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Flexibility Scheduling for Large Customers

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***Abstract*—Large customers are considered as major flexible electricity demands which can reduce their electricity costs by choosing appropriate strategies to participate in demand response programs. However, practical methods to aid the large customers for handling the complex decision making process for participating in the programs have remained scarce. This paper proposes a novel decision-making tool for enabling large customers to determine how they adjust their electricity usage from normal consumption patterns in expectation of gaining profit in response to changes in prices and incentive payments offered by the system operators. The proposed model, formulated as a mixed-integer linear programming problem, simultaneously determines the optimal integration of the flexibility options including shifting demand and utilizing onsite generation and energy storage systems, along with energy procurement from the grid that allows the large customers to optimize their energy portfolio from different sources including bilateral contracts and the market. The characteristics of the proposed integrated flexibility scheduling and energy procurement model and its benefits are investigated through several case studies conducted on a test large industrial load.**

***Index Terms*—Demand response, flexible load, energy storage systems, onsite generation, energy procurement, large customers, mixed-integer linear programming.**

I. Nomenclature

A. Indices

$t\,(t')$	Primary (Auxiliary) index of time.
z	Index of time interval types.
j	Index of production cost function segment of OG.
k	Index of flexible loads.
b	Index of bilateral contracts.

B. Sets

T	Set of study time horizon intervals.
$T_{LR}\,(T_{RC})$	Set of load reduction (recovery) time intervals.
T_{bz}	Set of time interval type z of contract b.
$K\left(K_f\right)$	Set of flexible loads (with functional limits).
K_s, K_g, K_{gs}	Sets of flexible loads that can be supplied by ESS, OG, and exclusively by either OG or ESS.
B	Set of bilateral contracts.
J	Set of production cost function segments of OG.

C. Constants

Δt	Duration of optimization interval.
$\gamma^k\left(C^k\right)$	Load (Rescheduling cost) of k^{th} flexible load.
$T_k^{\min}\left(T_k^{\max}\right)$	Min (Max) off time of k^{th} flexible load.
$NC_k^{\max}$	Maximum No. of curtailment of k^{th} flexible load.
$P_j^{\max}\left(f_j\right)$	Size (Slope) of segment j of OG.
$P^{\min}\left(P^{\max}\right)$	Min (Max) generation limit of OG.
RU^{OG}	Ramping up limit of OG.
RD^{OG}	Ramping down limit of OG.
C^{FX}	Fixed-cost of running OG
P^r	Rated power of ESS.
$E^{\min}\left(E^{\max}\right)$	Min (Max) energy capacity of ESS.
$\eta^{ch}\left(\eta^{dch}\right)$	Charging (Discharging) efficiency of ESS.
D_t^{est}	Estimated demand during t.
λ_{bt}^B	Reference price for contract b during t.
λ_t^{est}	Estimated market price at t.
$E_{bz}^{\min}\left(E_{bz}^{\max}\right)$	Lower (Upper) bound of energy bought from contract b during time interval type z.

D. Variables

$L_t^{red}\left(L_t^{rec}\right)$	Load reduction (recovery) stemmed from flexible loads rescheduling during t.
C_t^{res}	Rescheduling costs of flexible loads during t.
$u_t^k\left(\upsilon_t^k\right)$	Binary variable associated to k^{th} flexible load that is equal to 1 if it is scheduled (recovered) during t and 0 otherwise.
$D_t^{flx}\left(C_t^{flx}\right)$	Demand flexibility (flexibility cost) scheduled for time t.
D_t^{mod}	Modified demand of customer during t.
$P_t^{OG}\left(C_t^{OG}\right)$	Generation (cost) of OG during t.
P_{jt}	Generated power in segment j of OG during t.
ρ_t	Binary variable equal to 1 if OG is running during t and 0 otherwise.

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E_t	Energy stored in ESS during t.
$S_t^{ch}\left(S_t^{dch}\right)$	Energy drawn (released) by ESS during t.
β_t	Binary variable equal to 1 if ESS is charging during t and 0 otherwise.
$\rho_t^{fl}\left(\rho_t^{il}\right)$	Binary variable equal to 1 if OG supplies flexible (inflexible) loads during t and 0 otherwise.
$\beta_t^{fl}\left(\beta_t^{il}\right)$	Binary variable equal to 1 if ESS supplies flexible (inflexible) loads during t and 0 otherwise.
$P_t^P\left(P_{bt}^B\right)$	Total power purchased from the market (contract b) during t.

II. Introduction

PROLIFERATION of smart energy technologies at customer sites enables the customers to take part in wholesale electricity markets and make profits by procuring their energy needs from different resources and also participating in Demand Response (DR) programs. A savvy customer can optimize its energy consumption profile by intelligently modifying and thence procuring it from available resources so that its total electricity cost is minimized.

Apart from the energy procurement problem of large customers that has been extensively studied in the literature [1]-[4], multiple research works have been devoted to address potential benefits of DR participation in wholesale electricity markets [5]-[9]. Moreover, the potential of industrial customers to provide DR capacity is highlighted in [8], [9], where the DR provided by industrial customers represented 16,505MW (53%) of total potential peak reduction in 2014 across U.S [9].

