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Central Energy Facility Optimization with Integrated Incentive and Price-Based Demand Response Programs

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ABSTRACT

A cascaded approach for optimizing Central Energy Facility (CEF) operations with integrated incentive-based and price-based demand response programs is presented. The approach is geared towards the Economic Load Demand Response (ELDR) program and the Peak Load Contribution (PLC) charge structure in the Pennsylvania, Jersey, Maryland (PJM) region. However, it can be extended to accommodate other programs in different regions. The developed approach allows for an optimal allocation of CEF assets to guarantee the curtailment of the commitment in the ELDR program, in addition to minimizing the customer's PLC during projected Coincidental Peak (CP) hours. Given predicted central energy facility loads, day-ahead and/or real-time Locational Marginal Prices (LMP), and PLC and resource rates, the optimization problem is solved over a horizon into the future using a mixed integer linear programming framework. Furthermore, it is adaptive as it updates the allocation of assets based on feedback from the ELDR market and any changes in the projected CP hours. A case study of ELDR program integration in CEF optimization at Kent State University (KSU) is presented.

1. INTRODUCTION

Increasing efforts have been dedicated recently towards the development of advanced system controls to optimize Central Energy Facility (CEF) operations in order to reduce energy consumption, and, consequently, energy cost. Reduction of electricity consumption is beneficial for both consumers and the Regional Transmission Organization (RTO) managing the power grid. Therefore, RTOs have setup Incentive-Based Demand Response (IBDR) and Price-Based Demand Response (PBDR) programs to incentivize customers to lower or shift their electricity usage or loads. IBDR programs are voluntary programs where consumers are compensated for reducing their electricity usage. On the other hand, PBDR programs motivate consumers to actively respond to peak charges and time-based rates to, consequently, lower their electricity cost (Albadi and El-Saadany, 2008). These strategies also help electricity suppliers reduce their costs due to reductions in peak demand and the ability to defer construction of new power plants and delivery systems. In addition, they help in maintaining the stability of the power grid by balancing supply and demand during peak periods.

IBDR and IBDR programs have evolved over the years and so has the variety of these programs. There has been significant research examining the evolution of these programs and their reliability (Nikzad and Mozafari, 2014) and (Paterakis *et al* 2017). The type of programs offered differ from one RTO to another. In the region managed by the Pennsylvania, Jersey, Maryland (PJM) Interconnection, several IBDR programs are offered (Walawalkar *et al* 2010). These include, but not limited to, Economic Load Demand Response (ELDR) and Frequency Regulation (FR). The ELDR program allows consumers to choose when and by how much to curtail their electric consumption in response to market prices. The consumer is then compensated for the amount of power curtailed at the Real-Time Locational Marginal Prices (RT LMP). In the PJM region, consumers are also subject to PLC charges, which is a type of a PBDR program. A PLC charge, which prompts consumers to shave or shift their peak load consumption, is a demand charge structure based on a consumer's contribution to the demand peaks which occur in a region or a zone managed by an RTO at certain hours over a base period. Charges associated with PLC are significant and a consumer is billed, in addition to the regular energy consumption and demand charges, a monthly charge during the billing period, based on their PLC during the base period in the prior year.

The advent of IBDR and PBDR programs has resulted in an extensive research in the field of optimization and dynamic control of consumer assets in order to meet commitments in IBDR programs, while minimizing costs due to PBDR programs. Applications span residential to large-scale consumers and different types of assets. Kim *et al* (2017) addressed the optimization of multiple battery energy storage systems of a large-scale customer with a time-based energy rates. Muratori and Rizzoni (2015) studied the dynamic management of residential energy consumption for different electricity rate structures. Prodan and Zio (2014) developed a model predictive framework for energy management of a microgrid consisting of a local consumer, a renewable generator, and a storage facility. Shafie-khah *et al* (2017) studied the optimal behavior of smart households under different types of demand response programs. Wenzel *et al* (2014) developed an approach to the optimization of central plants with thermal energy storage. In this work, CEF optimization with integrated IBDR and PBDR programs is addressed.

Given the diversity of assets within a CEF, the challenge becomes how to efficiently run the facility and allocate assets while meeting commitments to IBDR programs and minimizing cost due to PLC charges, electricity rates, and demand charges. A general cascaded approach is developed, which optimizes the asset allocation in a CEF in order to meet commitments to IBDR programs and actively respond to PBDR programs. The developed approach shows how any event based IBDR program can be modeled as an energy rate adjustment. Focus is given to the ELDR program and PLC charge structure in the PJM region. The CEF may consist of any combination of chillers, heat-recovery chillers, combustions turbines, boilers, thermal energy storage, battery energy storage systems, etc.

