Priority-based Residential Demand Response for Alleviating Crowding in Distribution Systems

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***Abstract*—The dynamic pricing environment offers flexibility to the consumers to reschedule their switching appliances. Though the dynamic pricing environment results in several benefits to the utilities and consumers, it also poses some challenges. The crowding among residential customers is one of such challenges. The scheduling of loads at low-cost intervals causes crowding among residential customers, which leads to a fall in voltage of the distribution system below its prescribed limits. In order to prevent crowding phenomena, this paper proposes a priority-based demand response program for local energy communities. In the program, past contributions made by residential houses and demand are considered as essential parameters while calculating the priority factor. The non-linear programming (NLP) model proposed in this study seeks to reschedule loads at low-cost intervals to alleviate crowding phenomena. Since the NLP model does not guarantee global optima due to its non-convex nature, a second-order cone programming model is proposed, which captures power flow characteristics and guarantees global optimum. The proposed formulation is solved using General Algebraic Modeling System (GAMS) software and is tested on a 12.66 kV IEEE 33-bus distribution system, which demonstrates its applicability and efficacy.**

***Index Terms*—Crowding strategy, demand response, distribution system, General Algebraic Modeling System (GAMS), local energy community, second-order cone programming.**

Nomenclature

A. Indices

₹	Indian rupee
i, j	Bus indices
ij	Branch index
k	House index
m	Prosumer index
n	Customer index
t	Time interval index

B. Sets

A	Set of appliances connected at critical bus i
B^{Sub}	Set of sub-station buses
B^{Load}	Set of load buses
B^{NCB}	Set of non-critical buses
B^{CB}	Set of critical buses
h	Set of houses
$N(i)$	Set of buses connected to bus i through line
T	Set of time intervals

C. Parameters

ϕ_{ij}	Phase angle difference between bus i and bus j for identifying sensitive node
B_{ij}	Susceptance of branch ij
DL_t	Demand limit at time interval t
E_{apSLNL}	No load capacity of schedulable load appliances
E_{apSLFL}	Full load capacity of schedulable load appliances
F^T	Electricity price
G_{ij}	Conductance of branch ij
$I_{ij,\max}$	The maximum current carrying capacity of branch ij
IP	Integer programming
$L_{k,t}^{B}$	Base load of house k at time interval t
$L_{k,t}^{SL}$	Schedulable load of house k at time interval t
$L_{k,t}^{INSL}$	Interruptable and schedulable load of house k at time interval t
p_{ij}	Active power of branch ij for identifying sensitive node
$P_{m,S}$	Contribution of prosumer m
$P_{n,g}$	Demand of customer n

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$P_{k,ct}$	Load at sensitive node of house k at time interval t
$P_{k,t}$	Total demand of house k at time interval t
$P_{k,St}$	Excess power from house k at time interval t
$P_{i,t}^{Load}$	Active power demand at bus i and time interval t
$P_{ij,\max}$, $Q_{ij,\max}$	Active and reactive power capacity limits of branch ij
q_{ij}	Reactive power of branch ij for identifying sensitive node
$Q_{i,t}^{Load}$	Reactive power demand at bus i and time interval t
r_{ij}	Resistance of branch ij
$S_{k,t}$	Solar energy of house k at time interval t
v_i	Sending-end node voltage for identifying sensitive node
v_j	Receiving-end node voltage for identifying sensitive node
$V_{i,\max}, V_{i,\min}$	The maximum and minimum bounds of voltage of bus i
$V_{\max}, V_{\min}$	The maximum and minimum bounds of bus voltage V
x_{ij}	Reactance of branch ij
z_{ij}	Impedance of branch ij

D. Variables

$A_{t,apSL}^{h}$	On and off state
$P_{i,t}^{Sub}, Q_{i,t}^{Sub}$	Continuous variables corresponding to active and reactive power of upper grid (sub-station)
$P_{ij,t}, Q_{ij,t}$	Continuous variables corresponding to active and reactive power of branch ij
$u_{i,t}$, $R_{ij,t}$, $T_{ij,t}$	New defined continuous variables corresponding to conic reformulation
$V_{i,t}, \theta_{i,t}$	Continuous variables corresponding to voltage magnitude and angle of bus i
$X_{t,ap}^{k}$	Continuous variable corresponding to appliance schedule
$X_{t,ap}^{h}$	Feasible solution of schedulable appliances

I. INTRODUCTION

THE existing distribution systems are being transformed into smart distribution systems. With technological advancements, the integration of renewable energy sources and demand-side management techniques have emerged as critical components of smart grid implementation. The growing penetration of renewable energy sources also decreases the dependency of distribution system load on baseload generation plants, which reduces the electricity cost. A smart grid operator can alleviate peak-time loading by implementing appropriate dynamic pricing schemes. Demand response (DR) programs can not only be addressed to big commercial and industrial customers, but also to residential customers. In this context, DR programs act on deferrable loads (e.g., dishwashers, iron, washing machines, etc.). The residential loads are particularly relevant considering the big share of the total energy demand that comes from buildings. Therefore, the focus of this study is the impact of residential DR on a distribution system. Here, individual residential consumers are self-motivated to switch on their schedulable loads during low-cost intervals. However, it is observed that scheduling at low-cost intervals leads to crowding discomfort, demand limit violation, and voltage stability issues in the distribution systems [1], [2].

From the demand-side point of view, researchers have studied the above issues and provided solutions through various power management schemes for solar photovoltaic (PV) systems [3], [4]. Though these management schemes are efficient, the total investment cost is high. In [5], a case study about the supply-side profitability using solar PV units is presented. In contrast, it does not guarantee to solve the rapid solar penetration problem in the distribution system. DR studies have shown that cost minimization and demand-side management can be accomplished by collaboration between utilities and customers by maintaining the advantages of both [6].