The technical literature is rich on research works addressing the system operators' operation problem with DR. For instance, the hourly DR has been incorporated into security-constrained unit commitment (SCUC) for economic and security purposes in [10] and [11]. In addition, two DR programs have been designed which aim to enable customers' participation in day-ahead energy markets in [12] and market clearing problems including DR offer packages are presented from the operators' points of view. A DR program is designed in [13] where the participants submit their offer packages embodying price-quantity pairs and load characteristics to provide flexibility in the wholesale day-ahead energy market. Subsequently, the system operator clears the market by considering submitted load reduction offer packages. An optimization model for the DR aggregation in wholesale electricity markets is presented in [14]. In the proposed model, DR aggregators offer customers various contracts for load curtailment, load shifting, and utilizing onsite generation (OG) and energy storage systems (ESS) as possible DR strategies and exploiting ensuing hourly load reductions into their self-optimization schemes. The common akin attribute amidst all literature resources in [10]-[14] is that, submitted offer packages and DR contracts are all assumed to be known from the ISO and aggregators' viewpoints; yet the question is "how do customers design the so-called DR offer packages?"

Despite the ample research efforts dedicated to incorporate DR and load flexibilities into system operators and the aggregators' problems, there are a few research works addressing the customers' problem to optimally participate in DR programs. The potential of demand-side management activities and customers price elasticities to impact power system operation is investigated in [15]-[18]. The customer models in [15]-[18] merely include demand shifting procedure based on price elasticities which does not precisely reflect customers' optimal behavior. Additional works look at enabling customers to respond to price-based DR programs [19]-[23]. A linear programming model is proposed in [19] that enables customers to adjust their hourly load levels in response to hourly electricity prices. Wang et al. [20] have analyzed the electrical load tracking capability of energy intensive enterprises by scheduling local power plants to track their load curve considering time-of-use (TOU) tariffs. A new TOU tariff is introduced in [21] that incentivizes selected customers to shift their loads into other time periods. In [22], Zhang et al. have developed an optimal bidding strategy for an aluminum smelter facility to participate in day-ahead energy and spinning reserve markets. A formulation to determine the optimal operating strategy of a cogeneration system in proposed in [23] that reduces the peak demand of a typical petrochemical facility under TOU tariff. We argue that the technical literature lacks detailed models looking at various flexibility options of customers, and a new decision-making tool is required for enabling customers to scrupulously design their optimum offer packages considering all the available flexibility options.

In this context, this paper proposes a novel decision-making tool for large customers to optimally adjust their electricity demand by integrating all possible flexibilities including flexible loads, operating OG, and utilizing ESS while minimizing the customer's electricity cost. The proposed integrated model, formulated as a mixed-integer linear programming problem, simultaneously optimizes the integrated flexibility of the customers for hourly load reductions in the system, as well as energy portfolio procurement from different sources including bilateral contracts and the market.

The rest of this paper is organized as follows: Section III models the customer's consumption flexibility in terms of available options by which customers provide hourly load reductions. The proposed model for integrated flexibility scheduling and energy procurement of large customers is expounded and formulated through Section IV. Section V demonstrates the application of the proposed decision-making tool on a sample large industrial customer. The conclusions are drawn and discussed in Section VI.

III. Characteristics of Customers Flexibility Options

In this paper, *customer flexibility* is defined as any activity at the customer site that supports a net change in the energy supplied by the grid to the customer. Large customers, such as industrial facilities, usually have energy intensive loads and production processes that may be rescheduled in order to provide the flexibility in power systems operation. In addition, customers with local generation and/or energy storage devices

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are given with further options to make a net change in the power delivered by the grid and participate in DR program [5], [8]. There are, however, different costs associated with the load reduction associated with different flexibility options, which requires analysis and optimization before making decisions about submitting DR offers in the markets. For instance, customers who are capable of shifting their normal consumption patterns may incur rescheduling costs from labor rescheduling, overtime pay or productivity losses from adjustments to their production processes. Rescheduling cost is the cost of curtailing and shifting the consumption of flexible loads. Utilization of OG would impose fuel and maintenance costs while utilizing ESS would impose costs associated with charging/discharging losses [5]. The potential flexibility options of customers are discussed below in detail. Note that, this paper focuses on customer flexibility services in energy markets, and options to provide ancillary services are not discussed. Further, energy efficiency measures that permanently modify the demand, such as installing higher efficiency lighting, cooling and heating systems are not considered.

A. Flexible Load

In this option, customers reschedule their electricity consumption away from DR program execution intervals to other hours. Rescheduling large flexible loads that provide significant change in the customer's load are suitable for this application. For instance, an industrial facility might reschedule a batch production process to the prior points in the time (preceding) or to the subsequent times (postponing). Flexile loads and processes typically belong to one of the following categories [24]: Inert thermal processes (heating, cooling), inert diffusion processes (ventilation, irrigation, etc.), mass transport (pumps with tanks, conveyor belts, etc.), and logistics (schedules, dependencies, lunch-breaks, etc.). Identifying the available load flexibility propels customers to prioritize the potential flexible loads with respect to their corresponding rescheduling costs derived from indispensable cost analysis.

Assume that the customer identifies a set of flexible loads, K, whose elements are modeled by the pair (γ^k,C^k) reflecting the load and the rescheduling cost of k^{th} flexible load in MW and \$/MWh. The total load reduction and the rescheduling cost associated with the flexible loads are formulated in (1) and (2) respectively as:

$$L_t^{red} = \sum_{k \in K} u_t^k \gamma^k , \quad \forall t \in T_{LR} \tag{1}$$

$$C_t^{res} = \sum_{k \in K} \left(C^k u_t^k \gamma^k \right) \Delta t , \quad \forall t \in T_{LR} \tag{2}$$