Given actual and predicted ELDR market prices, an initial decision on participation is made. The initial set of participation hours along with the projected PLC coincidental peaks translate to an electricity rate adjustment in the objective function. The objective or cost function to be minimized consists of resource cost and revenue terms. The resulting optimization problem is then solved over a horizon into the future subject to operational constraints and given the adjusted electricity rates, demand charges, measured and predicted loads, weather forecast, and equipment efficiency curves using a mixed integer linear programing framework.

The paper is divided as follows. The following section provides a brief description of the ELDR program. In section 3, the PLC charge structure in the PJM region is presented. Section 4 shows the developed approach to CEF optimization with integrated IBDR and PBDR programs. The paper is then concluded with a case study of Kent State University, which actively participates in ELDR and where the developed approach has been implemented.

2. ECONOMIC LOAD DEMAND RESPONSE PROGRAM

The program description provided in this section is based on the program rules set forth by PJM (PJM, 2017). ELDR is an IBDR program, which allows consumers to generate revenue by reducing their electricity consumption during certain hours of the day. The consumer chooses the hours in the day during which to participate and the corresponding curtailment amount commitment and is then compensated for the amount curtailed at either the RT LMP or the Day-Ahead LMP (DA LMP). The RTO measures the actual curtailment at a given participation hour in an event day by comparing the electricity usage during the event hour against a calculated baseline load referred to as the Customer Baseline Load (CBL). An event day is a day during which a customer participates in ELDR. Event hours are the hours in an event day during which the customer committed to participate in ELDR. Customer transactions in ELDR are usually managed by a Curtailment Service Provider (CSP), who handles the bidding and settlement processes with the RTO for the customer.

There are two markets in PJM's ELDR program, the Day-Ahead market and the Real-Time market. A customer can participate in either or both markets. The two markets differ in terms of the rate at which the customer gets compensated, the existence of a dispatch by the RTO, and the bidding process (PJM, 2018). In this work, it is assumed that the customer is participating in the Real-Time market and a description of the operations that take place in this market are described in the following subsection.

2.1 ELDR Real-Time Market

In the Real-Time market of ELDR, the customer can participate at any valid hour of the Operating Day as long as the bid is submitted at least 70 minutes prior to the top of the desired participation hour. Depending on the type of CBL assigned to a customer, some of the hours of the day may not be allowed for participation and these are referred to as restricted hours. In the Real-Time Market, customers with submitted bids will be dispatched by PJM. When a customer is dispatched, committed curtailment amounts must be met. The customer receives credit for any participation hour where the corresponding RT LMP, r_{RT_i} , is greater than or equal to the Net Benefits Test (NBT) threshold and where a dispatch was issued by PJM as shown in (1). The NBT is a threshold point on the PJM Supply Curve where the net benefit exceeds the cost to load. It is the point where elasticity is equal to 1. The NBT is updated and posted by PJM for a calendar month on the 15th day of the prior month. The NBT results can be found on the PJM website by selecting markets & operations/ Demand Response/ Net Benefits Test Results. If a customer is dispatched and the RT LMP is lower than the NBT, the customer is compensated at the offer price, when the offer price is above the NBT threshold.

$$R_{RT_i} = \begin{cases} \left(e_{CBL,i} - e_i\right) \times r_{RT_i} & r_{RT_i} \geq NBT \\ 0 & otherwise \end{cases} \tag{1}$$

where R_{RT_i} is the consumer revenue or credit received for participating at the i^{th} hour, $e_{CBL,i}$ is the customer baseline load, e_i is the electricity import, and r_{RT_i} is the RT LMP.

A Balancing Operating Reserve (BOR) charge is assessed for each hour where the actual power reduced deviates from the committed power by more than 20%. For a given rate, the BOR charge for a given hour is calculated as follows:

$$C_{BOR} = \begin{cases} \left|\left(e_{CBL,i} - e_i\right) - e_{com_i}\right| r_{BOR_i} & \left|\left(e_{CBL,i} - e_i\right) - e_{com_i}\right| > 0.2 e_{com_i} \\ 0 & otherwise \end{cases} \tag{2}$$

where C_{BOR} is the balancing operating reserve penalty at the i^{th} hour and e_{com_i} is the participation amount commitment. Deviations rates are usually less than one dollar per 1 MWh, based on historical deviations rates data from PJM.

