Stochastic Energy Management of Microgrid with Nodal Pricing

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Abstract—This paper develops a stochastic framework for the energy management of a microgrid to minimize the energy cost from the grid. It considers the uncertainties in solar photovoltaic (PV) generation, load demand, and electricity price. Furthermore, the opportunity of flexible load demand, i.e., the effect of demand response (DR), on the test system is studied. The uncertainties are modeled by using Monte Carlo simulations and the generated scenarios are reduced to improve the computational tractability. In general, microgrid scheduling is implemented by using substation (source node) price as a reference, but that reference price is not the same at all nodes. Therefore, this paper develops the nodal price based energy management in a microgrid to improve the scheduling accuracy. The stochastic energy management framework is formulated as a mixed integer non-linear programming (MINLP). Four case studies are simulated for a modified 15-node radial distribution network integrated with solar PV and battery energy storage system (BESS) to validate the effectiveness of the energy management framework for a microgrid with nodal pricing.

Index Terms—Battery energy storage system (BESS), demand response (DR), distributed generation, microgrid, mixed integer non-linear programming (MINLP), scheduling, stochastic optimization.

I. INTRODUCTION

MICROGRIDS realize the coordination of local generation and loads which are controlled in a defined boundary to meet the load demand. It should be capable of operating in both grid connected and autonomous modes. Microgrids with the integration of information technology such as monitoring, bi-directional communication infrastructure, and the controlling of loads and generation are evolved as smart grids. The designs of smart grids take advantage of advanced power system technologies for the decentralized control of energy resources [1]. The control of load demand with demand response (DR) and battery energy storage system (BESS) helps improve the energy management in a microgrid. The practical implementation of DR in a distribution network with diversified customers need robust mathematical frameworks to achieve satisfactory negotiations between the customers and the microgrid operators. However, in a residential community or industrial load type of distribution networks, microgrid operators can manage the energy resources to get the techno-economical benefits as much as possible by exploring the load behavior, and BESS features in response to electricity price. And it keeps the renewable generation in operation constraints.

The microgrid related literature focuses on placement and sizing of renewable energy resources, uncertainty modeling, decentralized control, modeling of DR, renewable and network integration, and wholesale market integration. The location and sizing of the local energy resources and BESS are discussed in [2]-[5]. The proper placement of BESS improves the reliability of system for different contingencies and minimizes the power losses of the network and peak power. BESS is a significant component in microgrids [5], [6]. It has both technical and economic advantages, which include the minimization of energy by charging at lower prices and discharging at higher prices [7] and the reduction of peak power. It can be used as an arbitrage when purchasing the energy in the day-ahead electricity market at a lower price and selling in the real-time market at a higher price. The uncertainty is a major concern in microgrids due to the intermittent generation from renewable energy sources (solar and wind power), the variation in load demand (heating, ventilation and air-conditioning (HVAC) and electric vehicle) and electricity price.

The uncertainty is modeled by using stochastic programming [7]-[9], robust optimization [10], and chance-constrained programming [11]. Each of the modeling has its own merits. The objective of the microgrid operators is to minimize the cost of energy to meet the load demand while satisfying the network constraints. The challenge in energy management implementation is peak power shaving. Most of the load curves follow the duck-shaped waveform due to simultaneous power consumption. To overcome various pricing schemes, coordination-based algorithms are developed [12]-[14]. In DR programs, the consumers have to alter/re-schedule the energy consumption profiles according to the variable prices (time-of-use price, critical peak price, inclined blocked rate, etc.) to minimize the peak power by shifting or curtailing the load demand from high pricing peri-

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methods to low pricing periods and from peak load periods to off-peak load periods [15], [16]. The DR has been an assuring measure for balancing generation and load demand in active distribution network (ADN) by facilitating the accommodation of distributed renewable energy sources. Price-based DR has the potential to increase the use of renewable energy in industrial and community-type ADNs. The solution is obtained in centralized algorithms due to computational complexity and time consumption, while the privacy issues lead to decentralized algorithms. Lagrangian-based decentralized algorithm is developed in [17] to minimize the peak-to-average ratio (PAR) and computational time.