Where, the binary variable u_t^k models the scheduling status of k^{th} flexible load which is equal to 1 if the load is curtailed at $t \in T_{LR}$ and 0 otherwise. Moreover, in practice, depending on the customers' processes, the identified flexible loads might have operational limits such as *minimum/maximum off time durations*, and *maximum number of curtailments*, which are formulated as:

$$\sum_{t'=t}^{t+T_k^{\min}-\Delta t} u_{t'}^k \ge T_k^{\min} \left(u_t^k - u_{t-\Delta t}^k \right), \ \forall k \in K_f , t \in T_{LR} \tag{3}$$

$$\sum_{t'=t}^{t+T_k^{\max}-\Delta t} u_{t'}^k \le T_k^{\max} \left(u_t^k - u_{t-\Delta t}^k \right), \ \forall k \in K_f , t \in T_{LR} \tag{4}$$

$$\sum_{t \in T_{LR}} u_t^k \le NC_k^{\max} , \quad \forall k \in K_f \tag{5}$$

where constraints (3) and (4) represent the minimum and maximum off time constraints of k^{th} flexible load, respectively. In addition, constraint (5) bounds the number of curtailments of k^{th} flexible load during DR execution time T_{LR}. Note that K_f is a subset of flexible loads with functional constraints ($K_f \subseteq K$). Here we assume that the operation processes of the flexible loads are functionally independent. Accordingly, the operation of each flexible load does not affect the operation status of the others. In case of functional interdependencies between the flexible loads, those flexibilities are aggregated into single ones, where the processes of engendered flexible loads will be functionally independent.

In addition to the load reduction procedure modeled in (1)-(5), the essential load recovery process of the flexible loads is formulated as follows:

$$0 \le L_t^{rec} \le \sum_{k \in K} \upsilon_t^k \gamma^k , \quad \forall t \in T_{RC} \tag{6}$$

$$\sum_{t \in T_{LR}} L_t^{red} \Delta t - \sum_{t \in T_{RC}} L_t^{rec} \Delta t = 0 \tag{7}$$

$$\sum_{t \in T_{RC}} \upsilon_t^k = \sum_{t \in T_{LR}} u_t^k , \quad \forall k \in K \tag{8}$$

where constraint (6) states that the total amount of load recovery during t belongs to the recovery time intervals T_{RC} must be less than or equal to the curtailed flexible loads during DR execution time intervals (T_{LR}). Constraint (7) ensures that the total recovered load equals to the total load reduction. Moreover, constraint (8) ensures that the reduced flexible loads would be recovered during load recovery time intervals (T_{RC}).

In addition to rescheduling the operation of flexible loads, the customers may utilize OG and/or ESS in order to supply some or all of reduced loads during the DR program execution time. Although the customers may have little or no interruption to their electrical usages by the flexible loads, their net load requirement on the power system would be reduced. The utilization of OG and ESS is modeled next.

B. Onsite Generation

Running OG in large customer sites is common and has had a large increase in recent years, such that onsite energy generation in industrial sector in 2012 amounts for approximately 4% of the total U.S. electric energy (MWh) generated throughout the same year [25]. Although the primary use of OG is to functioning as a backup generator during emergencies, the customers can also operate these generators to compensate some or all of the reduced load during DR program execution time. Assuming piecewise linear production cost function with j segments [13], the total power generation of OG can be modeled by:

$$P_t^{OG} = \rho_t P^{\min} + \sum_{j \in J} P_{jt} , \quad \forall t \in T \tag{9}$$

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$$0 \le P_{jt} \le \rho_t P_j^{\max}, \quad \forall j \in J, t \in T \tag{10}$$

where, the binary variable ρ_t reflects the commitment status of the OG that is equal to 1 if the unit operates at t and 0 otherwise. The constraint (10) limits the power generation of the OG in each segment by the corresponding upper capacity limits. The total generation cost of OG is calculated in (11), and the OG ramping constraint is formulated in (12).

$$C_t^{OG} = \rho_t C^{FX} + \sum_{j \in J} f_j P_{jt}, \quad \forall t \in T. \tag{11}$$

$$-RD^{OG} \le P_t^{OG} - P_{t-1}^{OG} \le RU^{OG}, \quad \forall t \in T \tag{12}$$

C. Energy Storage System

The availability and utilization of ESS devices at customer sites facilitates the rational arbitrage of energy for the customers, where the customers may purchase additional electric energy during low prices to charge the ESS, and consuming the stored energy at the times of high prices and/or the DR program execution time to compensate some or all of reduced loads. By utilizing ESS, the net load of DR participants will be reduced as ESS is discharged, and will increase as it is being charged. The charge and discharge process of the ESS can be mathematically modeled as:

$$0 \le S_t^{ch} \le (1-\beta_t) P^r, \quad \forall t \in T \tag{13}$$

$$0 \le S_t^{dch} \le \beta_t P^r, \quad \forall t \in T \tag{14}$$

$$E_t = E_{t-\Delta t} + \eta^{ch} S_t^{ch} \Delta t - \frac{1}{\eta^{dch}} S_t^{dch} \Delta t, \quad \forall t \in T \tag{15}$$

$$E^{\min} \le E_t \le E^{\max}, \quad \forall t \in T \tag{16}$$

where the binary variable β_t models the charging status of ESS. The charge/discharge power of the ESS is limited to the rated power of ESS in (13) and (14). Moreover, the dynamic energy balance of the ESS is modeled in (15), and the energy capacity limits of ESS are presented in (16). In addition, the constraint (17) ensures that the total stored energy is consumed locally by the customer and is not sold back to the grid.

$$\sum_{t \in T} \eta^{ch} S_t^{ch} \Delta t - \sum_{t \in T} \frac{1}{\eta^{dch}} S_t^{dch} \Delta t = 0 \tag{17}$$

IV. Integrated Flexibility Model

The individual flexible strategies for large customers, including scheduling flexible loads, OG and ESS, are discussed in detail in Section III. We argue that although the individual flexibility strategies would equip customers to participate in the DR program, the three options could be integrated to capture the interdependencies and the relative costs and benefits among the strategies, delivering additional flexibility at lower costs. More specifically, while shifting loads and processes can be quite costly for large customers, the availability of OG and/or ESS can be leveraged to substitute the costly load shifting, yet achieving comparable benefits for the customers.

