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The Consumer Rationality Assumption in Incentive Based Demand Response Program via Reduction Bidding

Muhammad Babar†, Imthias Ahamed T.P.* and Essam A. Alammar**

Abstract – Because of the burgeoning demand of the energy, the countries are finding sustainable solutions for these emerging challenges. Demand Side Management is playing a significant role in managing the demand with an aim to support the electrical grid during the peak hours. However, advancement in controls and communication technologies, the aggregators are appearing as a third party entity in implementing demand response program. In this paper, a detailed mathematical framework is discussed in which the aggregator acts as an energy service provider between the utility and the consumers, and facilitate the consumers to actively participate in demand side management by introducing the new concept of demand reduction bidding (DRB) under constrained direct load control. Paper also presented an algorithm for the proposed framework and demonstrated the efficacy of the algorithm by considering few case studies and concluded with simulation results and discussions.

Keywords: Aggregator, Demand side management, Direct load control, Dynamic bidding, Dynamic programming

1. Introduction

The advancements in information and communication technology and burgeoning challenges in supply and demand of electrical power have led to the concept of Smart Grid [1]. Smart Grid is expected to improve the efficiency, quality, reliability, economics and sustainability of complete Supply and Demand chain of the Electricity [2]. In brief, Smart Grid is an energy management system of electrical power grid using advanced data communication and networking in order to cope with skyrocketing demand and provide economical benefit to all stakeholders.

Demand Side Management is one of the most important management strategy in the Smart Grid paradigm that aims to balance electrical supply and demand by reducing the power demand during critical periods instead of increasing the power generation [3].

Researchers have identified significance of demand response in demand-side management program and consequently have presented many scheduling algorithms and formulated policies and strategies for demand-side management [4, 5]. It has been a crucial challenge to introduce various Demand Response (DR) programs in the electricity market and increase demand-side participation of the commercial as well as domestic consumers in electricity markets either through price signals or incentives, and carry out integrated resource planning (IRP) to coordinate both supply-side and demand-side resources [6, 7]. Accordingly, DR programs could be generally classified into two basic categories: price-based DR and incentive-based DR [8].

Though, Incentive-based DR refers to the program in which consumers switch OFF their dispatchable loads to an event during a peak demand. Incentive-based DR usually include direct load control (DLC), interruptible/curtailable (I/C) service, demand bidding/buyback (DB), emergency demand response programs (EDRP), capacity market programs (CMP), and ancillary services market programs (ASMP). Moreover, Consumers participating in incentive based DR programs can either receive discounted retail rates or separate incentive payment against load reductions.

However, the implementation of Incentive-based direct load control (IB-DLC) program is very demanding for the utility because in this program the utility has to directly

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communicate and control the thousands of consumers at an event during the peak period. Therefore, in the current emerging electricity market, new third party business entity is introduced which implements IB-DLC program for the utility. Till today, there is no precise definition for these third party entities but they are generally known as “Energy service provider” or the “Aggregators” between the utility and the consumers as shown in Fig. 1. The energy service providers and the utility usually has “directed interaction” which means the utility directs the service provider that it has to curtail certain power through direct load controlling of the dispatchable loads of the participating consumers whenever it requires. For this service, it would be rewarded by the utility [11, 12].

Moreover, it could be noted that the utility usually want to reduce the bulk of power during peak hours and it is normally not in the capacity of any individual service provider. So, the utility signs an agreement with number of service providers and sees them as a large consumers as shown in Fig. 1. Accordingly, each service provider have an objective to shave the peak demand and support the utility in supplying uninterrupted and high quality power to commercial, industrial, institutional and domestic as well as electric vehicles during peak hours with ancillary services [13]. For reference, PG&E has started non-tariff program named “Aggregator Managed Portfolio program” according to which it signs bilateral contracts with service providers by which it may call power curtailment events during high-price periods, emergencies and tests with price-responsive pricing mechanism [14].

Besides all, it has been an issue for the service provider to attract the consumers for IB-DLC program and retain them. Therefore, lot of effort has been made by the service providers in order to attract and motivate the consumers such that they allow the service provider to directly control their dispatchable loads during the peak hours [15-18].

In short, in this paper, innovative framework for incentive based DR program is designed which enables consumers to directly interact with energy market by bidding against their power curtailment as well as effectively satisfy the consumer by considering their defined constraints. These constraints include the power ratings of the dispatchable loads, price bids corresponding to each dispatchable load, maximum time allowed for control, the minimal time required between two consecutive controls and total control period of each dispatchable load of every consumer. Thus, the implementation of incentive based control program with these “consumer constraints” will attract a large number of consumers to perform IB-DLC program and gain full benefit from it without altering their life style and personal space. In addition, a design of the proposed framework will also help the service provider in achieving the Win-Win situation i.e. maximize its own revenue, minimize utility’s operational cost by shaving the demand peak and satisfy the consumers through “consumer constraints”.

This also paper presents an algorithm for the service provider which generates a Consolidated Demand Reduction Bid (CDRB) which support it in materializing the concept of IB-DLC program with “energy bidding” at consumer level and help in obtaining the full benefits. The rest of the paper structured as follows. Section 2 presents the proposed framework in detail and introduces the complete concept of CDRB. Section 3 formulates and develops the proposed algorithm which by using “Multiple Decision Making Problem (MDMP)” Section 4 presents the simulation results to discuss the applicability of the framework and efficacy of the algorithm in the light of three scenarios. Finally, section 5 concludes the paper.