The impact of the DR program on optimizing the operation of the distribution system has been studied by the researchers using various techniques such as air conditioning system scheduling, distributed generation, and distributed storage system [7]-[9]. These studies mainly concentrate on demand-side management to accommodate supply-side generation based on a dynamic pricing scheme. Here, researchers have focused on the DR program for electricity cost minimization along with supply-side management. Reference [10] proposes a real-time pricing algorithm to encourage desired energy consumption, but the study does not include renewable energy. Reference [11] develops a convex optimization technique for reducing the peak load with distributed sources and energy storage devices, which results in a significant reduction of peak loading with proper energy distribution. Reference [12] presents bi-level programming for balancing the demand curve without solar integration. Reference [13] proposes a new metering system with better connectivity as a decentralized solution for effective DR in the smart distribution system. Reference [14] discusses various DR methods such as load shedding, peak flattening, storage, load building, filling load valley, and versatile loading effect. Reference [15] summarizes the multi-energy systems and smart energy hub for the DR program to stimulate the demand-side resources. Based on the literature, all residential customers connected at the distribution nodes are willing to participate in DR programs since they know the advantages of solar penetration and dynamic pricing schemes. Even though most of the available DR programs with renewable energy integration provide significant results, they still lack crowding overcoming strategies to mitigate voltage collapses along with DR programs. Generally, commercial power system software platforms such as PSCAD and ETAP [16], [17] use linear integer programming (LIP) for scheduling appliances in line with DR programs. These LIP techniques are extremely challenging due to high-dimensional risks [18]. In recent years, a lot of research has been done for load scheduling in the area of DR schemes by using heuristic and conventional algorithms like genetic, bacterial foraging, differential evolution, and binary particle swarm optimization [19] - [22]. These evolutionary and swarm intelligence based algorithms require a common controlling parameter such as population size or generation number. In addition to the common control parameters, each algorithm has its own set of control parameters. For example, a genetic algorithm uses the mutation and crossover probability. Particle swarm optimization makes use of inertia weight and social and cognitive parameters. Similarly, other algorithms need the respective specific parameters such as bacterial foraging and differential evolution. These parameters either increase the computational effort or produce the local optimal solution. Besides, these heuristic algorithms are bio-inspired. Multiple runs do not produce the same result. Thus, these algorithms are not industrially accepted for effective scheduling in a smart distribution system.

Therefore, to overcome the above-mentioned difficulties, this paper proposes a second-order cone programming (SOCP) model for scheduling schedulable loads in the DR scheme. Rapid solar penetration reduces the electricity cost (solar available intervals) in a dynamic pricing environment. Thereby, an individual residential consumer is self-motivated to switch on their schedulable loads at these low-cost intervals. This sudden switching of loads at solar intervals may lead to a crowding phenomenon among residential consumers. For example, day-ahead market (DAM) in India is a physical electricity trading market for deliveries for 15-min time blocks within 24 hours of the next day starting from midnight. Here, the grid-connected solar PV reduces the prices during solar available time blocks. Besides, one of the most common motivation for an 11 kV secondary distribution consumer is to schedule schedulable loads from peak time periods to off-peak time periods in order to prevent penalties whenever the contractual volt-ampere limits are violated. Scheduling at the minimum price intervals leads to crowding discomfort, demand limit violation, and voltage stability issues in the distribution system. Therefore, the aforementioned risks can be mitigated by a priority-based DR program. The major contributions made in this study are given as follows.

1) This paper proposes a priority-based DR program at the sensitive node with the participation of local energy communities (LECs) to mitigate the voltage problems in the distribution system due to crowding phenomena.

2) The past contributions made by the residential houses and the amount of demand are considered as essential parameters for calculating priority factors (PFs).

3) The scheduling problem is formulated as SOCP model which captures the distribution system characteristics and provides an exact solution. A detailed simulation of the proposed program for the distribution system is performed in a General Algebraic Modeling System (GAMS) to test its applicability and efficacy.

The rest of this paper is structured as follows. Section II presents the sensitive node identification of distribution systems. Section III briefs the system architecture. Section IV describes the proposed methodology. Section V explains the problem formulation. Section VI summarizes the results and discussion. Finally, the conclusion of this paper is given in Section VII.

II. Sensitive Node Identification of Distribution Systems

If any stability issue occurs in a distribution system, it first impacts the sensitive node and then spreads to other nodes of the distribution system. Sensitive node analysis is conducted to determine the more vulnerable node to voltage stability problems. The most vulnerable node of the distribution system under consideration is identified using the voltage stability index (VSI). The node with the minimum VSI is considered to be the sensitive node of the distribution system. The VSI of a distribution system is identified using the equation given below [23].

$$v_j^4 + 2v_j^2(p_{ij}r_{ij} + q_{ij}x_{ij}) - v_i^2 v_j^2 + (p_{ij}^2 + q_{ij}^2)z_{ij} = 0 \tag{1}$$

From (1), the receiving active power and reactive power of the branch are given as:

$$p_{ij} = \pm\frac{\sqrt{v_j^4\cos^2(\phi_{ij}) - v_j^4 - v_{ij}^2 q_{ij}^2 - 2v_j^2 q_{ij}x_{ij} + v_j^2 v_i^2}}{z_{ij}} - v_j^2\cos(\phi_{ij}) \tag{2}$$

$$q_{ij} = \pm\frac{\sqrt{v_j^4\sin^2(\phi_{ij}) - v_j^4 - z_{ij}^2 p_{ij}^2 - 2v_j^2 p_{ij}r_{ij} + v_j^2 v_i^2}}{z_{ij}} - \frac{v_j^2\sin(\phi_{ij})}{z_{ij}} \tag{3}$$

From (2) and (3), it is clearly observed that the actual value of the active and reactive power at the receiving end is subjected to the condition of (4) and (5).

$$v_j^4\cos^2(\phi_{ij}) - v_j^4 - z_{ij}^2 q_{ij}^2 - 2v_j^2 q_{ij}x_{ij} + v_j^2 v_i^2 \geq 0 \tag{4}$$

$$v_j^4\sin^2(\phi_{ij}) - v_j^4 - z_{ij}^2 p_{ij}^2 - 2v_j^2 p_{ij}r_{ij} + v_j^2 v_i^2 \geq 0 \tag{5}$$

The sum of (4) and (5) gives the VSI of the distribution system, and it is used to identify the sensitive node of the distribution system, which is given as:

$$VSI = 2v_j^2 v_i^2 - 2v_j^2(p_{ij}r_{ij} + q_{ij}x_{ij}) - v_j^4 - z_{ij}^2(p_{ij}^2 + q_{ij}^2) \tag{6}$$

III. System Architecture

The system proposed in this study consisting of LEC architecture with solar integration is grouped at the sensitive node of the test system, as illustrated in Fig. 1.