Here we aim to develop an integrated flexibility model for the customers by capturing the complementary nature of the three flexibilities during the DR program events. The integrated model intends to combine the three models in Section III into a unified flexibility scheduling model where the power generation by OG and/or energy stored in ESS are utilized in order to compensate some or all of the curtailed flexible loads and/or supplying inflexible parts of customer's demand. Here we assume that the energy generated by OG and/or power discharge of ESS is not being sold to the market, and is consumed locally by the customer during optimum time intervals.

In the proposed integrated flexibility scheduling model, during the DR program events, the customer may choose to utilize OG and/or ESS in order to either: 1) substitute flexible load shifting, or 2) supply inflexible loads while load shifting is scheduled to provide flexibility to the grid. These two options would incur different costs to the customers, so a trade-off should be made based on the costs and benefits of implementing each option. Thus, the integrated flexibility of the customers demand, D_t^{flx}, and the associated cost function, C_t^{flx}, during the DR program time intervals T_{LR} are formulated in (18) and (19) as:

$$\begin{aligned} D_t^{flx} &= \sum_{k \in K} u_t^k \gamma^k + \beta_t^{il} \left[S_t^{dch} - \beta_t^{fl} \left(\sum_{k \in K_s} u_t^k \gamma^k \right) \right] \\ &+ \rho_t^{il} \left(1 - \beta_t^{fl}\right) \left[P_t^{OG} - \rho_t^{fl} \left(\sum_{k \in K_g} u_t^k \gamma^k \right) \right] \\ &+ \rho_t^{il} \beta_t^{fl} \left[P_t^{OG} - \rho_t^{fl} \left(\sum_{k \in K_{gs}} u_t^k \gamma^k \right) \right], \quad \forall t \in T_{LR} \end{aligned} \tag{18}$$

$$\begin{aligned} C_t^{flx} &= \sum_{k \in K} C^k u_t^k \gamma^k \Delta t - \beta_t^{fl} \left(\sum_{k \in K_s} C^k u_t^k \gamma^k \right) \Delta t \\ &- \rho_t^{fl} \left(1 - \beta_t^{fl}\right) \left(\sum_{k \in K_g} C^k u_t^k \gamma^k \right) \Delta t \\ &- \rho_t^{fl} \beta_t^{fl} \left(\sum_{k \in K_{gs}} C^k u_t^k \gamma^k \right) \Delta t, \quad \forall t \in T_{LR} \end{aligned} \tag{19}$$

where two pairs of new binary variables, (ρ_t^{fl},ρ_t^{il}) and (β_t^{fl},β_t^{il}), are defined to model the trade-off that should be made for substituting the flexible (*fl*) and inflexible load (*il*) with OG and/or ESS. Accordingly, (20) and (21) below guarantee that if OG and/or ESS are available, at least one of the two options are opted during DR execution time intervals T_{LR}:

$$\rho_t \le \rho_t^{fl} + \rho_t^{il}, \quad \forall t \in T_{LR} \tag{20}$$

$$\beta_t \le \beta_t^{fl} + \beta_t^{il}, \quad \forall t \in T_{LR} \tag{21}$$

In (18), K_s and K_g are given subsets of K representing flexible loads that can be respectively substituted by ESS and OG, while K_{gs} represents the set of flexible loads that can be exclusively substituted by either OG or ESS. Defining the subsets, in (18), the first term presents the load reduction of flexible loads, the second and third term present the flexible loads that are substituted by ESS and OG operation, and the fourth term presents the flexible loads that are exclusively substituted by ESS or OG. The fourth term in (18) avoids any interferences in substituting the flexible and/or inflexible loads, at times when OG and ESS are both available. Constraints (22), (23) ensure that, at each time, the ESS and OG have enough power

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capacity to substitute the scheduled flexible loads.

$$\beta_t^{fl}\left(\sum_{k\in K_s} u_t^k \gamma^k\right) \le S_t^{dch}, \quad \forall t \in T_{LR} \tag{22}$$

$$\rho_t^{fl}\left(\sum_{k\in K_g} u_t^k \gamma^k\right) \le P_t^{OG}, \quad \forall t \in T_{LR} \tag{23}$$

The equation (19) defines the costs associated with the integrated flexibility model (18), where the negative terms represent the net-reduction in costs associated with supplying the flexible loads by OG and/or ESS, and eliminating the rescheduling costs of scheduled flexible loads. Note that the flexible loads can be only substituted with OG or ESS in (18), if the flexible loads are scheduled. This is expressed in (24), (25) and (26) where the binary variables ρ_t^{fl} and β_t^{fl} can be equal to 1 only if at least one of the flexible loads in sets K_s, K_g, or K_{gs} is scheduled.

$$\beta_t^{fl} \le \sum_{k\in K_s} u_t^k, \quad \forall t \in T_{LR} \tag{24}$$

$$\rho_t^{fl}\left(1-\beta_t^{fl}\right) \le \sum_{k\in K_g} u_t^k, \quad \forall t \in T_{LR} \tag{25}$$

$$\rho_t^{fl}\beta_t^{fl} \le \sum_{k\in K_{gs}} u_t^k, \quad \forall t \in T_{LR} \tag{26}$$