2. Design of the Framework

Assume there are N number of consumers which are in contract with the service provider and agreed to participate in the DRB based incentive program. For instance, assume any nth consumer out of N consumers which has identified D loads having ratings \( R^n = \{ p^n_1, p^n_2, \ldots, p^n_D \} \). Moreover, in this framework which presents the demand reduction bid based incentive program for consumers, where consumer also identifies bids to decommit each dispatchable load during a control interval [H] which is denoted by \( Q^n \). However, these bids for each load are referred as Ex-ante bids which mean these bids are mutually decided by the consumer and the service provider at the time of agreement. Because, the service provider has to ex-ante validate these bids which means the bids by the consumers should be within the price limits specified by the service provider. Depending on the importance of each load, user specifies \( Q^n = \{ q^n_1, q^n_2, \ldots, q^n_D \} \) . On the other hand, over expected load utilization and curtailment capability of every dispatchable load, the consumer also provide “duration constraints” that are

\[
T_{\text{On}}^{\text{min}} = \{ t_{\text{On}}^{\text{min}}_1, t_{\text{On}}^{\text{min}}_2, \ldots, t_{\text{On}}^{\text{min}}_N \}
\]

i.e. the set of minimum durations for which each load of n

\[
T_{\text{Off}}^{\text{max}} = \{ t_{\text{Off}}^{\text{max}}_1, t_{\text{Off}}^{\text{max}}_2, \ldots, t_{\text{Off}}^{\text{max}}_D \}
\]

i.e. the set of maximum duration for which each load could be OFF continuously and

\[
T_{\text{D}}^{\text{max}} = \{ t_{\text{D}}^{\text{max}}_1, t_{\text{D}}^{\text{max}}_2, \ldots, t_{\text{D}}^{\text{max}}_D \}
\]

i.e. the set total durations for which each load of nth consumer can participate in load reduction such that:

\[
t_{\text{Off}}^{\text{max}}_d \leq t_{\text{D}}^{\text{max}}_d \quad \forall d = 1 \ldots D
\]

Thus, \( Q^n \) and \( R^n \) are referred as load parameters and
The Consumer Rationality Assumption in Incentive Based Demand Response Program via Reduction Bidding

\( T_{ON}^{\text{max}} \), \( T_{OFF}^{\text{max}} \) and \( T_{n}^{\text{mix}} \) are referred as duration constraints defined by the consumer to the service provider for all the dispatchable loads at the time of the agreement. The consideration of load parameters by the service provider in its demand response program will motivate the consumers to participate as well as it help in portraying consumer’s “Desire of Use”. In addition, the given duration constraints with load parameters will also help the consumers in completely translating their needs and wants. In this proposed framework, load parameters and duration constraints will be collectively referred as Consumer Constraints and represented as:

\[
\{ Q^n, R^n, T_{ON}^{\text{mix}}, T_{OFF}^{\text{mix}}, T_{n}^{\text{mix}} \} \quad n = 1 \ldots N
\]

For an explanation of the consumer constraints, assume an example of a consumer who signed an agreement with the service provider for 6 dispatchable loads i.e. \{d1, d2, d3, d4, d5, d6\} and at the time of deal, consumer has identified load parameters and duration constraints as shown in Table 1. So, it can also be observed from Table 1 that consumer depending on his/her “Desire of Use” bid highest to d2 and bid least to d5. In addition, it can also observed that the maximum OFF time for the load d2 is merely 0.5 hours which signifies its importance to the consumer. d2 also has a significantly greater continuous ON time as compared to other loads while the total maximum OFF time is only 30 mins i.e. the service provider can only turn it OFF for just 30 mins in a day. As, it can be recalled that d2 also has the highest bid among all the dispatchable loads. Thus, it can be inferred that any consumer can express the criticality or significance of any particular load (e.g. d2) through these parameters and constraints which eventually discourages the service provider to curtail this load repeatedly.

Moreover, the given duration constraints shown in Table 1 helps the service provider in coping Payback Effect. For instance, it can be observed from Table 1.

<table>
<thead>
<tr>
<th>Load</th>
<th>( Q^n ) (units)</th>
<th>( R^n ) (kW)</th>
<th>( T_{ON}^{\text{mix}} ) (mins)</th>
<th>( T_{OFF}^{\text{mix}} ) (mins)</th>
<th>( T_{n}^{\text{mix}} ) (Hrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>d1</td>
<td>0.2</td>
<td>0.5</td>
<td>35</td>
<td>20</td>
<td>2.5</td>
</tr>
<tr>
<td>d2</td>
<td>0.3</td>
<td>0.5</td>
<td>15</td>
<td>5</td>
<td>0.5</td>
</tr>
<tr>
<td>d3</td>
<td>0.25</td>
<td>1</td>
<td>30</td>
<td>20</td>
<td>1.9</td>
</tr>
<tr>
<td>d4</td>
<td>0.07</td>
<td>2.5</td>
<td>50</td>
<td>30</td>
<td>7</td>
</tr>
<tr>
<td>d5</td>
<td>0.04</td>
<td>1.5</td>
<td>55</td>
<td>20</td>
<td>3</td>
</tr>
<tr>
<td>d6</td>
<td>0.11</td>
<td>1.5</td>
<td>55</td>
<td>30</td>
<td>3</td>
</tr>
</tbody>
</table>

that the maximum time for which the load d3 can be turned OFF continuously is 20 mins. It means that after turning it ON if it was switched OFF earlier, then d3 must be continuously ON for 35 mins i.e. the service provider has to wait for 35 mins to again turn it OFF. Furthermore, \( T_{n}^{\text{mix}} \) is a duration constraint which shows that a particular load cannot be turned OFF more than 1.9 hours i.e. 144 mins during a day. Thus, these duration constraints will help the service provider to analyze and schedule the all available loads such that overall energy payback effect should be eradicated as well as achieve consumer’s satisfaction.