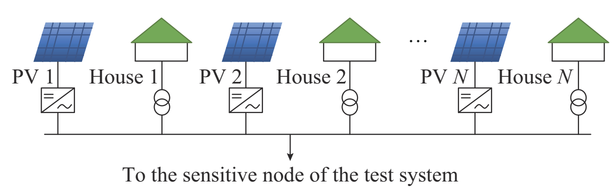

Fig. 1. System architecture.

Hence, in this analysis, the constant load at the sensitive node is altered as a dynamic load obtained from the typical LEC with different solar units. In an LEC, each house consists of different types of electrical loads that are considered as base-loads (e.g., fans, lighting, and television). These loads cannot be rescheduled from one time slot to another. Interruptible non-schedulable loads (INSLs) such as air conditioners and geysers can be interrupted but cannot be scheduled from one time slot to another. Schedulable loads are loads like vacuum cleaners, washing machines, and electric vehicles. These loads can be turned on and off intermittently without degrading their efficiency. Let the scheduling length of the total time period be finite, i.e., one day. A day is divided into T sub-intervals, each lasting 15 min. The total demand at the sensitive node of the test system is regarded as the sum of the interconnected demand of each house. The total demand of house k at time interval t is given by:

$$P_{k,t} = L^{B}_{k,t} + L^{SL}_{k,t} + L^{INSL}_{k,t} \tag{7}$$

The PV and the distribution system can meet the connected load at this node. If the available solar energy exceeds the connected demand, the house receives no power from the power grid. The excess from the solar unit is shared with the neighbouring houses. If the available solar power is less than the connected load, the distribution system can help alleviate the shortage, as shown in (8) and (9).

$$P_{k,ct} = \begin{cases} P_{k,t} - S_{k,t} & S_{k,t} = 0, S_{k,t} < P_{k,t} \\ 0 & S_{k,t} > P_{k,t} \end{cases} \tag{8}$$

$$P_{k,St} = \begin{cases} S_{k,t} - P_{k,t} & S_{k,t} > P_{k,t} \\ 0 & S_{k,t} < P_{k,t} \end{cases} \tag{9}$$

IV. Proposed Methodology

This section presents the calculation of the PF for each house at the sensitive node, GAMS for load scheduling, and dynamic power flow to evaluate the voltage profile of the test system. Once the PF of all customers is identified, NLP and SOCP schedule the schedulable loads without any crowding by ensuring the voltage stability of the system. Here the dynamic power flow takes care of the voltage stability of the test system.

A. PF Calculation

In the case of LEC, if the utility initiates a dynamic pricing scheme, it may cause crowding among the residential customers affecting the sensitive node of the test system primarily. Therefore, to avoid this crowding strategy and preserve the voltage stability of the system, each customer's PF has to be determined. Schedulable loads at the sensitive bus of the test system can be rescheduled based on their PFs. Thus, the careful identification of PFs at the sensitive node of the test system makes the distribution system stable. While calculating the PF for a typical residential customer, two factors have to be taken into consideration: ① the contribution made by the residential customer to the power grid, i.e., the excess solar power, which reduces the amount of power drawn from the power grid; ② past power demanded by the residential customer.

PF of LECs can be identified as:

$$PF = \frac{P_{m,S}}{\sum P_{m,S}} + \frac{P_{n,g}}{\sum P_{n,g}} \tag{10}$$

where $\sum P_{m,S}$ is the total contribution made by LECs; and $\sum P_{n,g}$ is the total demand of LECs at the sensitive node of the test system. The prosumer whose contribution to the distribution system is larger is assigned with a higher PF. When identifying PF, if any customer has the same priority index, the re-scheduling of the appliances can be carried out based on their past contributions.

B. Dynamic Power Flow

In this analysis, the rapid solar penetration and DR program may affect the voltage stability of the test system; hence it requires continuous monitoring. Therefore, this subsection presents the continuous monitoring of the system stability using a dynamic power flow algorithm, as shown in Algorithm 1. That is, forward and backward sweep power flow is carried out for every 15 min interval [24]. The dynamic power flow algorithm reads the bus and line data of the test system and identifies the sensitive node using (6), as discussed in Section II. Once the sensitive node is identified, the power flow can be used to calculate the branch current, sensitive node voltage, and absolute change in voltages. Once the power flow converges, the algorithm updates the voltage profile of the corresponding time interval.

Algorithm 1: dynamic power flow algorithm

Result: update voltage profile
Initialization
Step 1: sensitive node identification
if node is sensitive node **then**
  Update data at sensitive node and go to *Step 2*
else
  Go to *Step 1*
end
Step 2: power flow calculation
while $\Delta V < \epsilon$ **do**
  Compute the branch currents
  Determine the drop in voltage
  Determine the critical bus voltage
  Determine the voltage variation in absolute terms (ΔV)
  Update iteration times $i_{ter} = i_{ter} + 1$
end

V. Problem Formulation

This section presents the problem formulation for load scheduling subject to different constraints. The objective is formulated to reschedule the schedulable loads within the demand limit by ensuring the voltage stability limit. The objective function for the optimal load scheduling is given as:

$$f(X^{k}_{t,ap}) = \min \sum_{k=1}^{h} F^{T} (L^{B}_{k,t} + X^{k}_{t,ap} + L^{INSL}_{k,t}) \tag{11}$$

The residential houses have the ability to program the operating schedules of each schedulable load in advance, which is represented as a constraint in (12).

$$X_{t,ap}^{k}=\{X_{t,ap}^{h}|E_{ap,SLNL}\leq X_{t,apSL}^{k}\leq E_{ap,SLFL},\forall A_{t,apSL}^{h}=1,\forall t\in T\} \tag{12}$$

In this case, in order for an appliance to complete its task within its operating interval, the available power for that appliance should be within its maximum capacity $E_{ap,SLFL}$.