In addition, the proposed integrated flexibility model includes constraints (27)-(31) for coordinating the load recovery of the scheduled flexible loads during T_{RC}, with the substitution decisions made through (18)-(26).

$$0 \le D_t^{flx} \le \sum_{k\in K} \upsilon_t^k \gamma^k, \quad \forall t \in T_{RC} \tag{27}$$

$$\begin{aligned}&\sum_{t\in T_{LR}}\left[\sum_{k\in K} u_t^k\gamma^k - \left(S_t^{dch} + P_t^{OG} - \left(D_t^{flx} - \sum_{k\in K} u_t^k\gamma^k\right)\right)\right]\Delta t \\ &- \sum_{t\in T_{RC}} D_t^{flx}\Delta t = 0\end{aligned} \tag{28}$$

$$\sum_{t\in T_{RC}} \upsilon_t^k = \sum_{t\in T_{LR}} u_t^k - \sum_{t\in T_{LR}} \beta_t^{fl}, \quad \forall k \in K_s \tag{29}$$

$$\sum_{t\in T_{RC}} \upsilon_t^k = \sum_{t\in T_{LR}} u_t^k - \sum_{t\in T_{LR}} \rho_t^{fl}, \quad \forall k \in K_g \tag{30}$$

$$\sum_{t\in T_{RC}} \upsilon_t^k = \sum_{t\in T_{LR}} u_t^k, \quad \forall k \notin \left\{K_s \cup K_g\right\} \tag{31}$$

The constraint (27) ensures that the amount of load recovery does not exceed the load reduction of the scheduled flexible loads, while (28) adjusts the amount of load recovery given the scheduled OG and ESS substitutions. The innermost negative term in parentheses in (28) reflects the amount of load reductions provided by OG and/or ESS. In addition, equations (29)-(31) ensure that the load recovery should be continued for the number of hours that the load reduction is scheduled, considering the adjustment made by the OG or ESS substitutions.

The proposed integrated flexibility model in (18)-(31), includes nonlinear expressions in (18), (19), (22), (23) and (25), (26) that would complicate the solution of the proposed flexibility scheduling problem. In order to preserve the MILP format of the proposed model, the nonlinear terms are casted in linear forms in Appendix A.

Implementing the integrated flexibility model, would modify the customers' normal consumption patterns to achieve a modified demand profile, as seen by the system operator. The customer's modified demand, D_t^{mod}, during different time intervals is presented in (32)-(34), which includes the estimated demand profile D_t^{est} adjusted by the load reduction and recovery of flexible loads, the charging and discharging of ESS, and the power generation of OG.

$$D_t^{\mathrm{mod}} = D_t^{est} - D_t^{flx} + S_t^{ch}, \ \forall t \in T_{LR} \tag{32}$$

$$D_t^{\mathrm{mod}} = D_t^{est} + D_t^{flx} + S_t^{ch} - S_t^{dch} - P_t^{OG}, \ \forall t \in T_{RC} \tag{33}$$

$$D_t^{\mathrm{mod}} = D_t^{est} + S_t^{ch} - S_t^{dch} - P_t^{OG}, \ \forall t \notin \left\{T_{LR} \cup T_{RC}\right\} \tag{34}$$

V. Integrated Flexibility Scheduling and Energy Procurement for Large Customers

In this section, we present the proposed model for co-optimization of the flexibility schedules and the energy procurement decisions for large customers. The large customers' energy sources include signing bilateral contracts that makes it possible for customers to cover part of their electricity demand before its physical delivery. The reference energy prices as well as the upper and lower limits of the energy traded over the scheduling horizon are specified through the contrasts. Moreover, customers can buy part of their electricity needs from the wholesale forward market at times the prices are low. Here we assume that energy arbitrage, i.e., purchasing energy through bilateral contracts and selling it to the market is not considered [1], [4], [26]. The objective function of the proposed model is to minimize the total energy procurement costs that is formulated as follows:

$$\begin{aligned}&\sum_{t\in T}\left[\left(\lambda_t^{est}P_t^P + \sum_{b\in B}\frac{\lambda_{bt}^B + \lambda_t^{est}}{2}P_{bt}^B\right)\Delta t + C_t^{OG}\right] \\ &+\sum_{t\in T_{LR}}\left(C_t^{flx} - \lambda_t^{est}D_t^{flx}\Delta t\right)\end{aligned} \tag{35}$$

Where, the terms in the first line respectively include the costs of purchasing energy from the market, available bilateral contracts and energy production by OG. In (35), the final prices of each bilateral contract at each time interval are equal to the average of the contract reference prices and the market prices [1], [4]. The second line in (35) models the cost of providing flexibility to the market formulated in (19), minus the incentive payments received from the system operator. The amount of incentives offered by the system operator is dependent to their respective market regulations. One option is to pay customers according to the energy market prices, which is consistent with the current FERC order 745 regulations [27]. The hourly forecast for prices of energy is an input to the optimization problem and considered to be given by applying numerical techniques like time series and artificial neural network [28]. Accordingly, customers utilize historical data in order to forecast hourly market prices. The objective function (35) is subjected to the upper and lower limits on the energy bought from bilateral contract b during hours of type z (e.g., on-peak or off-peak hours) formulated as:

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$$E_{bz}^{\min} \le \sum_{t\in T_{bz}} P_{bt}^{B}\Delta t \le E_{bz}^{\max},\ \forall z, \forall b \in B \tag{36}$$

Further, the power balance constraint (37) ensures that the energy bought from the market and the bilateral contracts balance the modified demand of the customer formulated in (32)-(34), which takes into account the integrated flexible options at the customer site.

$$P_t^{P} + \sum_{b\in B} P_{bt}^{B} = D_t^{\mathrm{mod}},\ \forall t \in T \tag{37}$$

VI. Case Study and Results

Numerical studies are conducted to delineate the merits of the proposed model. Here we adapt the model to solve the flexibility scheduling and energy procurement for a sample large industrial manufacturer over a one-week period. Each working day is decomposed into three load levels in Table I.