Let suppose, the utility in-advance directs an instruction to the service provider that shave the demand peak for the identified peak period during a day. This identified peak period is called as control period \( H \) by the service provider and is divided into \( K \) control intervals such that each interval should be equal to “m” mins.

Since, it could be possible that because of the consumer constraints all the dispatchable loads may not be available for control during a particular control interval \( k \), where \( k \) is referred as index to \( K \) i.e. total number of control intervals. Thus, this framework defines a variable \( a_n^k(k) \) which could be called as availability variable for \( d_n \) load of \( n \)th consumer. \( a_n^k(k) \) has four possible values i.e \{ 0, 1, x, z \}, where:

- \( a_n^k(k) \) is equal to “x”; means dispatchable load is ON and can be switched OFF.
- \( a_n^k(k) \) = 0; means the load was switched OFF during the \( k \)th interval.
- \( a_n^k(k) \) = 1; means the load is ON and it can not be controlled during \( k \)th interval.
- \( a_n^k(k) \) = z; means the load is not in control mode i.e. it is either physically switched OFF by the consumer or it is not participating at all during the control period due to any reason.

The logical transition of the \( a_n^k(k) \) during each control would be explain in detail in the next section. However, to understand the functionality of \( a_n^k(k) \), consider an example shown in Table 1 and assume that availability variables for the loads \{1, 3, 5, 2, 3, 1\} are \{x,x,x,0,1,z\}. Corresponding to the given value of \( A^k(k) = [x x x 0 1 z] \), following combination of devices will be available for control during the \( k \)th interval.

\[
\{1,2,3,1,3,2,3\}
\]

It is further assumed that the service provider has to know Demand Reduction Bid (DRB) of all \( N \) consumer during each interval \( k \). Thus, various possible power levels that could be curtailed at the corresponding bid must be considered. These power levels are denoted as

\[
P_n^k = \{ P_{1n}^k, P_{2n}^k, \ldots, P_{n}^k \}
\]

Thus, \( \mathbf{r}(P^k(k)) \) are the corresponding bids. To explain these notations, let consider a case corresponding to availability vector \( A^k(k) = [x x x 0 1 z] \). For the given \( A^k(k) \); different possible power levels are \( P^k(k) = \{0.5kW, 1.0kW, 1.5kW, 2.0kW\} \). It may be noted that for each power level, different combinations of dispatchable loads could be switched OFF to curtail the specific power level, such that:
Thus, for the first power level \( P_{1}^{(n)} = 0.5kW \), there could be two possible control actions i.e. either switch OFF 1st load or 2nd. For instance, for first power level i.e. 0.5kW, the two possible control strings are \( \{1\} \rightarrow s_{11}^{(1)} = [010000] \) and \( \{2\} \rightarrow s_{12}^{(1)} = [001000] \) and for second power level i.e. 1.0kW, the possible control strings are \( \{1,2\} \rightarrow s_{112}^{(1)} = [100000] \) and \( \{3\} \rightarrow s_{22}^{(1)} = [001000] \) and so on. Each element of the control string presents the control action applied to the \( d^{th} \) dispatchable load of \( n^{th} \) consumer in terms of Boolean variable. If it is “1”, then load will be controlled to that particular device. Each element of the control string is denoted by \( \alpha_{ij}^{(n)} \). Thus, these control string could be generally denoted as \( s_{ij}^{(n)}(k) \) such that

\[
\begin{align*}
s_{ij}^{(n)}(k) & = [\alpha_{i1}^{(n)}(k), \alpha_{i2}^{(n)}(k), \ldots, \alpha_{ij}^{(n)}(k), \ldots, \alpha_{iD}^{(n)}(k)] \\
\end{align*}
\]

Hence, the set of all possible control strings for each power level during a given \( k^{th} \) interval is denoted by \( s(k) \) such that

\[
\begin{align*}
s(k) & = \{ s_{11}^{(n)}(k), s_{12}^{(n)}(k), \ldots, s_{ij}^{(n)}(k), \ldots \} . \\
\end{align*}
\]

It could be recalled that during each control interval \( k \), there are different possible power levels \( P_{1}^{(k)}, P_{2}^{(k)}, \ldots, P_{i}^{(k)} \), \( P_{k}^{(k)} \) for curtailing and corresponding to each power level there are different possible control signals for the devices i.e. \( s_{i}^{(n)}(k) \). Thus, the DRB corresponding to each power level is obtained by solving the optimization problem given below:

\[
f(P_{k}(k)) = \min_{s_{ij}^{(n)}(k) \in s(k)} \sum_{d=1}^{D} \{ q_{ij}^{(n)} \times \alpha_{ij}^{(n)}(k) \} \quad (1)
\]