In a dynamic pricing scheme to avoid crowding phenomena during solar available time periods, i.e., the minimum electricity price time periods, GAMS is initiated as discussed in Section IV. It generates a feasible solution of $X_{t,ap}^{k}$ for each of the schedulable appliances "ap" of the t^{th} interval. The total demand at each subinterval is less than or equal to the demand limit DL_t [25], i.e.,

$$\sum_{k=1}^{h}(L_{k,t}^{B}+X_{t,ap}^{k}+L_{k,t}^{INSL})\leq DL_t \tag{13}$$

The above formulated objective is minimized by rescheduling the loads using priority-based DR with GAMS, as shown in Fig. 2.

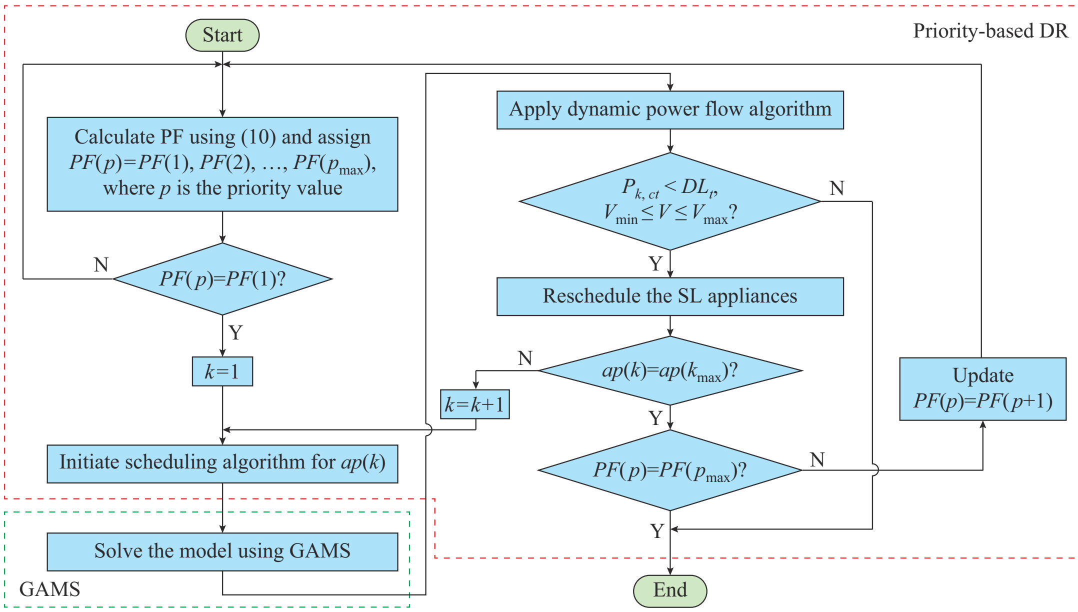

Fig. 2. Flow chart of priority-based DR with GAMS.

A. Nonlinear Programming Formulation

In the distribution system, active and reactive power flows from bus i to bus j are given as:

$$\begin{cases}P_{ij,t}=G_{ij}V_{i,t}^{2}-G_{ij}V_{i,t}V_{j,t}\cos\theta_{ij,t}-B_{ij}V_{i,t}V_{j,t}\sin\theta_{ij,t}\\ Q_{ij,t}=-B_{ij}V_{i,t}^{2}+B_{ij}V_{i,t}V_{j,t}\cos\theta_{ij,t}-G_{ij}V_{i,t}V_{j,t}\sin\theta_{ij,t}\end{cases}\quad\forall t,\forall ij \tag{14}$$

Active and reactive power balances in the distribution system are given as:

$$P_{i,t}^{Sub}\Big|_{i\in B^{Sub}}-P_{i,t}^{Load}\Big|_{i\in B^{NCB}}-\sum_{a\in A}X(a,t)\Big|_{i\in B^{CB}}=\sum_{j\in N(i)}P_{ij,t}\quad\forall t,\forall i \tag{15}$$

$$Q_{i,t}^{Sub}\Big|_{i\in B^{Sub}}-Q_{i,t}^{Load}\Big|_{i\in B^{Load}}=\sum_{j\in N(i)}Q_{ij,t}\quad\forall t,\forall i \tag{16}$$

$$V_{i,\min}\leq V_{i,t}\leq V_{i,\max}\quad\forall t,\forall i\in B^{Load} \tag{17}$$

$$V_{i,t}=1\quad\forall t,\forall i\in B^{Sub} \tag{18}$$

$$\begin{cases}-P_{ij,\max}\leq P_{ij,t}\leq P_{ij,\max}\\ -Q_{ij,\max}\leq Q_{ij,t}\leq Q_{ij,\max}\end{cases}\quad\forall t,\forall ij \tag{19}$$

$$I_{ij,t}^{2}=(G_{ij}^{2}+B_{ij}^{2})(V_{i,t}^{2}+V_{j,t}^{2}-2V_{i,t}V_{j,t}\cos\theta_{ij,t})\leq I_{ij,\max}^{2}\quad\forall t,\forall ij \tag{20}$$

Voltage should be restricted by (17) and (18), and power flowing through each line is limited by (19). The square of current limit of a line is restricted by (20) [26].