The customer has option to procure energy through two weekly bilateral contracts with reference prices and the energy consumption limits as in Tables II and III. It is assumed that the customer has a precise knowledge of its future demand, whose forecast is plotted in Fig. 1 (demand on Tuesday extracted from [1] and extended to whole week). The day-ahead wholesale market prices of the Iberian Peninsula for the first week of October 2004, depicted in Fig. 1, are utilized for the studies. It is assumed that the system operator decides to schedule DR in working days during hours 12–21. The quantity of energy previously contracted is assumed to be zero.

The proposed model is solved using the CPLEX 12 solver under GAMS [29] on a computer with a core i5-3337U processor at 1.80 GHz and 4GB of RAM. The computation times in all the studies were trivial, while the upper bound on the duality gap is set to be zero. Two cases are studied below.

Table I
Hour Type within a Week

Hour Type	Hours of the day
Working Day - Valley	2-7
Working Day - Shoulder	1;8-10;15-18;23-24
Working Day - Peak	11-14;19-22
Weekend Day	1-24

Table II
Bilateral Contracts Prices for a Week

Hour Type	Price ($/MWh)	
	Bilateral contract 1	Bilateral contract 2
Valley	15	10
Shoulder	35	30
Peak	45	50
Weekend	35	30

Table III
Energy Consumption Limits of Bilateral Contracts (MWh)

Hour Type	Bilateral contract 1		Bilateral contract 2	
	$P_{bz}^{\min}$	$P_{bz}^{\max}$	$P_{bz}^{\min}$	$P_{bz}^{\max}$
Valley	750	2,500	500	2,300
Shoulder	1,500	3,200	1,700	3,000
Peak	1,000	3,000	1,200	2,750
Weekend	2,000	3,300	1,700	3,000

A. Case 1

In this base case, it is assumed that the customer does not participate in the DR program, and looks for optimally procuring its normal consumption pattern from the available energy resources, without utilizing flexibility options. The numerical results, including the amount and cost of energy procured from the two weekly bilateral contracts and the market over the one-week horizon are shown in Table IV. In addition, the percentage of energy procured from the resources is shown in Fig. 2.

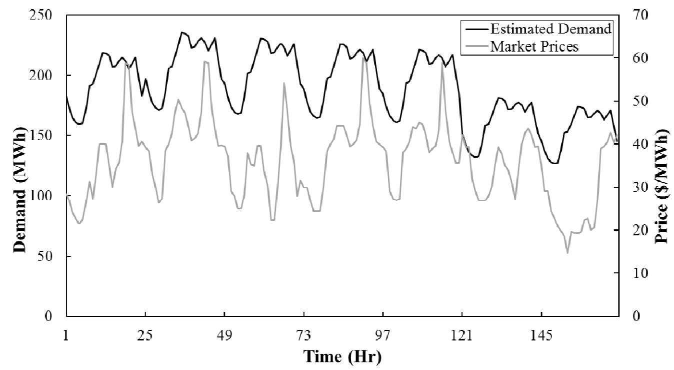

Fig. 1. Estimated demand and energy market prices.

Table IV
Numerical Results for Case 1

Demand (MWh)	Total energy supplied	31,837.2
	Procured from bilateral contracts	18,653.3
	Procured from the energy market	13,183.9
Energy Costs ($)	Energy Market	430,780.8
	Bilateral contracts	653,762.1
	Total Costs (Objective Function)	**1,084,542.9**

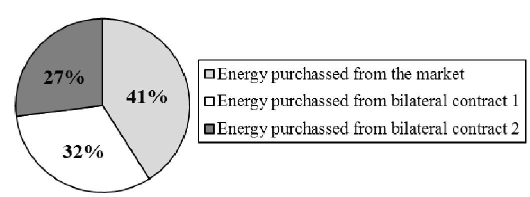

Fig. 2. Optimal mix of electricity sources to procure demand in Case 1

B. Case 2

In this case, we assume that the customer participates in the DR program and runs the proposed model to co-optimize the energy procurement decision and the available flexibility schedules. The customer has identified five flexible loads that can be utilized to participate in the DR program. The characteristics of the flexible loads are presented in Table V. The flexible loads FL1-FL3 in Table V can be recovered prior in time between hours 1-11 at the same day, while the load FL4 can be postponed to hours 1-11 of the next day (slow recovery), and load FL5 can be postponed to hours 22-24 at the same day (fast recovery). The flexible load FL4 should remain off for at least 2 hours after being turned off, and the load FL5 can be only curtailed 2 hours per day. In addition to the flexible loads, the customer owns a battery ESS with rated power of 3.7 MW and maximum energy capacity of 14.8 MWh, and charging/discharging efficiencies of 90%. The customer also owns and operates a 4 MW OG, with the technical and economic data presented in tables VI and VII.