The procedure to update \( t_{0}^{(n)}, t_{0}^{(n)}, t_{0}^{(n)}, t_{0}^{(n)} \) is explained in the next section. Thus, on the basis of the consumer constraints provided by the consumer, service provider finds the different possible levels of power reduction \( P^{(k)}(k) \) which may be curtailed during \( k^{th} \) interval by the nth consumer with corresponding optimal bids \( f(P_{k}(k)) \) and respective optimal control strings

\[
\begin{align*}
S_{i}^{(n)}(k) & = [s_{i1}^{(n)}(k), s_{i2}^{(n)}(k), \ldots, s_{ij}^{(n)}(k), \ldots, s_{iL}^{(n)}(k)] \\
\end{align*}
\]

such that

\[
\begin{align*}
S_{i}^{(n)}(k) & = s_{i}^{(n)}(k) \quad \forall \; i = 1 \ldots L. \\
\end{align*}
\]

Thus,

\[
\langle f(P_{k}^{(n)}(k)), S_{i}^{(n)}(k), P_{k}^{(n)}(k) \rangle_{i=1 \ldots L}
\]

constitutes demand reduction bid (DRB) for nth consumer at a particular power level during kth interval.

In this framework, service provider also introduces a consumer participation vector \( c = \{ c_1, c_2, \ldots, c^N \} \). Here, each element is a boolean variable such that if nth consumer is willing to participate during a particular control period, then \( c_i = 1 \) else \( c_i = 0 \).

Suppose, if \( f(P_{1}(k)), f(P_{2}(k)), \ldots, f(P_{N}(k)) \) be the DRBs evaluated by the service provider for \( N \) consumers during \( k^{th} \) interval. Then, the final decision making problem for service provider is to obtain the cumulative power reduction levels \( CP_{1}(k), CP_{2}(k), \ldots, CP_{N}(k) \) and \( CP(k), \ldots, CP_{N}(k) \) and corresponding consolidated demand reduction bids (CDRB) by solving given optimization problem.

\[
F(CP_{k}(k)) = \min_{P_{k}^{(n)}(k) \in CP_{k}(k)} \sum_{n=1}^{N} (f(P_{n}^{(k)}(k)) \times c^{(n)}) \quad (2)
\]

such that

\[
P_{1}^{*} + P_{2}^{*} + \ldots + P_{n}^{*} + \ldots + P_{N}^{*} = CP_{k}(k) \quad (3)
\]

Where

\[
P_{i}^{*} + P_{k}(k) = f(P_{i}^{*}(k)) + f(P_{k}(k)) \quad \forall \; n = 1 \ldots N
\]

In order to further explain the cumulative power \( CP_{k}(k) \), consider two consumers i.e. \( n = \{1,2\} \). For \( n = 1 \), let \( R^{1}(k) = \{0.5,0.5,1,1.5\} \) and all the four devices are fully committed for the given \( k^{th} \) interval such that \( \Lambda^{1}(k) = [x \times x] \). Similarly for \( n = 2 \), let \( R^{2}(k) = \{1,1.5,1.5\} \) and all the three devices are fully committed for the given \( k^{th} \) interval such that \( \Lambda^{2}(k) = [x \times x] \). It can be recalled that for the given two consumers, the possible power levels \( P^{1}(k) \) and \( P^{2}(k) \) could be expressed as:

\[
P^{1}(k) = \{0.0,0.5,1,0,1.5,2,0,2.5,3,0,3.5\}
\]

\[
P^{2}(k) = \{0,1,0.1,1.5,2,5,3,0,4,5\}
\]

For the given example, cumulative power can be expressed as:

\[
CP_{1} = 0.5kW \rightarrow \{P_{1}^{1} = 0.5,P_{0}^{2} = 0\}
\]

\[
CP_{2} = 1.0kW \rightarrow \{P_{1}^{2} = 1,P_{0}^{2} = 0\}(P_{0}^{1} = 0,P_{1}^{2} = 1)
\]

\[
CP_{3} = 1.5kW \rightarrow \{0.5,1),(1,5),(0,1.5)\}
\]

\[
CP_{4} = 2.0kW \rightarrow \{0.5,1.5),(1,1)\}
\]

... and so on.

Thus, it may be noted that for each cumulative power level, different combinations of power levels that could be curtailed from the corresponding to \( N \) consumers. It can also be observed that at \( CP_{k}(k) \), there are two possible power levels. So, by executing the Eq. (2) for \( CP_{k}(k) \), it will result in optimal set of power levels corresponding to

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each consumer \((P_{11}^k, P_{21}^k, \ldots, P_{n1}^k, P_{12}^k, P_{22}^k, \ldots, P_{n2}^k, \ldots, P_{1N}^k, P_{2N}^k, \ldots, P_{nN}^k)\) during the given \(k^{th}\) interval as shown in Eq. (3). On the other hand, the summation of DRBs corresponding to optimal power levels for the given \(CP_i(k)\) results in consolidated demand reduction bid (CDRB) as shown in Eq. (4). Hence,

\[
\begin{align*}
DRB^1_{i1}(k) &= \{ f(P_{11}^1(k)), s_1^{1*}(k), P_{11}^{1*}(k) \} \\
DRB^2_{i2}(k) &= \{ f(P_{22}^2(k)), s_2^{2*}(k), P_{22}^{2*}(k) \}
\end{align*}
\]

\[
\begin{align*}
DRB^*_{i} (k) &= \{ f(P_{i}^{n*}(k)), s_i^{n*}(k), P_{i}^{n*}(k) \} \\


\end{align*}
\]

present optimal demand reduction bid (DRB) of each \(N\) consumers for a particular \(i^{th}\) cumulative power reduction level during \(k^{th}\) interval. Simply,

\[
CDRB_i(k) = \{(CP_i(k), F(CP_i(k)), DRB_i^*(k))\}_{i=1,\ldots, I}
\]

3. Algorithm

In this section, the algorithm for the proposed model of the framework is presented. In order to find out the optimal solution of the discussed control problems, algorithm is divided into five blocks as shown in Fig. 2. Following subsection discusses these blocks in detail.