B. Second-order Cone Programming Formulation

From NLP formulation, it is observed that (15) is nonlinear and nonconvex. Therefore, it does not provide a guaranteed global optimum solution. Hence, this study proposes a conic relaxation-based power flow [27], which extracts distribution system characteristics and provides a guaranteed global optimum solution. The required power flow equations are given as:

$$u_{i,t}=\frac{V_{i,t}^{2}}{\sqrt{2}}\quad\forall t,\forall i \tag{21}$$

$$R_{ij,t}=V_{i,t}V_{j,t}\cos\theta_{ij,t}\quad\forall t,\forall ij \tag{22}$$

$$T_{ij,t}=V_{i,t}V_{j,t}\sin\theta_{ij,t}\quad\forall t,\forall ij \tag{23}$$

The nonlinear equation (15) can be linearized using (18)-(20) as follows [27]:

$$P_{ij,t}=\sqrt{2}\,G_{ij}u_{i,t}-G_{ij}R_{ij,t}-B_{ij}T_{ij,t}\quad\forall t,\forall ij \tag{24}$$

$$Q_{ij,t}=-\sqrt{2}\,B_{ij}u_{i,t}+B_{ij}R_{ij,t}-G_{ij}T_{ij,t}\quad\forall t,\forall ij \tag{25}$$

$R_{ij,t}$ and $T_{ij,t}$ are constrained in (22) and (23) such that

$$2u_{i,t}u_{j,t}=R_{ij,t}^{2}+T_{ij,t}^{2}\quad\forall t,\forall ij \tag{26}$$

The above equation is still nonlinear due to quadratic equality constraints. Therefore, (26) is relaxed to inequality to make it convex [27].

$$2u_{i,t}u_{j,t}\geq R_{ij,t}^{2}+T_{ij,t}^{2}\quad\forall t,\forall ij \tag{27}$$

Bounds for the new defined variables are:

$$\frac{V_{i,\min}^2}{\sqrt{2}} \le u_{i,t} \le \frac{V_{i,\max}^2}{\sqrt{2}} \quad \forall t, \forall i \in B^{Load} \tag{28}$$

$$u_{i,t} = \frac{1}{\sqrt{2}} \quad \forall t, \forall i \in B^{Sub} \tag{29}$$

$$0 \le R_{ij,t} \le V_{i,\max} V_{j,\max} \quad \forall t, \forall ij \tag{30}$$

$$-V_{i,\max} V_{j,\max} \le T_{ij,t} \le V_{i,\max} V_{j,\max} \quad \forall t, \forall ij \tag{31}$$

The square of current limit (21) can be linearized using new defined variables, which is given as:

$$I_{ij,t}^2 = \sqrt{2}\,(G_{ij}^2 + B_{ij}^2)(u_{i,t} + u_{j,t} - 2R_{ij,t}) \le I_{ij,\max}^2 \quad \forall t, \forall ij \tag{32}$$

VI. Results and Analysis

The proposed DR program is validated for 30 residential customers in an LEC, and the data are generated using microgrid load and modeling software LCOE. A typical load of an average Indian house is considered. Power ratings of schedulable loads of all the prosumers and consumers are presented in Table I. The LEC consists of 10 prosumers and 20 consumers. The details of the PV capacities of the prosumers are given in Table II. Loads of all the prosumers and consumers shown in Table I are lumped at the sensitive node of the distribution system. The single-line diagram of the IEEE 33-bus distribution system [26] with LEC connected at the sensitive node is shown in Fig. 3. The node 18 of the IEEE 33-bus distribution system is identified as the sensitive node which has the lowest VSI, as shown in Fig. 4. Among 30 residential houses, the load curves of a typical prosumer (house 10) and a typical consumer (house 17) without priority-based DR are demonstrated in Figs. 5 and 6, respectively, where each time interval represents 15 min duration.

TABLE I
Power Ratings of Schedulable Loads

Load	Power rating (kW)	Load	Power rating (kW)
Grinder	0.5	Dryer	0.5
Well pump	2.0	Water sprayer	1.0
Washing machine	1.5	Vacuum cleaner	0.8
Dishwasher	1.0	Iron	0.8

TABLE II
PV Capacities of Prosumers

House No.	PV capacity (kW)	House No.	PV capacity (kW)
1	1	6	6
2	2	7	3
3	7	8	8
4	9	9	4
5	5	10	10

From Fig. 5, it is observed that the solar power generation is more than its required consumption. This surplus energy is shared to the distribution node, as shown in (9). In a dynamic pricing scheme, the LEC at the sensitive node tries to reschedule the schedulable loads (shown in Figs. 5 and 6) to low-cost intervals, thereby leading to crowding phenomena.

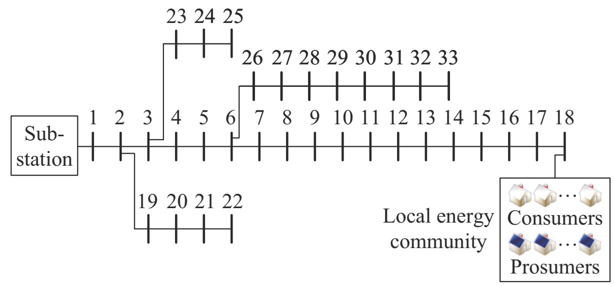

Fig. 3. Single-line diagram of IEEE 33-bus distribution system with LEC connected at sensitive node.

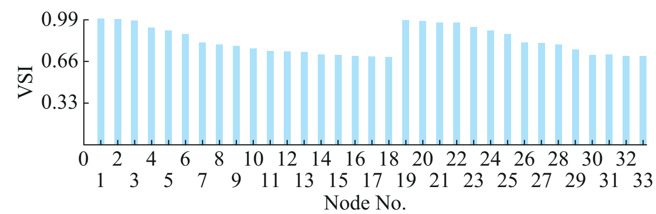

Fig. 4. VSI of IEEE 33-bus distribution system.

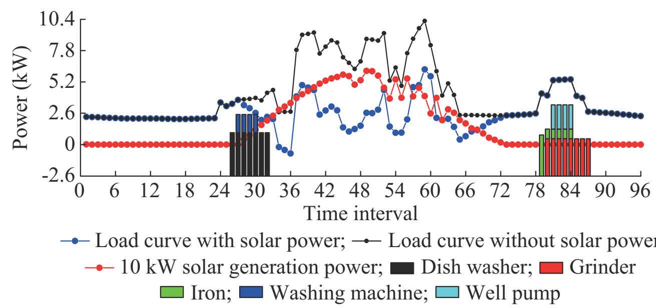

Fig. 5. Load curves of a typical prosumer (house 10) without priority-based DR.

