode when equipment must be taken out of service. In a large plant there is constantly maintenance to be done. Requiring all equipment available to perform economic MPC would drastically reduce the amount of time the system spends in autonomous mode.

When equipment is not to be run the operator can remove the equipment from service using the user interface. Using this interface the operator tells the operational tool that the equipment cannot be used during a certain time period. Both the energy distribution and equipment selection sub-algorithms use this information to produce a dispatch that is optimal subject to the new constraints. As in the previous examples, if the equipment is scheduled out of service in advance it should not cause much of a disturbance in current operations. In Figure 6 two chillers have been scheduled out of service.

The expected dispatch is available for a horizon so that the operator has time to decide if anything must be overridden. This also gives the operator the ability to plan short term maintenance. If chiller 2 is not scheduled to be turned on for the next two hours, it would be a good time to perform any maintenance that requires a short amount of time. Likewise, if the operator sees that the chiller subplant is not scheduled to run for the next five days then it is possible for all the chillers to be taken out of service and more substantial maintenance performed with no substantive change to the central energy facility's operations cost.

3.4 Setpoint and Equipment Control Overrides

Changes in the setpoints determined by an operational tool and the low level equipment control that realize those setpoints should rarely be overridden. No user interface is provided to override these items in the operational tool. However, these points can be overridden in the building automation system. If a point in the building automation

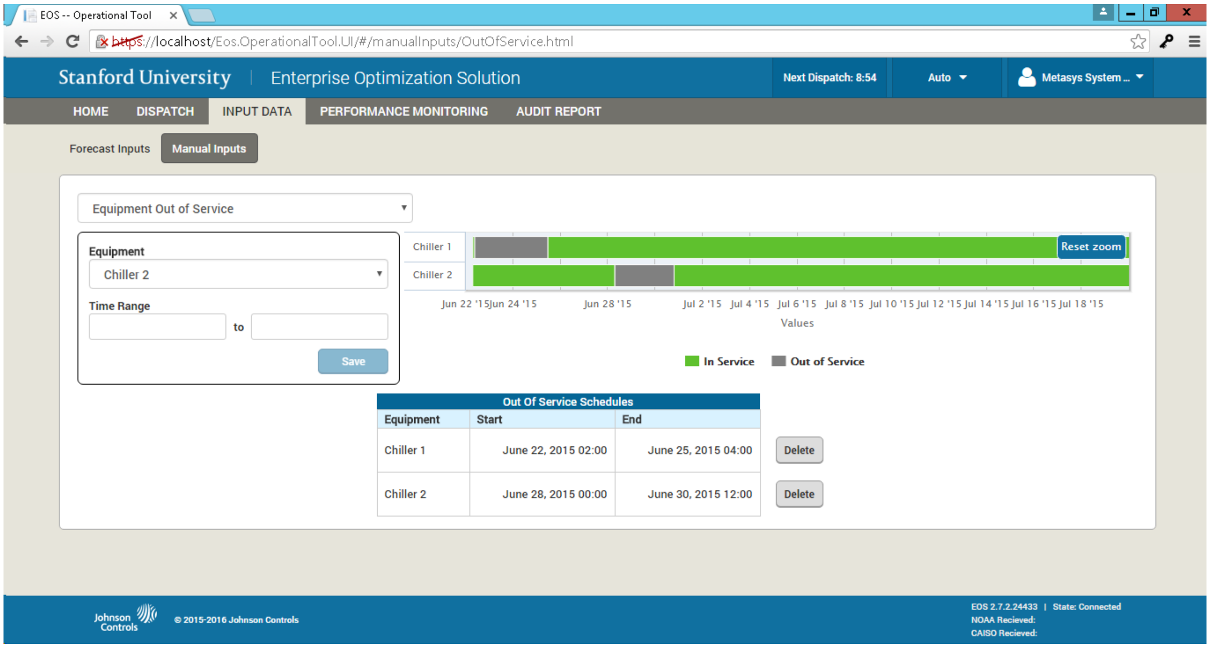

Figure 6: Interface of the operational tool showing two chillers taken out of service. This will cause the model predictive control algorithm to choose the optimal dispatch without using this equipment at the specified times.

system is overridden an operational tool will not be able to write the setpoint and it will be impossible to carry out an unadjusted dispatch. While it is not optimal for any of the setpoints or low level control logic to be overridden and in "hand" mode, it is likely to happen. Instead of forcing the operator to take the operational tool offline when overriding the BAS logic, it is better to respond to the overrides. The operational tool looks to verify that none of the logic it must interact with has commands that are sent at a higher priority than the priority at which the operational tool writes. If there is a higher priority command, the equipment controlled by that logic is "unavailable" to the operational tool and optimization must be performed with the new constraints.