2.2 Customer Baseline Load (CBL)

The Customer Baseline Load (CBL) is the threshold an RTO uses to calculate a customer's electricity usage reduction for each hour the customer participates in the ELDR program. The CBL is used to determine the total amount of credits earned and charges accrued by a demand resource participating in ELDR on a given day (PJM, 2018). The CBL is determined for each event day. In general, a CBL is dependent on when the first and last participation hours occur on a given event day. There are several methods that PJM approves for CBL calculation, which leads to different CBL types. PJM has a testing scheme to help decide which CBL is suitable for a given customer. For a list of the different types of CBLs allowed, refer to the PJM manual on energy and ancillary services market operations (PJM, 2017). In this work, it is assumed that the customer has a Same Day (3+2) CBL, which is used for Kent State University. The latter assumption is made for simplification purposes and without loss of generality of the proposed approach to other types of CBLs.

For a given operating day, the Same Day (3+2) baseline is the average of the hourly electricity usage during the first 3 hours during the 4 hour period prior to the first event hour and the last 2 hours during the three hour period after the last event hour. The hour preceding the first event hour and the hour right after the last event hour are buffer or transition hours and are not used in the calculation of the baseline. This is a constant baseline type, which is used for each event hour in the operating day. If there are multiple non-contiguous events during the same day, the earliest 3 hours and last 2 hours from the same day are used to calculate the baseline. For a resource with a Same Day (3+2) participation is not allowed in Hour Start (HS) 0, 1, 2, 3, 21, 22, 23 to ensure there are enough hours to calculate the CBL. The Same Day CBL is calculated as follows:

$$e_{CBL,k} = \frac{\sum_{i=m-4}^{m-2} e_i + \sum_{j=n+2}^{n+3} e_j}{5} \qquad \forall k = 0 \cdots 23 \tag{3}$$

where $e_{CBL,k}$ is the Same Day (3+2) baseline for the operating day, e_i is the electric load during the i^{th} hour, m is the hour start of the first event hour in an operating day, and n is the hour start of the last event hour in an operating day. Figure 1 shows an example of the calculation of the Same Day (3+2) CBL. The participation hours are from HS 11 to HS 19. The hours used to calculate the CBL in this example are thus, HS 7, 8, 9, 21, and 22. The curtailment amount is the difference between the CBL and the actual electricity usage during the participation hours.

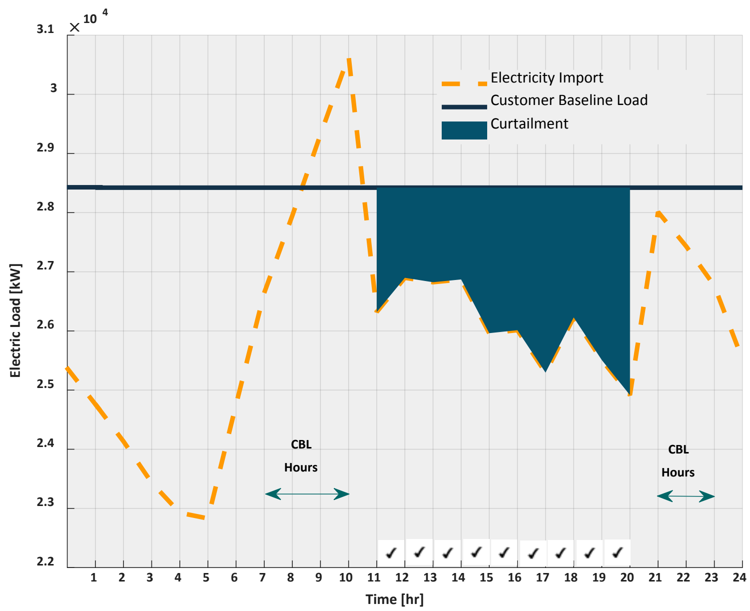

Figure 1: Example of ELDR program participation with Same Day (3+2) CBL

3. PEAK LOAD CONTRIBUTION

Peak Load Contribution (PLC) is a customer's contribution to the demand peaks which occur in a region or a zone managed by an RTO at certain hours over a base period. Charges associated with PLC are significant. Customers are billed, in addition to the regular energy consumption and demand charges, a monthly charge during the billing period, based on their PLC during the base period in the prior year. The hours during a region's or zone's demand peaks occur are known as Coincidental Peaks (CP) hours. The CP hours are determined by the RTO over its entire footprint or the region it manages during a base period. These hours are then used to calculate a customer's PLC and the customer is billed with a PLC charge over the billing period. The billing period takes place the year after the base period. In other words, in a given year, customers set their PLC charge for the following year. The base period, billing period, and CP hours differ from one RTO to another. In PJM, during the Peak-Setting Period or Base Period, the peak days are recorded during June 1st of year Y to Sept 30th of year Y. The delivery year or billing period is June 1st of year Y+1 to

May 31st of year Y+2. Coincidental Peaks hours are the 5 hours with the highest loads over the 5 highest peak load days across PJM's region or footprint. The CP hours usually occur during on-peak hours on weekdays. A customer's PLC during year Y is the product of the average of the customer's electric load during the 5 CP hours and a Capacity Loss Factor (CLF) as shown in (4).

$$e_{PLC} = \alpha_{CLF} \times \sum_{l=1}^{5} \frac{e_{cp,l}}{5} \tag{4}$$

where e_{PLC} is the customer's peak load contribution calculated during year Y, α_{CLF} is the capacity loss factor, $e_{cp,l}$ is the customer's electric load at the l^{th} CP hour. A typical value for a CLF is 1.05.