From the literature, most of microgrid energy management research is implemented by considering wholesale market price or source node price for the resource scheduling purpose. If the aggregator is purchasing energy from the wholesale market at a certain electricity price, while it is unknown that at what price an aggregator has to sell that energy. This paper focuses on the accurate scheduling of generation and load of microgrid resources by calculating the nodal prices in distribution network. It has been implemented in two stages: firstly, the nodal prices are calculated based on the concept of marginal pricing, and thereafter, the flexible load demands and the local resources presented in the network are optimally scheduled. The major contributions of this paper are as follows:

1) An unified mathematical framework is formulated to schedule the generation, BESS and load demand presented in the territory of the microgrid operator. Moreover, DR is also integrated with the framework to study the effect of load flexibility on the total cost of energy.

2) Nodal price based scheduling is developed, and its effect is studied with the local renewable generation.

3) The developed framework is tested on a 15-node active radial distribution network. It is observed from the simulation results that the integration of local generation and DR leads to techno-economical benefits compared to the base case.

The rest of the paper is organized as follows: Section II presents system modeling and the mathematical models for the network resources, BESS, diesel generator (DG), and DR. The simulation results for various cases are thoroughly discussed in Section III. Section IV concludes the paper.

II. SYSTEM MODEL

The paper considers a radial distribution network as a microgrid which has $n \in N$ number of nodes. Local energy resources (solar photovoltaic (PV) and DG) and BESS are connected at different nodes of the network. The load is assumed to be connected at all nodes except the substation node, which is a combination of fixed and controllable loads. The controllable loads have to specify the limits of energy consumption and time consumption. The microgrid is connected to the main grid via an interconnecting switch. The role of the microgrid operator is to optimally schedule all the available resources, both the load and generation, to maximize social welfare. The interaction of microgrid operator with different available resources is shown in Fig. 1. The uncertainties in the solar PV generation, load demand and electricity price affect the objectives of microgrid operators [18]. Hence the analysis of microgrid with the uncertainty gains attention in the literature.

A. BESS Modeling

The BESS is modelled by the following equations:

\[ P_{bat,i,t} = P_{cha,i,t} - P_{dis,i,t} \]
\[ P_{cha,i,t} \leq x_{i,t} P_{cha,\text{max}} \]
\[ P_{dis,i,t} \leq (1-x_{i,t}) P_{dis,\text{max}} \]
\[ \text{SOC}_{i,t} = \text{SOC}_{i,t-1} + \left( \eta_{cha} P_{cha,i,t} - \frac{P_{dis,i,t}}{\eta_{dis}} \right) \Delta t \]
\[ \text{SOC}_{\text{min}} \leq \text{SOC}_{i,t} \leq \text{SOC}_{\text{max}} \]
\[ x_{i,t} \in [0,1] \]

where $P_{cha,i,t}$, $P_{dis,i,t}$ are charging and discharging power of BESS, respectively; $P_{cha,\text{max}}$, $P_{dis,\text{max}}$ are upper limits of charging and discharging power, respectively; $\text{SOC}$ is state of charge (SOC); $\text{SOC}_{\text{min}}$, $\text{SOC}_{\text{max}}$ are the limits of state of charge; $\eta_{cha}$, $\eta_{dis}$ are charging and discharging efficiency, respectively; $P_{bat}$ is the effective BESS power; and $x_{i,t}$ is binary variable. The equations are self-explanatory.
B. DG Modeling

The DG is modelled by the following equations.

\[
\begin{align*}
\sum_{i=k}^{t+UT-1} u_{i,t} & \geq UT_i \cdot y_{i,t} \quad \forall t \\
\sum_{i=k}^{t+RD-1} (1-u_{i,t}) & \geq DT_i \cdot z_{i,t} \quad \forall t \\
y_{i,t} - z_{i,t} & = u_{i,t} - u_{i,t-1} \quad \forall t \\
y_{i,t} + z_{i,t} & \leq 1 \quad \forall t
\end{align*}
\]