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TABLE V
Characteristics of Identified Flexible Loads

Flexible Load	Consumption (MW)		Rescheduling Cost ($/MWh)	
FL1	γ^1	1	C^1	35
FL2	γ^2	2	C^2	40
FL3	γ^3	4	C^3	45
FL4	γ^4	5	C^4	50
FL5	γ^5	7	C^5	55

TABLE VI
Characteristics of the OG Unit

$P^{\min}$ (MW)	RU^{OG}, RD^{OG} (MW/min)	Fixed Cost ($/h)
0	0.72	100

TABLE VII
Piecewise Linear Cost Function of the OG Unit

Segment	$P_j^{\max}$ (MW)	Cost ($/MWh)
1	2	45
2	2	50

Table VIII summarizes the numerical results for the one-week scheduling horizon in Case 2. In Table VIII, the total energy procurement cost is reduced as compared to Case 1, by utilizing the various flexibility options optimized through the proposed integrated flexibility model. This provides the customer with incentives for participation in the DR program. More specifically, the utilization of flexibility options has reduced the cost of procuring energy through bilateral contracts. However, this has come with the cost of operating OG and also the rescheduling cost of the flexible loads, while extra charging energy of ESS has contributed to increase the cost of buying power from the market. The optimal mix of the electricity sources in Case 2 is illustrated in Fig. 3, where the optimized flexibility has reduced the share of more expensive bilateral contracts in providing the customer's energy needs, as compared to Case 1.

TABLE VIII
Numerical Results of Case 2

Generation (MWh)	Total energy generated by OG	192.0
Demand (MWh)	Total energy supplied	31,837.2
	Procured from bilateral contracts	18,223.4
	Procured from the energy market	13,431.2
	Scheduled load reduction	686.1
Energy Costs ($)	OG	13,920.0
	Energy market	434,135.3
	Bilateral contracts	633,751.4
Cost ($)	Flexible load rescheduling cost	20,065.0
	Total Costs (Objective Function)	**1,067,886.7**
Revenue ($)	Incentive payments by the system operator	32,350.1

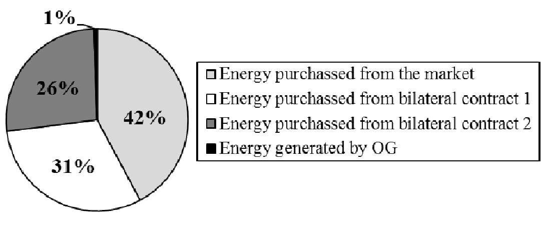

Fig. 3. Optimal mix of electricity sources to provide the customer's demand in Case 2

Optimal utilization of the flexibility options in Case 2 has modified the customer's load profile as shown in Fig. 4. In summary, a total of 686.1 MWh load reduction is provided to the grid during the one week scheduling horizon, 63.3% (434.0 MWh) of which is provided by shifting the demand of the flexible loads FL1-FL5. In addition, 28% (192.0 MWh) of the load reduction delivered to the system operator is provided by OG, and 8.7% (60.102 MWh) is provided by the ESS operation. As an example, the scheduled flexibility options and the resulting hourly load reductions for the forth working day of the one-week scheduling horizon are illustrated in Fig. 5. The optimal mix of hourly energy procurement schedules from different sources for the same representative working day is depicted in Fig. 6. In Fig. 5, different mix of flexibility options are utilized in different hours of the day, depending on the option constraints and costs. For instance, during hour 19, the scheduled load reduction is 26.0 MWh, 3.0 MWh of which is provided by the ESS, 4.0 MWh by the OG, and remaining 19 MWh by rescheduling the flexible loads FL1-FL5 that are totally recovered during optimal hours of recovery time intervals. In addition, the results not only satisfy functional constraints of the flexible loads FL4 and FL5, but also authenticate the optimal contributions of both the OG and the ESS in making a tradeoff pertinent to optimal use of flexible and inflexible loads. In Fig. 5, the ESS supplies only inflexible parts of the demand while OG supplies both flexible (31%) and inflexible (69%) loads. Moreover, it should be noted that OG is scheduled to operate only during DR execution time intervals in the entire study time horizon.

As expected, very little amounts of the flexibility options are utilized during the weekend days, as compared to the weekdays. In Fig. 4, the difference between the estimated demand and the modified demand during the early hours of the first weekend day is caused by recovery of the flexible load FL4 whose operations is postponed from the last working day. Moreover, while ESS is optimally operated during the weekend days, OG is not scheduled for operation on the same days.

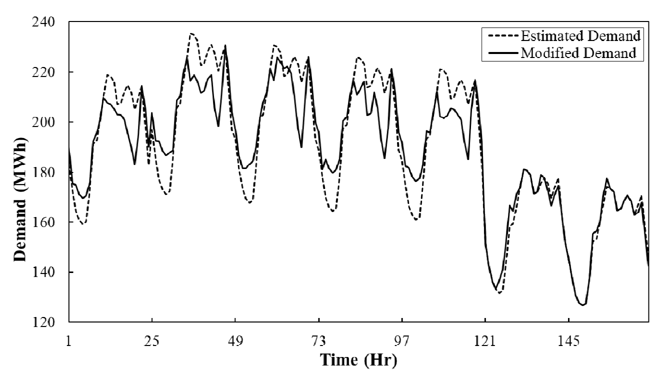

Fig. 4. Estimated and modified demands of the customer in Case 2

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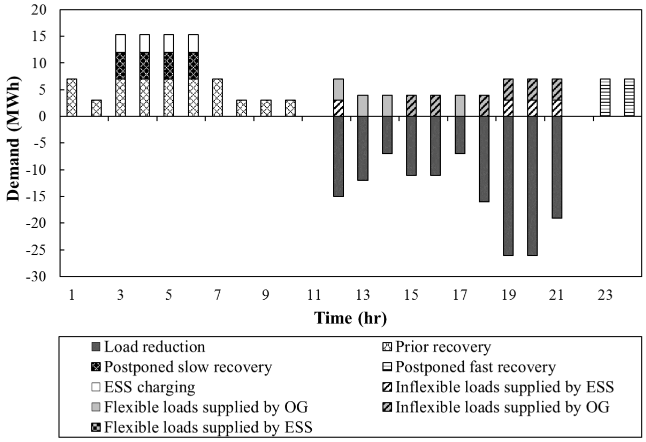