The customer's PLC charge for year Y+1, assuming a constant PLC rate, is:

$$C_{PLC} = r_{PLC} \times e_{PLC} \tag{5}$$

where C_{PLC} is the customer's total PLC charge billed over the delivery year Y+1 and r_{PLC} is the PLC rate.

For PJM, if a customer is participating in an ELDR event during one of the CP hours, the utility will reconstitute the customer's load, so that they cannot reduce their PLC value while earning ELDR revenue at the same time. If customers want to reduce their load during projected CP day for the purpose of reducing their capacity, transmission, and/or demand charge costs, they may submit a bid for the same hours in the ELDR market. However, if any of those hours ended up being a CP hour, the CP hour cannot be settled for revenue in the ELDR market.

4. INTEGRATION OF IBDR AND PBDR PROGRAMS INTO THE OPTIMIZATION PROBLEM

The multi-objective cost function of the optimization problem of a CEF of any size, with any set of assets, and different kind of resources can be written in a general format as shown in (6). The objective of the optimization problem is to determine the asset allocation that minimizes the total cost associated with the purchase of any resource, while meeting commitments to IBDR programs (Wenzel *et al* 2018). Electricity costs, for example, are a combination of electricity rates, single or multiple demand charges, and PLC charges. In the case of incentives, an example would be revenue generated from commitment to the ELDR program.

$$J = \sum_{s=S^1}^{S^N} \left(\sum_{i=k}^{k+h-1} C\left(S_{p,i}^s, i\right) - \sum_{v=1}^{M} \sum_{i=k}^{k+h-1} R_v\left(S_{com,i}^s, i\right) \right) \tag{6}$$

Where $s^1 ... s^N$ are the sources of a given resource, $C\left(S_{p,i}^s, i\right)$ is the cost associated with a resource amount $S_{p,i}^s$ purchased from source s , $R_v\left(S_{com,i}^s, i\right)$ is the revenue associated with a commitment $S_{com,i}^s$ in an incentive program for a given resource, and M is the total number of incentive programs.

The optimization problem is subject to the following constraint, which guarantees the balance between resources purchased, produced, and discharged and those consumed and requested over the optimization horizon h . Other constraints include CEF operational constraints and assets minimum turndowns and capacities based on equipment models.

$$\sum_{s=1}^{N_{source}} S_{p,i}^s + \sum_{su=1}^{N_{subplant}} S_{pr,i}^{su}\left(\gamma_{su}, X, \Phi\right) - \sum_{su=1}^{N_{subplant}} S_{c,i}^{su}\left(\gamma_{su}, X_{su}, \Phi\right) + \sum_{st=1}^{N_{storage}} D_{r,i}^{st}\left(\gamma_{st}, X_{st}, \Phi\right) - \sum_{j=1}^{N_{loads}} L_{j,i} = 0 \\ \forall resource, \forall i \in \left[k, k+h-1\right] \tag{7}$$

Where $S_{pr,i}^{su}\left(\gamma_{su}, X, \Phi\right)$ is the amount of resource produced by a subplant, $S_{c,i}^{su}\left(\gamma_{su}, X_{su}, \Phi\right)$ is the amount consumed by a subplant, $D_{r,i}^{st}\left(\gamma_{st}, X_{st}, \Phi\right)$ is the amount discharged by a subplant, and $L_{j,i}$ is the load on a given subplant. γ_{su}, X, Φ are the equipment or subplant parameters, the subplant decision variables, and weather variables, respectively.