where \( P_{i,t}^{dg} \) is the power generated by DG; \( P_{\text{max}}^{dg} \) and \( P_{\text{min}}^{dg} \) are upper and lower limits of DG power, respectively; \( u_{i,t} \) is a binary variable indicating ON and OFF states of DG; \( RU_{i,t}^{dg} \) and \( RD_{i,t}^{dg} \) are ramp-up, ramp-down, minimum-up, and minimum-down time, respectively; and \( u_{i,t}, y_{i,t}, z_{i,t} \) are binary variables. Constraints (7)-(9) define that the generated DG power, ramp-up and ramp-down rates shall be within the limits. Equations (10) and (11) represent the minimum-up time and minimum-down time. The cost function of DG is considered as a quadratic cost function, which is defined as:

\[
C(P_{i,t}^{dg}) = a_{i,t}^{dg} + b_{i,t}^{dg} P_{i,t}^{dg} + c_{i,t}^{dg} P_{i,t}^{dg2}
\]

where \( a_{i,t}^{dg}, b_{i,t}^{dg} \) and \( c_{i,t}^{dg} \) represent the cost coefficients of the DG; and \( C(\cdot) \) is the cost function of the DG.

C. Network Modeling

The active and reactive power equations are modelled as follows:

\[
\begin{align*}
P_{i+1,t} = & \ P_{i,t} - 2r_{i,t}I_{i,t} - P_{i,t}^{load} - P_{i,t}^{en} \quad \forall t \\
Q_{i+1,t} = & \ Q_{i,t} - 2r_{i,t}Q_{i,t} - Q_{i,t}^{load} \quad \forall t \\
v_{i+1,t} = & \ v_{i,t} - 2(r_{i,t}P_{i,t} + x_{i,t}Q_{i,t}) + z_{i+1,t}I_{i,t} \quad \forall t \\
P_{i,t}^2 + Q_{i,t}^2 & \leq I_{i,t}^2 \\
v_{\text{min}} & \leq v_{i,t} \leq v_{\text{max}} \\
P_{i,t}^{en,i} & = P_{i,t}^{if} + P_{i,t}^{inf} + P_{i,t}^{bf}
\end{align*}
\]

where \( P_{i,t} \) and \( Q_{i,t} \) are power flows in the lines; \( P_{i,t}^{if}, P_{i,t}^{inf} \) and \( P_{i,t}^{bf} \) are the power from DG, solar PV and load demand at that node \( i \), respectively; \( P_{i,t}^{en} \) is the sum of local generation, i.e., DG, PV, and BESS; \( v_{i,t} \) is the voltage at the \( n \)th node at time \( t \); \( v_{\text{min}} \) and \( v_{\text{max}} \) are the minimum and maximum voltage, respectively; \( I_{i,t} \) is the branch current; \( r_{i,t} \) and \( x_{i,t} \) are resistance and reactance of the line, respectively; and \( z_{i+1,t} = r_{i+1,t} + x_{i+1,t}^2 \).

D. DR Modeling

To implement the DR, firstly the load demand \( P_{i,t}^{load} \) is divided into two categories: flexible demand \( P_{i,t}^{flex} \) and inflexible demand \( P_{i,t}^{inf} \). The inflexible load, which is also referred to as must-run or constant load, has to be supplied all the time. The flexible load has to specify the minimum and maximum energy consumption limits, and the total energy consumption to satisfy the requirement of the consumer.

\[
\begin{align*}
P_{i,t}^{load} = & \ P_{i,t}^{flex} + P_{i,t}^{inf} \\
P_{i,t}^{flex} \leq & \ P_{i,t}^{flex} \leq P_{i,t}^{flex} \quad \forall t \in (t_s, t_f) \\
\sum_{t=1}^{T} P_{i,t}^{flex} & \geq E_{\text{req}}^t
\end{align*}
\]

where \( E_{\text{req}}^t \) is the total energy required; and \( t_s \) and \( t_f \) are the starting and ending time of the load consumption which is given by the user, respectively.

E. Objective Function

The objective is to minimize the expected cost of energy, by which we can also analyze the microgrid with uncertainty. Various price scenarios with their probabilities have been generated and are used to calculate utility power cost. This objective is influenced by the solar PV generation and load demand scenarios as well.