Fig. 5. Optimal hourly load reductions along with scheduled flexibility options during 4th working day in Case 2

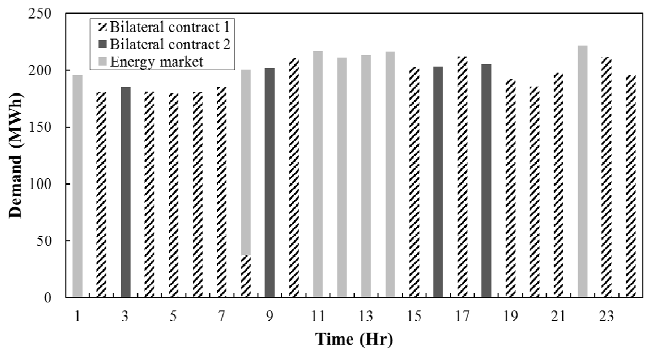

Fig. 6. Optimal mix of hourly energy procurement during 4th working day in Case 2.

C. Case 3

The available capacity of OG and ESS at the customer site may impact the scheduling results. In order to investigate this, the simulations are repeated for cases with different OG and ESS capacities, and total operation cost of the customer for the cases is presented in Tables IX and X. As shown in Tables IX and X, higher OG and ESS capacities would result in higher operation cost savings for customers. This analysis represents an application of the proposed model as a decision-aid tool for customers to assess the benefits of installing OG and ESS.

TABLE IX
Total Customer Cost for Different OG Capacity

OG Capacity	2 MW	4 MW	6 MW
Total Cost ($)	1,071,038.2	1,067,886.7	1,064,735.8

TABLE X
Total Customer Cost for Different ESS Capacity

ESS Power /Energy Rating	1.2MW/4.9MWh	3.7/14.8MW	6.2MW/24.7MWh
Total Cost ($)	1,071,184.0	1,067,886.7	1,065,540.6

VII. Conclusion

This paper presented a model for optimal utilization of various flexibility options for large customers in order to participate in DR program in the day-ahead energy markets. The proposed model co-optimized the flexibility options (including flexible loads and utilizing OG and ESS) and the decisions on procuring energy through the bilateral contracts and the energy market. The proposed model is formulated as a mixed-integer linear programming (MILP) problem which can be solved using any available MILP solvers. The simulation results, conducted on a test industrial customer, reveal that the proposed integrated flexibility scheduling model allows large customers to gain financial profits by modifying their normal consumption patterns in response to changes in prices and incentive payments achieved from the system operators. It is also observed that optimal scheduling of the flexibility options help customers to reduce the energy procurement costs by being flexible to modify demand and prevent buying energy at the more expensive hours.

Future works may include incorporating customers' arbitrage behavior along with the flexibility options and study their mutual impacts on the customers' energy procurement problem. In addition, consideration of renewable energy resources as an OG option in the proposed problem is in order.

Appendix A
Recasting Nonlinear Terms to Linear Form

The proposed formulation includes nonlinear terms in (18), (19), (22), (23) and (25), (26). In order to maintain the MILP format of the proposed model, we aim to show how the nonlinear terms (the product of decision variables) can be expressed as a set of linear inequality constraints. For the sake of presentation, here we present the method for the most complicated nonlinear term, $\rho_t^{il}\beta_t^{fl}P_t^{OG}$ taken from (18), where two binary variables and a bounded continuous variable are multiplied. First, we define the binary variable W_t as the product of the two binary variables, which is constrained as below:

$$W_t = \rho_t^{il}\beta_t^{fl}, \quad \forall t \in T_{LR} \tag{38}$$

$$W_t \geq 0,\ W_t \leq \rho_t^{il},\ W_t \leq \beta_t^{fl} \tag{39}$$

$$W_t \geq \rho_t^{il} + \beta_t^{fl} - 1. \tag{40}$$

When the two binary variables equal to zero, W_t is zero and (39) and (40) become inactive. Constraint (40) ensures that W_t is equal to 1 only if both ρ_t^{il} and β_t^{fl} are 1. Now let G_t be equal to the product of binary variable W_t and the bounded continuous variable P_t^{OG} where $0 \leq P_t^{OG} \leq \sum_{j\in J} P_j^{\max}$. The linear inequalities (42) and (43) ensure that G_t substitutes and models the behavior of the nonlinear term $\rho_t^{il}\beta_t^{fl}P_t^{OG}$. If W_t is equal to zero, G_t will be zero due to (42), and (43) becomes inactive. If W_t is equal to one, (43) ensures that G_t is equal to P_t^{OG}.

$$G_t = W_t P_t^{OG}, \quad \forall t \in T_{LR} \tag{41}$$

$$0 \leq G_t \leq W_t \left(\sum_{j\in J} P_j^{\max}\right) \tag{42}$$

$$P_t^{OG} - \sum_{j\in J} P_j^{\max}\left(1 - W_t\right) \leq G_t \leq P_t^{OG} \tag{43}$$

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