It can be recalled that the service provider and the consumers have already signed an agreement according to which each consumer has already validated its consumer constraints with the service provider. So, the database of the service provider already has complete information of all \(N\) consumers regarding their consumer constraints

\[
\{ Q^n, R^n, T^n_{OFN}, T^n_{OFD}, T^n_{OFF} \}_{n=1, \ldots, N}
\]

Therefore, if the consumer wants to make in change in any of its consumer constraint then it has to perform it before the control period, or in case he/she changes it in between any control period then it will be effective after that particular control period. Because, before the initialization of the algorithm for the given control period, it is uploaded with the consumer constraints that are in the database at that time. In Fig. 2, \([w, y, z]\) corresponds to intermediate duration variables \(t^n_{OFN}\), \(t^n_{OFF}\) and \(t^n_{OFD}\) and \([a, b, p]\) corresponds to \(\{A^n(k), Q^n, R^n\}\).

Moreover, the algorithm divides control period of ‘\(H\)’ hours into control intervals such that each control interval could be of few ‘\(n\)’ minutes. Thus, the total number of control intervals ‘\(K\)’ for the given control period would be

\[
K = \frac{H}{n}
\]

3.1 Load Monitoring

The algorithm starts from load monitoring block. In this block, at \(k = 0\) algorithm initially scans all the devices of each consumer by sending monitoring signals. In response, every device of each consumer acknowledge their status through the single boolean variable i.e. \(e^n_0(k)\). If \(e^n_0(k)\) is ‘0’, then it means that the particular \(d^n\) device of \(n^{th}\) consumer is physically OFF or not allowed for control. On other hand, If \(e^n_0(k)\) is ‘1’, then the particular \(d^n\) load of the \(n^{th}\) consumer is physically ON and is available for

---

Fig. 2: Block Diagram of the proposed algorithm.
control.

3.2 Finding DRB

Assume that the availability vector $A^0(0) = [a^0_1(0), a^0_2(0), \ldots, a^0_N(0)]$ is specified for $N$ consumers. This subsection will first explain how DRB for $k=0$ is obtained by all $N$ consumers and then how DRB for $k=1$ to $H$ will be obtained.

As explained earlier, once $A^0(0)$ is known, algorithm can find various power levels that can be curtailed, e.g. $P^0_1(0), P^0_2(0), \ldots, P^0_N(0)$ for all $N$ consumers. Once the power levels are determined, algorithm can obtain $f(P^0(0))$ by solving the optimization problem given in Eq. (1) by using dynamic programming (DP) for all $N$ consumers as explained in [19].

It can be recalled that the solution of the optimization problem will give

$$\{f(P^0_i(k)), S^0_i(k), P^0_i(k)\}_{i=1, \ldots, L}$$

Thus, the algorithm will find and store DRB for all consumers $n=1 \ldots N$.

At $k=0$; then these evaluated DRB will be communicated to the “Finding CDRB Block” of the algorithm. For $k=1 \ldots K$, this block will always have an updated availability vector $A^d(k)$, then the DRB($k$) for all $N$ consumers is computed as explained earlier.

3.3 Finding CDRB

Now, DRB $\{f(P^d_i(k)), S^d_i(k), P^d_i(k)\}_{i=1, \ldots, L}$ is known. Thus, this block will first find the different possible cumulative power levels that can be curtailed, e.g. $CP_1(0), CP_2(0), \ldots, CP_N(0)$ for all $N$ consumers. Once the cumulative power levels are determined, then this block can compute $F(CP_0(0))$ by solving the optimization problem given in Eq. (2) by using dynamic programming (DP) for all $N$ consumers as explained in [20].

Similarly, the solution of the problem is stored as

$$CDRB(0) = [CP_0(0), F(CP_0(0)), DRB^0(0)]_{i=1, \ldots, L}$$

Then, this set of CDRB is transferred to “Decision Block”, where the operator of the service provider will take a decision on the basis of the demand identified by the utility. Similarly, for all $k=1 \ldots K$, this block computes the CDRB whenever it is updated with the DRBs from the previous block as shown in Fig. 2.

3.4 Decision Block

If an operator selects the appropriate cumulative power level $CP_0(0)$ at $k=0$. Then in the response, the system will generate direct load control signals for all loads of each consumer by using the control string $S^0_1(k) = [S^0_1(0), S^0_2(0), \ldots, S^0_N(0), \ldots, S^0_L(0)]$.

It can be recalled that control string present the control actions i.e. ON or OFF for all $d^k$ load of the $N$ consumers. Then, the direct load control signals will be communicated to the consumer through two-way communication channel. Based on the communication received, controller in the consumer premise will switch ON or OFF the load. It may be noted that the availability vector $A^d(k)$ as it depends on the updated consumer constraints and hence CDRB will depend on the service provider choice $i^d$ for $k=1 \ldots K$.

On the other hand, if an operator does not want to curtail power from all $N$ consumers, then the operator selects $CP_d(k)$ for that particular $k^d$ interval. Afterwards, algorithm proceeds as described.