4. REMARKS AND CONCLUSIONS

Allowing the operator the ability to override has meant that the system is in autonomous mode a large majority of the time. The operational tool was installed on a new construction site during the commissioning of the new plant. Figure 7 shows a plot of system mode over a three week period from February 22 until March 15. The system was in autonomous mode for approximately 95% of the time. While it is desired that the amount of time spent in autonomous mode approach 100%, given that the plant was new construction and the operators were still managing chillers that tripped periodically, 95% autonomous mode shows that the operators trust their ability to make the proper control changes by modifying the constraints through the operational tool interface rather than completely removing it from manual mode.

Because of the large amount of time spent in autonomous mode the operational tool is able to save the money that was originally expected during the planning phase. Figure 8 shows the comparison of the central energy facility cost as run on site to the expected cost assuming the control algorithm had perfect knowledge of the loads and electrical rates and was always in automatic mode (i.e., a planning mode style run). The chart shows that the central energy facilities operational cost for this three week period is only 4% greater than the theoretical best the economic model predictive control algorithm could have done (with perfect prediction of loads and rates).

The model predictive control framework used to produce an operational tool for autonomous control of central energy facilities was shown to capture the majority of the 10 to 15% savings estimated by the planning tool. This would not be possible if the system did not remain in autonomous mode. However, by giving the operators the appropriate interfaces to augment their knowledge with the operational tools model predictive control kernel it was possible to keep the time spent in autonomous mode above 90%.

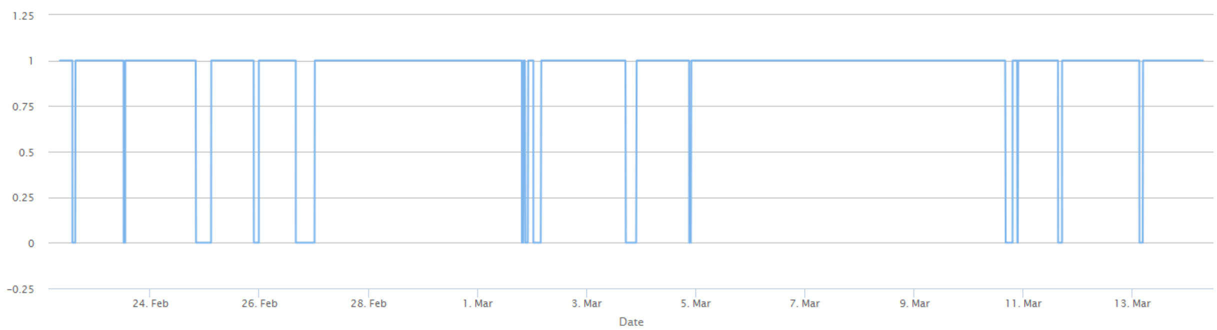

Figure 7: Screen capture of an operational tool while the operator is using the predictor override interface. A value of "1" incidates the economic MPC algorithm is in autonomous mode.

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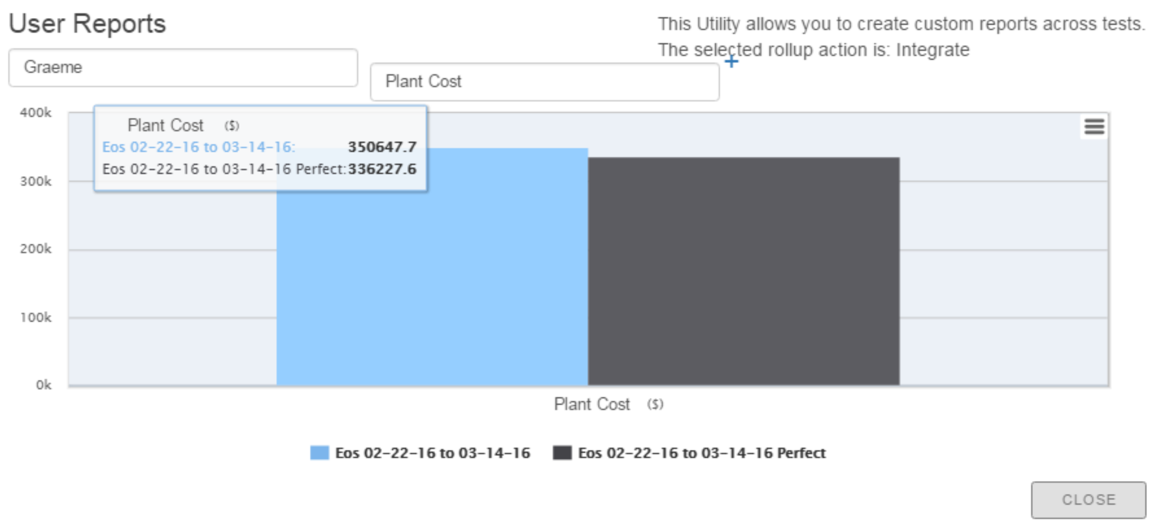

Figure 8: Comparison of energy facility operational cost as run on site (blue) to simulated run where all loads are perfectly predicted (grey).