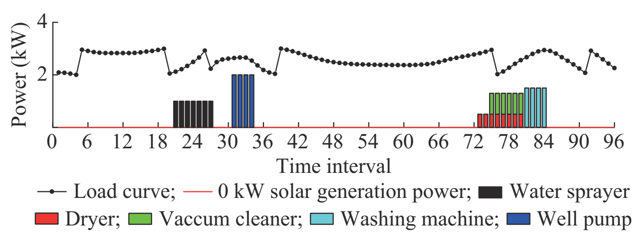

Fig. 6. Load curves of a typical consumer (house 17) without priority-based DR.

If no action is taken against this phenomenon, it may lead to voltage collapse at the minimum price intervals, as shown in Fig. 7. Therefore, to mitigate this scenario, the PF of each individual house is calculated using (10) and is shown in Fig. 8.

The customers are ranked according to their PFs, and the preference is given to the customer with a high PF. The proposed DR program schedules the schedulable loads by satisfying all the constraints in (13) to (32) without any crowding phenomena. Here, DR for scheduling and power flows for voltage stability analysis are carried out in the GAMS platform. The proposed DR program is evaluated on an HP

PC i7 (16 GB RAM, 3.19 GHz), coded in GAMS version 33.2. A typical Indian Energy Exchange (IEX) price is considered for scheduling. In this analysis, NLP with CONOPT solver and SOCP with MOSEK solver are used to illustrate the proposed DR program using GAMS. DR using NLP and SOCP for a typical IEX price is shown in Table III.

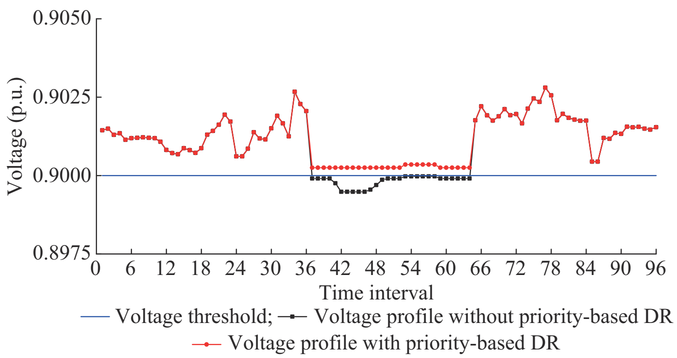

Fig. 7. Voltage profiles with and without priority-based DR.

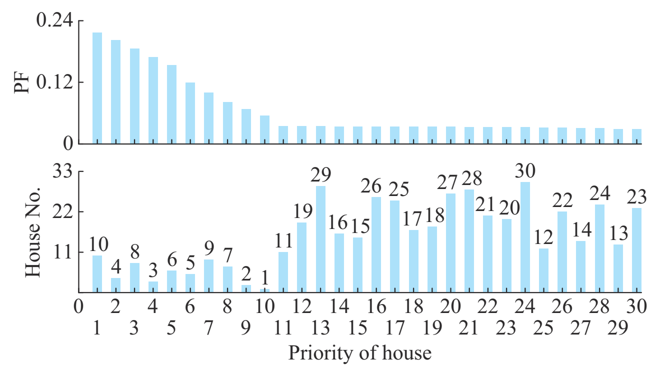

Fig. 8. PF of each individual house.

TABLE III
DR USING NLP AND SOCP FOR TYPICAL IEX PRICE

DR technique	Total cost without DR (₹)	Total cost with DR (₹)	Elapsed time (s)
NLP (regular pricing)	14227	14227	155.180
NLP using MATLAB	10811	10137	142.800
NLP with CONOPT solver	10811	10137	6.798
SOCP with MOSEK solver	10811	10137	2.515

The DR is conducted for regular pricing or fixed pricing and dynamic pricing schemes. The total cost incurred in the system with and without DR is ₹14227 in regular pricing scheme. Since the price is fixed in all time intervals, the consumer will not try to shift their consumption from one time interval to another. In dynamic pricing scheme without DR, the operational cost is ₹10811. While in dynamic pricing scheme with DR, the operational cost is ₹10137. Therefore, we can observe that ₹674 is saved due to the priority-based DR. Besides, we can observe that the SOCP with MOSEK solver provides an optimized solution with an improved voltage profile and reduces the electricity price within 2.515 s. As the dynamic pricing scheme is evaluated at a time interval of every 15 min, the solution time is considered to be significant. Therefore, SOCP with MOSEK is considered as an optimizer for further analysis.

The dynamic power flow algorithm is used to obtain the voltage profiles in the systems without priority-based DR. After scheduling, the load curves of a typical prosumer and a typical consumer with priority-based DR are shown in Figs. 9 and 10, respectively. The proposed DR program reschedules the schedulable loads from the 1st PF ranked house (house 10) to the 24th PF ranked house (house 30) within the low-cost sub-intervals 37 to 64. However, the remaining low PF ranked houses are not allowed to participate in these intervals as it will violate the voltage stability constraints.

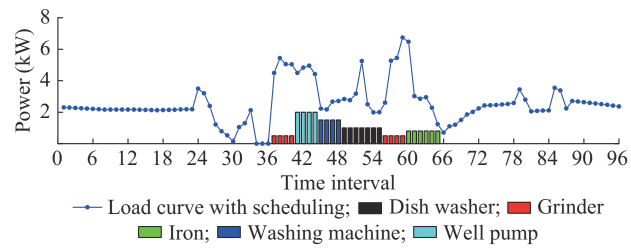

Fig. 9. Load curve of a typical prosumer (house 10) with priority-based DR.