As can be observed in (6), the objective function of the optimization problem may contain several revenue terms corresponding to different IBDR programs and several cost terms corresponding to different resource consumption. For the purpose of explaining the integration of the ELDR program and PLC charges in the optimization framework, consider the following objective, which specifically highlights the cost term corresponding to electricity consumption, ELDR revenue term, and the PLC charge.

$$J = J_o + \sum_{i=k}^{k+h-1} \hat{r}_{e_i} e_i - \sum_{i=k}^{k+h-1} p_i \hat{r}_{DA_i}\left(e_{CBL,i} - e_i\right) + r_{PLC} \sum_{i=k}^{k+h-1} \lambda_i e_i \tag{8}$$

where J_o represents the other cost, incentive, and penalty terms, $\hat{r}_{e_i}$ is the predicted or actual electricity rate, p_i is the participation decision variable, $\hat{r}_{DA_i}$ is the predicted or actual DA LMP, $e_{CBL,i}$ is the baseline value, and e_i is the electricity import decision variable, λ_i is the PLC decision variable, r_{PLC} is a generic rate associated with the PLC charge, and k is time instant at which the optimization is solved over the horizon h.

The PLC cost term is also a function of the electricity import over the horizon. Unlike the demand charge, where it is known over which period the demand is calculated, the hours during which the PLC is calculated are not known in advance. In order to allocate a given asset for the purpose of reducing customer's PLC charges, a projection of the hours where demand peaks occurs is necessary. The projected CP hours can then be used as an estimate of the actual CP hours by the optimization solver, which optimally allocates a given asset(s) to minimize the customer's consumption during those hours. Therefore, in order to minimize a customer's PLC using the optimization framework, an approach to predict the CP hours is required. Prediction of the 5 CP hours is beyond the scope of this work. Therefore, an alternative approach is to have an hourly mask λ_i representing which hours are projected to be CP hours and which are not. The hourly mask is predefined by the user as set of 0's and 1's, where 0 implies that the corresponding hour is not projected to be a CP hour and 1 implies that the corresponding hour is projected to be a CP hour. Using the hourly mask concept, the user, as a safety measure, can assume any number of hours over the PLC peak setting period to be CP hours. The hourly mask concept also allows for a generic implementation of the PLC reduction feature in the optimization problem shown in (8).

The electricity import over the horizon is a function of the campus electric load and the control decisions of any equipment that produces or requests electricity (combustion turbines, electric chiller, etc.). Based on ELDR operations, as mentioned earlier, a customer's compensation is based on the difference between a baseline value and the actual electricity import during participation hours. In (8), the ELDR revenue term is a bilinear term, where the integer variable p_i multiplies the decision variables that contribute to the electricity import over the horizon. However, in order to solve the optimization problem using mixed-integer linear programming in a reasonable time appropriate for online operation, it is necessary to linearize this term. In this case, linearization can be achieved by making the assumption that the participation decision variables are determined through an external process and are not part of the decision process of the optimization problem. Therefore, a cascaded approach to solving the optimization problem in this case is adopted. The cascaded approach assumes an initial participation hours selector, which gives a preliminary decision as to when to participate. This decision can be either based on a separate optimization problem, where the electricity import is assumed to be known, or simply on selecting the hours where the predicted RT LMP and/or the actual and predicted DA LMP are greater than or equal to the NBT. The preliminary participation decision is then passed to the main optimization problem shown in (8), where the final participation hours and amounts are determined.

Under the assumption of having preliminary values for the participation decision variables, where $p_i = 1$ indicates a participation hour and $p_i = 0$ otherwise, and given that λ_i is also given by the user, equation (8) can be rearranged yielding the following equivalent objective function:

$$J = J_o + \sum_{i=k}^{k+h-1} \left(\hat{r}_{e_i} + a_i \right) e_i \tag{9}$$

where

$$\begin{aligned} a_i &= f\left(-\hat{r}_{DA_j}\right) < 0 \qquad && \forall i \in \text{CBL hours}/p_j = 1 \\ a_i &= \hat{r}_{DA_i} && \forall i \,/\, p_i = 1 \\ a_i &= r_{PLC} && \forall i \,/\, \lambda_i = 1 \\ a_i &= 0 && \text{otherwise} \end{aligned} \tag{10}$$

Thus, the integration of the ELDR program revenue and the PLC charge in the optimization framework translates to a rate adjustment of the electricity rates as shown in (9). As shown in (10), the rates during the baseline hours are adjusted by an amount that is a function of the predicted or actual DA LMP. The latter adjustment varies from one type of baseline to another. For example, for a Same Day (3+2) CBL and for the participation scenario shown in Figure 1, the rate adjustment amount during the baseline hours is as shown below:

$$a_i = f\left(-\hat{r}_{DA_j}\right) = -\frac{\sum_{j=11}^{19} \hat{r}_{DA_i}}{5} \quad \forall i \in \text{CBL hours} \tag{11}$$

Assuming a constant electricity rate. The resulting adjusted rate is as shown in Figure 2.