3.5 Updating constraints

For $k=0$, variables $[t^0_{OFF_d}(k), t^0_{OFF_F}(k), t^0_{ON_d}(k)]$ are uploaded by algorithm with $[0,0,0]$. Now, Based on the monitoring signals, for $k=0$ algorithm updates the $a^d_n(k)$ such that

$$a^d_n(k) = \begin{cases} z & \text{if } c^d_n(k) = 0 \\ x & \text{if } c^d_n(k) = 1 \end{cases}$$

These uploaded values of constraints and availability variable is used for evaluating CDRB during $k=0$ control interval. Similarly, before evaluating CDRB for all control intervals i.e. $k=1 \ldots K$, the algorithm updates intermediate variables and $A^d(k)$ over the service provider’s choice $S^0_d(k-1)$.

Since, this block knows through monitoring block that which all devices are ON or OFF at that given interval. If the $d^k$ of $n^k$ consumer device is switched OFF, then for all $k=1 \ldots K$ interval these intermediate variables are calculated as:

$$t^n_{ON_d}(k) = 0$$

$$t^n_{OFF_d}(k) \begin{cases} t^n_{OFF_d}(k-1) + m & \text{if } d^k \text{ device of } n^k \text{ consumer is switched ON, then for all } k = 1 \ldots K \text{ interval these intermediate variables are calculated as:} \\
\end{cases}$$

$$t^n_{OFF_F}(k) = \begin{cases} t^n_{OFF_F}(k-1) + m & \text{if } d^k \text{ device of } n^k \text{ consumer is switched ON, then for all } k = 1 \ldots K \text{ interval these intermediate variables are calculated as:} \\
\end{cases}$$

Next step is to find $a^d_n(k)$ for all $d$. It may be recalled that $a^d_n(k)$ depends on $t^n_{OFF_d}$ and $t^n_{OFF_F}$ as well as $t^n_{ON_d}$ and $t^n_{OFF_d}$. Then, $a^d_n(k)$ is calculated as shown in state transition diagram in Fig. 3. In this state diagram, the transition conditions for the possible
To understand the functionality and transition of availability variable $a_d^n(k)$ from $(k-1)$th control interval to $k^{th}$ interval, consider the same $n^{th}$ consumer as shown in Table 1 having the availability vector $A^n(k) = \{a_1^n(k), a_2^n(k), \ldots, a_6^n(k)\}$ which is a set of availability variables for the stated six devices. Then, $a_1^n(k)$, $a_2^n(k)$ and $a_3^n(k)$ is equal to “x”; means 1st, 2nd and 3rd dispatchable load is ON and can be switched OFF. $a_4^n(k) = 0$; means the 4th load was switched OFF during the previous interval i.e. $(k - 1)$ and might remain switched OFF or turn ON during this $k^{th}$ interval on the condition that $t_{OFF}^n(k)$ ≤ $t_{ON}^n(k)$ where $t_{OFF}^n(k)$ denotes the duration for which the 4th load is continuously OFF during $k^{th}$ interval. Suppose, $t_{OFF}^n(k) = 20$ Min. Then, at $(k - 1)^{th}$ interval there could be two possible values of $a_4^n(k)$ i.e. “0” - it remains switched OFF even during $k^{th}$ interval otherwise $a_4^n(k) = 1$. $a_5^n(k) = 1$; means 5th load is ON and it can not be switched OFF until $t_{ON}^n(k)$ ≤ $t_{OFF}^n(k)$ where $t_{ON}^n(k)$ denotes the duration for which the 5th load is continuously OFF during $k^{th}$ interval. $a_6^n(k) = z$; means 6th load is not in control mode i.e. it is either physically switched OFF by the consumer or it is not participating at all during the control period due to any reason.

Thus, it can be observed the availability of a device $a_d^n(k)$ depends not only on $t_{ON}^n$, $t_{OFF}^n$ and $t_{max}$, but it also depends on the duration for which the particular device was continuously ON or OFF before the current interval. These intermediate variables are denoted by $[t_{ON}^n(k), t_{OFF}^n(k), t_{max}^n(k)]$ and will be explain in detail in the next section.

Once the $A^n(k)$ is updated for the preceding interval, then algorithm on the basis this monitoring signal, for $k = 1…K$ algorithm updates the $a_d^n(k)$ such that

$$a_d^n(k) = \begin{cases} 
    z & \text{if } e_d^n(0) = 0 \text{ and } t_{OFF}^n(k) > T_{max}^n \\
    a_d^n(k) & \text{otherwise}
\end{cases}$$

Thus, this time rest of the blocks of the algorithm uses intermediate duration variables and updated availability vector for the evaluation of CDRB.

### 4. Case Study

The aim of this case study is to discuss the efficacy of the proposed algorithm for the presented model of the framework. The proposed algorithm is investigated by considering five different domestic consumers. It is assumed that these consumers have signed up the bilateral contract with the service provider. It can be recalled that at the time of agreement, consumers identify their consumer constraints for all of their dispatchable load as illustrated in Table 2.

It is assumed that the energy service provider deploy direct load control program to the continuously running thermal loads. In DLC, the most significant and focused dispatchable loads for control are Electric Heaters or Air conditioners because they are usually the highest energy consuming domestic loads. However, many medium energy consuming loads like refrigerators are also considered as a targeted dispatchable loads in this case study.