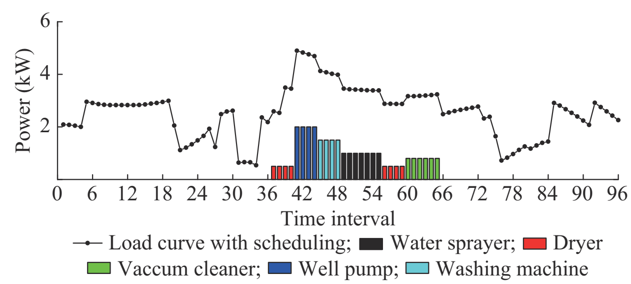

Fig. 10. Load curve of a typical consumer (house 17) with priority-based DR.

The total demand for LEC architecture with and without priority-based DR and the price curve at the sensitive node is shown in Fig. 11. The proposed program effectively reschedules the schedulable loads at low-cost intervals without any crowding phenomena by satisfying the demand limit constraint. It is also observed that there is a significant fluctuation of power due to solar penetration and load scheduling which may affect the voltage stability of the distribution node. This effect is simulated at the sensitive node (node 18) to understand the voltage profile variations, as shown Fig. 12. In this study, the proposed program effectively reschedules the schedulable loads at low-cost intervals up to their rated capacity. Therefore, the voltage profile along these low-cost intervals is almost constant, as shown Fig. 12. Even though the sensitive node of the test system is stabilized with priority-based DR, the bidirectional power flow at this node affects the stability of other nodes of the test system [28]. Hence, in this study, voltage stability at different nodes (nodes 16 and 17) is carried out with and without priority-based DR and is shown in Fig. 13. The priority-based DR also ensures voltage stability within the threshold limits. Therefore, the proposed program is stable enough for real-time implementation in the future smart distribution system with rapid solar penetration.

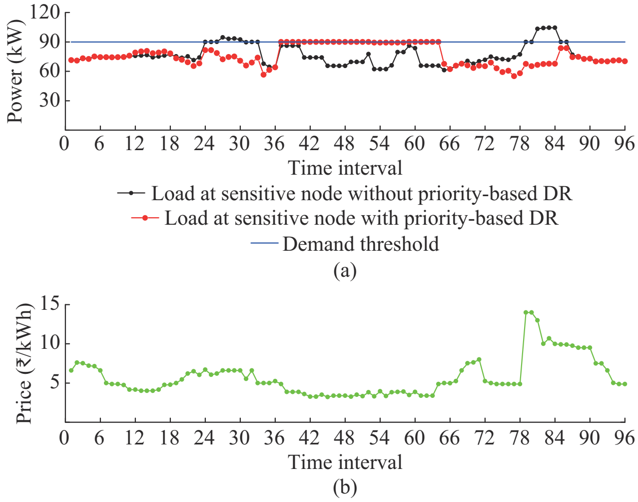

Fig. 11. Total demand for LEC architecture with and without priority-based DR and price curve at sensitive node. (a) Total demand for LEC architecture. (b) Price.

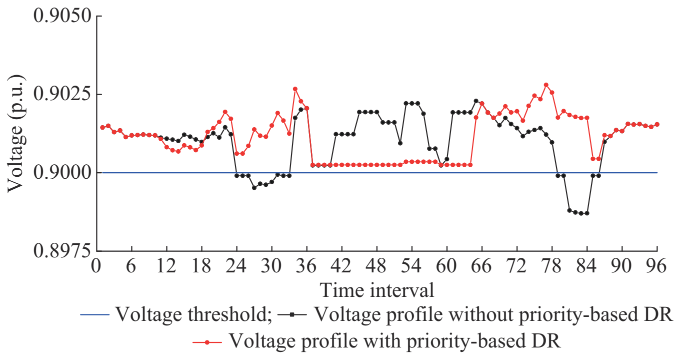

Fig. 12. Voltage profiles at sensitive node with and without priority-based DR.

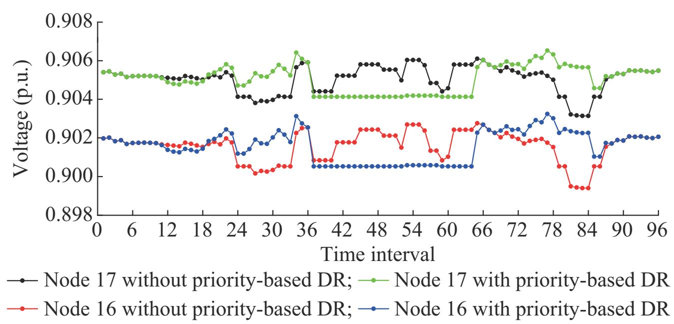

Fig. 13. Voltage profiles at different nodes with and without priority-based DR.

VII. Conclusion

The priority-based residential DR for alleviating crowding using conic programming is presented for the distribution system. The priority-based DR program with solar integration can reschedule the loads effectively for the LEC. The node 18 is identified as the sensitive node for the IEEE 33-bus distribution system using the VSI technique. The PF for each customer is calculated based on their previous contributions and connected demand, which facilitates ranking and mitigates the crowding phenomena observed in the sensitive node. The ranking of each customer based on PF ensures the fair distribution of excess solar energy and effective rescheduling of the schedulable loads. The SOCP model using GAMS efficiently reschedules the loads by satisfying both demand and voltage limit constraints. The voltages of all buses in the system are within limits using the proposed DR program. The computational time of the SOCP model is less than the NLP model. The results are effective and can be used for future smart distribution system with rapid solar penetration.

References

[1] IEX. (2022, Mar.). Indian Energy Exchange (IEX) limited. [Online]. Available: www.iexindia.com

[2] R. R. Eapen, S. P. Simons, K. Sundareswaran *et al*., "User centric economic demand response management in a secondary distribution system in India," *IET Renewable Power Generation*, vol. 13, no. 6, pp. 834-846, Apr. 2018.

[3] H. Bayat and A. Yazdani, "A hybrid MMC-based photovoltaic and battery energy storage system," *IEEE Power and Energy Technology Systems Journal*, vol. 6, no. 1, pp. 32-40, Jan. 2019.

[4] D. Lamsal, V. Sreeram, Y. Mishra *et al*., "Smoothing control strategy of wind and photovoltaic output power fluctuation by considering the state of health of battery energy storage system," *IET Renewable Power Generation*, vol. 13, no. 4, pp. 578-586, Mar. 2019.