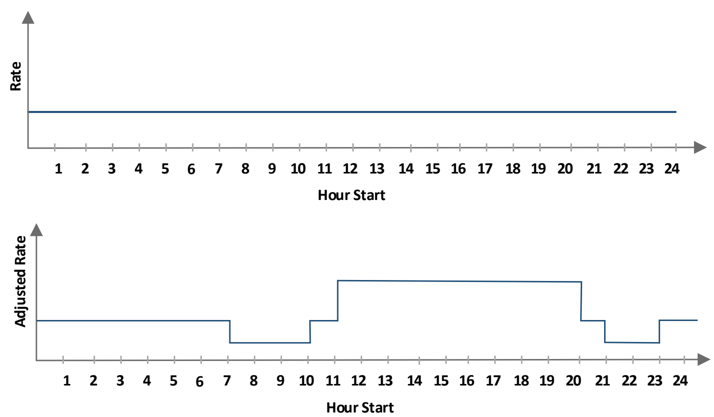

Figure 2: Example of rate adjustment due to a participation in ELDR with a Same Day (3+2) CBL

As can be observed in Figure 2, the electricity rate during the CBL hours are adjusted by a negative term, those during the participation hours are adjusted by a positive term, and the rates of the hours which are neither a CBL or a participation hour are not affected. The rate adjustment causes the optimization to make the appropriate decisions and optimally allocate assets in order to meet the commitments in the ELDR market. For the case of a PLC charge, where projected CP hours fall within the optimization horizon, the rate during the projected CP hours will be adjusted positively, which causes the optimization to turn on on-site generation equipment and/or reduce electricity consumption during those hours.

This simplifies the problem at hand and eliminates the need for solving a bilinear optimization problem, which would necessitate the introduction of a large number of auxiliary variables. The cascaded approach also allows for reducing the computational time of the optimization solver, which can increase exponentially for large-scale CEF. Consequently, it is then possible to implement this approach for real-time operation of CEF.

Figure 3 shows a high level view of the optimization framework of a CEF with integrated ELDR and PLC charges. At any instant in time, measurements of loads are obtained, along with a weather forecast. The latter is used to predicted loads and rates over the optimization horizon using the methods shown in ElBsat, M. N. & Wenzel, M. J. (2016). RT LMP, DA LMP, and NBT threshold are obtained from the ELDR market and passed to the initial participation hours selector. In addition, if PLC charges are applicable, a projected CP hours vector is passed to the optimization problem, along with the preliminary participation hours decision. The optimization problem is solved over the horizon and the CEF assets are allocated optimally subject to the set of constraint defined in the problem.

Recall that if a customer is participating in the ELDR program, the customer must not include the actual CP hours in the ELDR settlement for the days where the CP hours happen. Operationally, for projected CP hours, when the hourly mask λ_i is 1 for a given hour, the corresponding ELDR participation mask can be forced to 0 to reflect the possibility of not making ELDR revenue for said hour.