Generally, the power ratings of the domestic Electric Heater or Air-conditioners are around 750W upto 2.5kW and the power rating of refrigerators are around 350W to 800W depending on the capacity of the appliance. So, it can be observed that different power ratings are considered for the devices of each consumers in order to check the effectiveness of algorithm. Moreover, it can be recalled that

### Table 2. Consumer constraints of five consumers

<table>
<thead>
<tr>
<th>i</th>
<th>D^n</th>
<th>[Q^n, R^n, T_{min}^n, T_{max}^n]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$d_1^1$</td>
<td>[0.05, 500, 20, 10, 120]</td>
</tr>
<tr>
<td>1</td>
<td>$d_2^1$</td>
<td>(0.6, 500, 40, 20, 360)</td>
</tr>
<tr>
<td>2</td>
<td>$d_3^1$</td>
<td>(0.3, 600, 30, 10, 260)</td>
</tr>
<tr>
<td>3</td>
<td>$d_4^1$</td>
<td>(0.12, 650, 20, 10, 300)</td>
</tr>
<tr>
<td>4</td>
<td>$d_5^1$</td>
<td>(0.07, 1000, 30, 20, 310)</td>
</tr>
<tr>
<td>5</td>
<td>$d_6^1$</td>
<td>(0.47, 500, 30, 70, 150)</td>
</tr>
<tr>
<td>6</td>
<td>$d_7^1$</td>
<td>(0.3, 1000, 40, 20, 250)</td>
</tr>
<tr>
<td>7</td>
<td>$d_8^1$</td>
<td>(0.09, 1000, 30, 20, 300)</td>
</tr>
<tr>
<td>8</td>
<td>$d_9^1$</td>
<td>(0.15, 1600, 30, 10, 210)</td>
</tr>
<tr>
<td>9</td>
<td>$d_{10}^1$</td>
<td>(0.47, 500, 30, 70, 150)</td>
</tr>
<tr>
<td>10</td>
<td>$d_{11}^1$</td>
<td>(0.04, 300, 30, 10, 40)</td>
</tr>
<tr>
<td>11</td>
<td>$d_{12}^1$</td>
<td>(0.77, 300, 20, 10, 100)</td>
</tr>
<tr>
<td>12</td>
<td>$d_{13}^1$</td>
<td>(0.23, 560, 50, 10, 150);</td>
</tr>
<tr>
<td>13</td>
<td>$d_{14}^1$</td>
<td>(0.13, 1200, 60, 30, 490);</td>
</tr>
<tr>
<td>14</td>
<td>$d_{15}^1$</td>
<td>(0.32, 1750, 40, 10, 260)</td>
</tr>
<tr>
<td>15</td>
<td>$d_{16}^1$</td>
<td>(0.6, 300, 20, 60, 400)</td>
</tr>
<tr>
<td>16</td>
<td>$d_{17}^1$</td>
<td>(0.44, 500, 20, 10, 110)</td>
</tr>
<tr>
<td>17</td>
<td>$d_{18}^1$</td>
<td>(0.65, 1000, 40, 20, 150)</td>
</tr>
<tr>
<td>18</td>
<td>$d_{19}^1$</td>
<td>(0.19, 1450, 50, 10, 280)</td>
</tr>
<tr>
<td>19</td>
<td>$d_{20}^1$</td>
<td>(0.8, 2000, 60, 20, 300)</td>
</tr>
<tr>
<td>20</td>
<td>$d_{21}^1$</td>
<td>(0.47, 2500, 100, 50, 500)</td>
</tr>
</tbody>
</table>

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bidding to the each load by the consumers will identify the “Desire of Use” of the consumers. So, here, in the Table 2 it can be seen that consumer 5 assigns 0.54 units/hr to its 4th load while on the same side it assigns 1.8 units/hr to its 2nd load. It means that 2nd load has more significance than the 4th load for the 5th consumer.

It can also be recalled that the utility and the service provider has directed interaction as per their agreement. According to this, the utility has to provide an expected demand curve respective five consumers to the service provider, as shown in Fig. 4. In this Fig. 4, the utility wants that the service provider should control the loads from 9:00 AM till 9:00 PM i.e. the control period of 12 hrs. Moreover, it can be recalled that by the proposed framework, the utilities should also indicate the base line of the bulk of the power that the service providers has to maintain through load management and result in shaving the demand curve during the peak hours. In this case study, it is assumed that utility identifies the service provider to shave the demand curve at 18.5 kW. On the other hand, the service provider is also paid for it DLC services by the utility. Here, it is assumed that the utility will pay a fixed reward of 5 units/hour to the service provider.

Now, for the purpose of simulations, it is assumed that control period of 12 hours is divided into K=72 control intervals where each interval has a period of m=10 minutes. For daily operation, it is better to monitor the status of the loads of each consumer one interval before the execution of the scheduling program. This action will provide a better initial conditions for the smooth execution of the program.

Let $k=0$ be the initial interval when the consumer is ready to participate in direct load control program. If all the loads of the five consumers are available for curtailment then the availability vector $A^{(0)} = [xxxx]$, $A^{(0)} = [xxxx]$, $A^{(0)} = [xxxx]$, $A^{(0)} = [xxxx]$, $A^{(0)} = [xxxx]$. Then, at $k=0$ controller first calculates the DRB $^k$ for all $n$ consumers. Then, these demand reduction bids step of the algorithm and generate initial CDRB i.e. $(CP^0(0), F(CP^0(0)), f(P_{1}^{n*}(0)), S_{i}^{n*}(0), P_{1}^{n*}(0))_{i=1...I}$ as shown in Table 3 for the service provider.

According to the Table 3, the service provider can curtail the power up to 6.2 kW for the given interval. As, it can be recalled that the CDRB for the next interval depends on the selection of the power level $i^r$ during this current interval $k=0$. So, according to the algorithm CDRB for the next interval depends on $i^r$.