[5] H. Apostoleris, S. Sgouridis, M. Stefancich *et al*., "Utility solar prices will continue to drop all over the world even without subsidies," *Nature Energy*, vol. 4, no. 10, pp. 833-834, Oct. 2019.

[6] M. V. and A. Bhattacharya, "Peak power demand management by using SMC-controlled three-level CHB-based three-wire and four-wire SAPF," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 8, pp. 5270-5281, Aug. 2021.

[7] S. Mohseni, A. C. Brent, D. Burmester *et al*., "A game-theoretic approach to model interruptible loads: application to micro-grid planning," in *Proceedings of 2020 IEEE PES General Meeting (PESGM)*, Wellington, New Zealand, Aug. 2020, pp. 1-5.

[8] H. Gong, V. Rallabandi, D. M. Ionel *et al*., "Dynamic modeling and optimal design for net zero energy houses including hybrid electric and thermal energy storage," *IEEE Transactions on Industry Applications*, vol. 56, no. 4, pp. 4102-4113, Jul.-Aug. 2020.

[9] F. Wang, B. Xiang, K. Li *et al*., "Smart households' aggregated capacity forecasting for load aggregators under incentive-based demand response programs," *IEEE Transactions on Industry Applications*, vol. 56, no. 2, pp. 1086-1097, Mar-Apr. 2020.

[10] T. M. Aljohani, A. F. Ebrahim, and O. A. Mohammed, "Dynamic real-time pricing mechanism for electric vehicles charging considering optimal microgrids energy management system," *IEEE Transactions on Industry Applications*, vol. 57, no. 5, pp. 5372-5381, Jul. 2021.

[11] T. C. Chiu, Y. Y. Shih, A. C. Pang *et al*., "Optimized day-ahead pricing with renewable energy demand-side management for smart grids," *IEEE Internet Things Journal*, vol. 4, no. 2, pp. 374-383, Apr. 2017.

[12] L. Tao, Y. Gao, H. Zhu *et al*., "Distributed genetic real-time pricing for multiseller-multibuyer smart grid based on bilevel programming considering random fluctuation of electricity consumption," *Computer & Industrial Engineering*, vol. 135, pp. 359-367, Sept. 2019.

[13] M. Majidi and Z. Kazem, "Integration of smart energy hubs in distribution networks under uncertainties and demand response concept," *IEEE Transactions on Power Systems*, vol. 34, no. 1, pp. 566-574, Aug. 2018.

[14] Z. Sun, W. Si, Y. Xuan *et al*., "Real-time demand response strategy of temperature-controlled load for high elastic distribution network" *IEEE Access*, vol. 9, pp. 69418-69425, Jan. 2021.

[15] Y. Li, D. W. Gao, W. Gao *et al*., "Double-mode energy management for multi-energy system via distributed dynamic event-triggered Newton-Raphson algorithm," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 5339-5356, Jun. 2020.

[16] P. Faria, Z. Vale, J. Soares *et al*., "Demand response management in power systems using particle swarm optimization," *IEEE Intelligent Systems*, vol. 28, no. 4, pp. 43-51, Apr. 2011.

[17] A. Rajaei, S. Fattaheian-Dehkordi, M. Fotuhi-Firuzabad *et al*., "Developing a distributed robust energy management framework for active distribution systems," *IEEE Transactions on Sustainable Energy*, vol.

12, no. 4, pp. 1891-1902, Oct. 2021.
[18] L. Urbanucci, "Limits and potentials of mixed integer linear programming methods for optimization of poly generation energy systems," *Energy Procedia*, vol. 148, pp. 1199-1205, Aug. 2018.
[19] C. Elsido, B. Aldo, S. Paolo *et al*., "Two-stage MINLP algorithm for the optimal synthesis and design of networks of CHP units," *Energy*, vol. 121, pp. 403-426, Feb. 2017.
[20] Z. Zhang, C. Wang, H. Lv *et al*., "Day-ahead optimal dispatch for integrated energy system considering power-to-gas and dynamic pipeline networks," *IEEE Transactions on Industry Applications*, vol. 57, no. 4, pp. 3317-3328, Jul.-Aug. 2021.
[21] C. Li, X. Yu, W. Yu *et al*., "Efficient computation for sparse load shifting in demand side management," *IEEE Transactions Smart Grid*, vol. 8, no. 1, pp. 250-261, Feb. 2017.
[22] A. Imran, G. Hafeez, I. Khan *et al*., "Heuristic-based programable controller for efficient energy management under renewable energy sources and energy storage system in smart grid," *IEEE Access*, vol. 8, pp. 139587-139608, Jul. 2020.
[23] S. N. Gopiya-Naik, D. K. Khatod, and M. P. Sharma, "Analytical approach for optimal siting and sizing of distributed generation in radial distribution networks," *IET Generation, Transmission & Distribution*, vol. 9, no. 3, pp. 209-220, Feb. 2014.
[24] U. Eminoglu and M. H. Hocaoglu, "A voltage stability index for radial distribution networks," in *Proceedings of 2007 42nd International Universities Power Engineering Conference*, Kocaeli, Turkey, Sept. 2007, pp. 408-413.
[25] S. L. Arun and M. P. Selvan, "Intelligent residential energy management system for dynamic demand response in smart buildings," *IEEE Systems Journal*, vol. 12, no. 2, pp. 1329-1340, Jan. 2018.
[26] J. M. R. Munoz and A. Gomez-Exposito, "A line-current measurement based state estimator," *IEEE Transactions on Power Systems*, vol. 7, no. 2, pp. 513-519, May 1992.
[27] R. A. Jabr, "Radial distribution load flow using conic programming," *IEEE Transactions on Power Systems*, vol. 21, no. 3, pp. 1458-1459, Jul. 2006.
[28] S. A. A. Kazmi, M. K. Shahzaad, and D. R. Shin, "Voltage stability index for distribution network connected in loop configuration," *IETE Journal of Research*, vol. 63, no. 2, pp. 281-293, Mar. 2017.

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