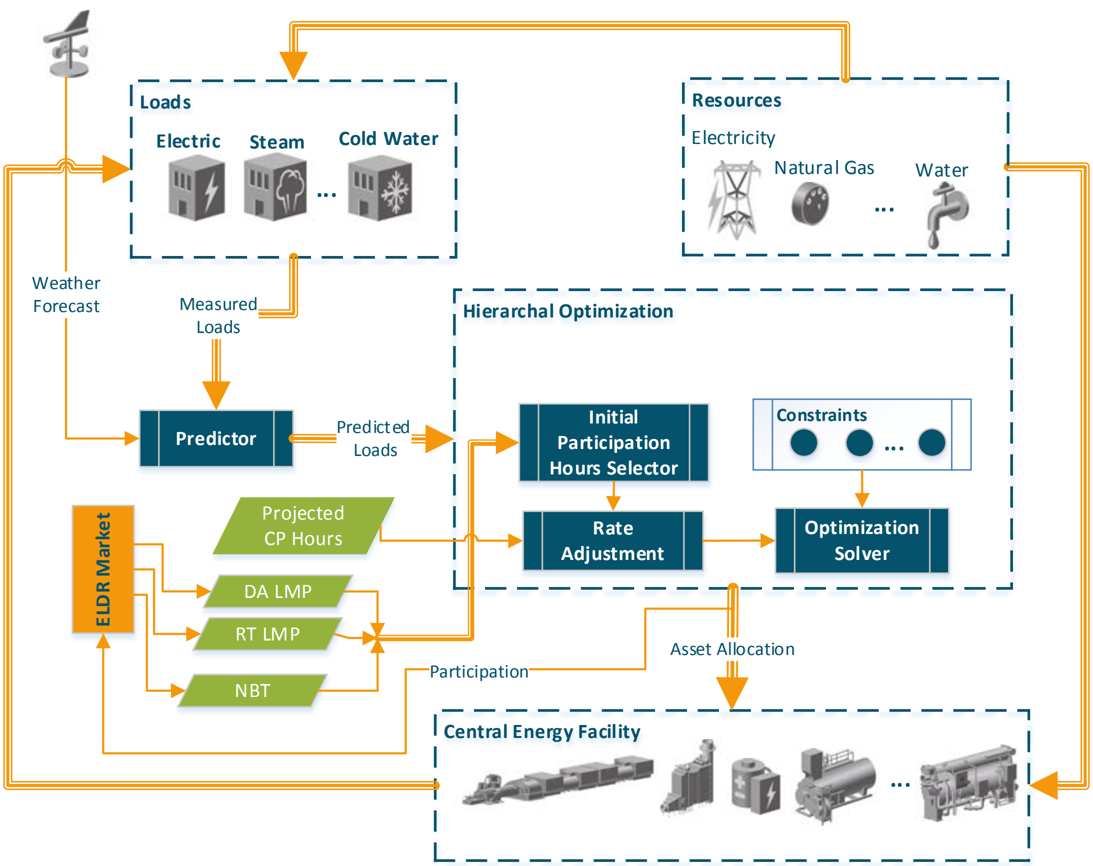

Figure 3: Example of CEF optimization with integrated ELDR and PLC

5. KENT STATE UNIVERSITY CASE STUDY

The central energy facility at KSU provides chilled water, steam, and on-site electricity generation to the campus. The facility consists of seven chilled water plants capable of providing a total of 40,716 kW of cooling over three chilled water loop. In addition, the facility is capable of meeting 99,620 kW of steam load using two boilers and two heat recovery steam generators. The facility also has two combustion turbines with 12 MW capacity. KSU is located in Kent, OH USA, which is within the region managed by PJM. KSU Power Plant is a participant in the ELDR program offered by PJM. KSU's CBL is of the Same Day (3+2) type. The developed approach has been implemented at KSU Power Plant, where the facility assets are allocated optimally to minimize resource costs, while determining which hours to commit to the ELDR program. The algorithm implemented at KSU does not currently include PLC charges. On-site operations thus far has shown the feasibility of the developed approach. The allocation of the combustion turbines is determined automatically in response to ELDR market prices, plant conditions, and predicted loads over the horizon. The latter guarantees that the power plant is capable of meeting any ELDR market commitments made. If, for example, one of the combustion turbines is scheduled out-of-service, the optimization algorithm takes this into consideration and reevaluates future ELDR commitments in order to avoid over or under performance in the market. Figures 4 through 7 show examples of actual KSU Power Plant ELDR participation performance. On 04/22/2018, participation started at 5 AM and ended at 8 PM. The combustion turbine is turned on during the hour between 4 AM and 5 AM, in preparation to meeting commitments made for the day. As can be observed, from 12 PM to 4 PM, the plant was not dispatched in the Real-Time market, but the combustion turbine was allocated to stay on due to the simultaneous minimization of electricity costs.