On the basis the information shown in Table 3, service provider will be able to choose any power level for reduction out of different possible power levels i.e. $CP^0(0)$, $CP_{2}^0(0)$, ..., $CP_{5}^0(0)$, ..., $CP_{2}^0(0)$. Every power level has its corresponding optional control string $S^r_i$ and aggregated bid $F(CP^0(0))$. For instance, if the service provider decides to curtail $CP_{5}^0(0)=4.36$ kW power it means $i^r=20$, so in this case the service provider has to pay a total of 0.73 units to the given five consumers and the individual payments to each consumer for this particular curtailment would be $0.07, 0.09, 0.17, 0.19, 0.21$ units to consumers $\{1,2,3,4,5\}$ respectively. As controller at the consumers end receives a control signal corresponding to power level "$i^r\" from the service provider and thus it switches OFF the $4^{th}, 5^{th}, 15^{th}, 4^{th}$ and $5^{th}$ loads of $\{1,2,3,4,5\}$ consumers respectively as denoted in control string $S^r_i = \{04h, 04h, 04h, 04h, 05h\}$.

Fig. 5 shows the load patterns resulted after executing the scheduling program for all $K$ intervals. Series 1 of Fig. 5 shows the load pattern before controlling which is

![Fig. 4. Demand curve supplied by the utility to the service provider.](http://www.jeet.or.kr)
The Consumer Rationality Assumption in Incentive Based Demand Response Program via Reduction Bidding

composed of both the controllable and uncontrollable loads. Series 2 of Fig. 5 shows the load pattern of ideal controlling in which program is executed with a fixed targeted level of 18.5kW and Fig. 6 shows the power reduced by each consumer as well as their aggregated reduction during each control interval.

Although, in reality, when a control of loads is over, demand immediately resumes and cause energy payback effect. In this phenomenon power demand increases rapidly and results in a new inadvertent peak. Therefore, in series 3 of Fig. 5 shows the load pattern in which program considers worst energy payback (i.e 50% of the total reduction of power during the last interval with an exponential die out [21]). So, it can be observed from Fig. 7 that each consumer reduced more power and more frequently than the ideal for the same targeted level of 18.5kW. Since, the energy payback effect exponentially decreases. Therefore, in order to completely avoid the payback effect, the service provider has to execute the load management program for few more intervals till the power consumption of the other uncontrollable loads reaches to a safe level.

It can be observed in the Fig. 6 and Fig. 7 that the dispatchable loads of the some consumers are cut off more frequently, this is because the loads especially with the lower bidding are more suitable for the program to select in order to fulfil its optimal policy (i.e. the minimization of the total payment to all the consumers). Though, this phenomenon exist when all the other consumer constraints are fully satisfied. That is why, because of \( T^{\text{max}} \), no signal dispatchable load of a particular consumer will be over-controlled. After executing program for both with/without energy payback effect, the total price that the service provider has to pay to the consumers are 27.5units/control period and 96.7units/control. Thus, it can also observed that the service provider has to pay around 3 times more in more realistic scenario than the ideal scenario. However, the profit of the service provider for ideal scenario is 110.5-27.5=83units/control period i.e. around and the profit in case of more-realistic scenario will be 110.5-96.7=13.8 units/control periods.

Moreover, it may not be possible that every time the targeted level of power consumption that has to be maintain is within the maximum curtailable capacity of the program. In this case, If the amount of required minimal load reduction is too large (i.e., the program fails to bring the system load below the target load level) or an unpredicted unit outage occurs, then the operator of the service provider have to select the maximum available level of power reduction as \( i \). For an explanation, consider that the utility request the service provider to maintain the base-line of 14kW instead of 18.5kW for the same demand curve. Now, this time the system of the service provider is not be able to main the requested level throughout the whole day as shown in Fig. 8. Thus, it can be observed that during the 1:00Pm to 10PM, the proposed algorithm try it’s best to maintain the requested level. But, even in this case, it successfully curtail around 60% of total power that is identified for curtailment.

Furthermore, many simulations were performed for possible different scenarios and some of the following observations are made:

By increasing the value of the maximum time allowed
for control $T_{OFF}$ and decreasing the minimal time required between control intervals $T_{ON}$, the service provider could increase its capability of power reduction but it will effect both the consumer “Desire of Use” and energy payback.

If the power to be curtailed during the interval is around one-third of the maximum capacity of the service provider. Then the service provider will never face a problem of incapability of power reduction.

5. Conclusion

In conclusion, the proposed framework of an aggregated demand response program for the constrained direct load control in order to achieve the grid stability and operational cost minimization during the peak demand is mathematically formulated. The framework by introducing the concept of demand reduction bidding and duration constraints in direct load control attempts to benefit and satisfy all the stakeholders i.e. the utility, the aggregator and the consumers.

The proposed algorithm for the framework computes the consolidated demand reduction bidding while considering all consumers’ load parameters and constraints. This in exchange gives optimal load scheduling to the aggregator. The simulation results of the case studies exemplify the proof-of-concept of the algorithm and the mathematical framework. Moreover, demand reduction bidding in constrained direct load control could achieve more consumer penetration and better load management than the conventional. Thus, it could also be evaluated that by this approach the aggregators could act more effectively in the smart grid paradigm.

References


[16] H. Jorge, C. Antunes, and A. Martins, “A multiple objective decision support model for the selection of


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