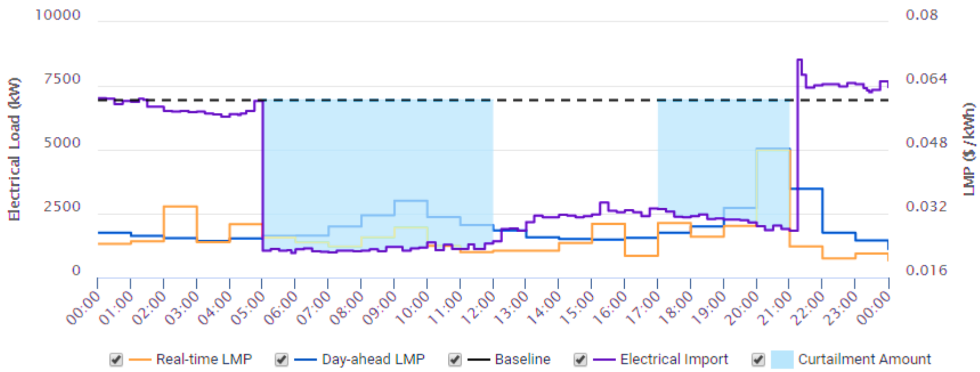

Figure 4: Actual ELDR participation performance at KSU Power Plant on 04/22/2018

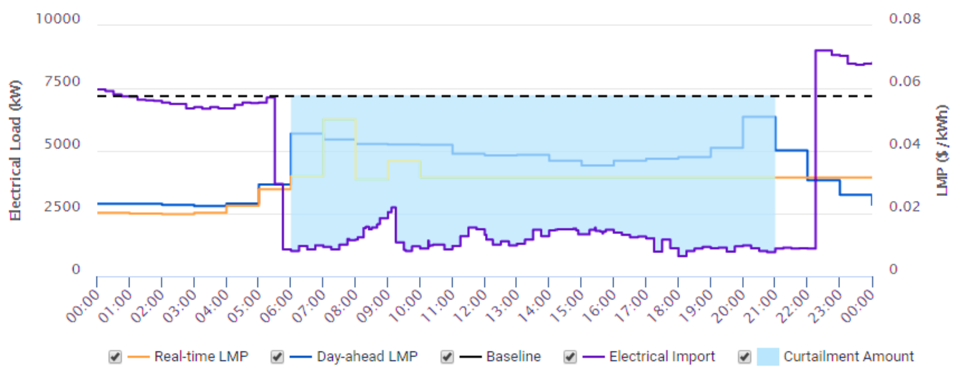

Figure 5: Actual ELDR participation performance at KSU Power Plant on 04/23/2018

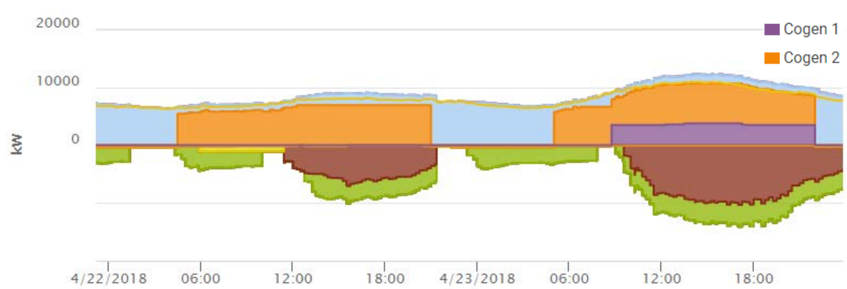

Figure 6: Allocation of the combustion turbines (Cogen 1 and 2) at KSU Power Plant in response of participation in ELDR

	00:00	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
4/22/2018						5,890 kW	5,878 kW	5,920 kW	5,855 kW	5,810 kW	5,738 kW	5,745 kW						4,448 kW	4,580 kW	4,720 kW	5,000 kW			
4/23/2018							6,060 kW	5,952 kW	5,254 kW	5,636 kW	6,020 kW	5,535 kW	5,845 kW	5,637 kW	5,349 kW	5,402 kW	5,560 kW	5,923 kW	6,170 kW	6,083 kW	6,110 kW			
4/24/2018							3,623 kW	3,885 kW	6,173 kW	6,160 kW	6,217 kW	6,257 kW	6,054 kW	6,110 kW	6,161 kW	6,261 kW	6,201 kW	6,256 kW	6,269 kW	6,218 kW	6,213 kW			
4/25/2018							5,955 kW	5,642 kW	5,145 kW	5,933 kW	5,947 kW	6,067 kW	6,040 kW	5,957 kW	6,082 kW	6,035 kW	6,090 kW	6,061 kW	6,022 kW	5,985 kW	6,107 kW			
4/26/2018						6,012 kW	5,940 kW	5,737 kW	4,937 kW	5,407 kW	6,007 kW	6,032 kW	6,052 kW	5,877 kW	5,422 kW	5,957 kW	5,945 kW	5,980 kW	6,030 kW	6,027 kW	6,087 kW			
4/27/2018								6,051 kW	5,458 kW	4,986 kW	6,032 kW	5,609 kW	6,042 kW	5,984 kW	6,077 kW	6,044 kW	6,044 kW	6,129 kW	6,057 kW	5,809 kW				
4/28/2018							3,338 kW	4,396 kW	4,196 kW	3,723 kW	3,531 kW	3,326 kW	3,561 kW			3,146 kW	3,226 kW	3,428 kW	3,409 kW	3,526 kW	3,613 kW			

Figure 7: KSU participation in ELDR from 04/22/2018 to 04/28/2018

6. CONCLUSIONS

A general framework for CEF optimization with integrated incentive-based demand response and price-based demand-response programs is developed. Assets of the CEF are allocated optimally to minimize costs associated with resource purchase, while meeting commitments to incentive-based demand response programs. It was shown by considering electricity as an example that the developed approach allows for the optimization of a CEF by transforming demand response program rates to a rate adjustment. The latter allows for a simplified linear optimization problem which can be solved using mixed –integer linear programing techniques. The developed approach has been implemented at Kent State University which is a participant in economic load demand response program. On site operations show the feasibility of the approach. Future work include developing methods for forecasting possible coincidental peak hours, which would serve as an input to the optimization problem.

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