The optimization problem is summarized as (24), which is subject to (1)-(23).

\[
\min \left[ \sum_{i=1}^{Q} \sum_{t=1}^{T} \left( P_{i,t}^{flex} + \sum_{\omega=1}^{\Omega} C(P_{i,t}^{en}) \rho(\omega) \Delta t \right) \right]
\]

where \( P_{i,t}^{flex} \) is the power from the utility grid; \( P_{i,t}^{en} \) is the power from DG connected at \( n \) node; \( \Pi_{i,t}^{en} \) is day-ahead electricity price at time \( t \); \( \rho(\omega) \) is probability of scenario; and \( \omega, \Omega \) are the index and set of scenarios, respectively.

F. Uncertainty Modelling

In general, uncertainty modelling or stochastic programming will be carried out in two stages: scenario generation and scenario reduction.

1) Monte Carlo Scenario Generation

The forecasted data is effective in scheduling the resources, however, there will be errors. Thus the knowledge of maximum and minimum limits of the uncertainty attributes is very important. The microgrid operator decides the uncertain environment. He has to know the maximum and minimum possible values of the unknown quantities to analyze the risk [19] associated with the objective. To know the bounds of the unknown quantities, the ample number of scenarios are generated for solar PV, load demand and electricity price. The Monte Carlo simulation is implemented by using normal distribution function with zero mean and fixed variance to generate the scenarios. These scenarios are further reduced to a set of fixed number scenarios with the classical scenario reduction techniques [20]-[22].

2) Technique of Kantorovich Distance Scenario Reduction

The set of scenarios generated originally are reduced to the desired set, and the distribution of the reduced set is close enough to the original one according to a given probability metric. These reduced scenarios are used by the microgrid operator to schedule the resources. The algorithm for obtaining the reduced number of scenarios is discussed in [20].

The Monte Carlo simulations with normal distribution function are used to generate 500 equiprobable scenarios of solar PV generation, day-ahead electricity price, and load de-
mand. To make the problem tractable, the numbers of scenarios of solar PV generation, day-ahead electricity price, and load demand are reduced to three, nine, and three, respectively. The reduced scenarios depend on the accuracy of the solution and the computation complexity of the problem. The larger numbers of scenarios lead to the complexity, and less numbers of scenarios lead to inaccurate results [7], [23], [24]. These reduced scenarios will be given as input data to the stochastic optimization problem to minimize the expected cost of energy subjected to BESS, network, and DG constraints.

G. Calculation of Nodal Prices

The marginal cost of each node depends on energy consumption at that particular node $\lambda_{n,t}$ power loss $\lambda_{t}^{loss}$, line congestion $\lambda_{t}^{flow}$ and voltage congestion component $\lambda_{t}^{v}$. [25]

$$\lambda_{t}^{i,j} = \lambda_{n,t} + \lambda_{t}^{loss} + \lambda_{t}^{flow} + \lambda_{t}^{v}$$  \hspace{1cm} (25)

where $\lambda_{t}^{i,j}$ is dual variable associated with active power balance equation. Lagrangian function is formulated to calculate the marginal value.

$$L = P_{t} \Pi_{i,t} + (P_{c,t} - D_{c,t} - P_{i,t}^{load})\lambda_{n,t} + L_{c,t}^{load} + L_{v}^{v} + (P_{c,t} - D_{c,t} - P_{i,t}^{load})\lambda_{n,t} + L_{c,t}^{load} + (v_{t} - v_{i}^{min})\lambda_{i,t}^{v} + (v_{t} - v_{i}^{max})\lambda_{i,t}^{v} + (v_{t} - v_{i}^{max})\lambda_{i,t}^{v} + (v_{t} - v_{i}^{max})\lambda_{i,t}^{v} + (v_{t} - v_{i}^{max})\lambda_{i,t}^{v} + (v_{t} - v_{i}^{max})\lambda_{i,t}^{v} + (v_{t} - v_{i}^{max})\lambda_{i,t}^{v}$$  \hspace{1cm} (26)

where $\lambda_{n,t}, \lambda_{t}^{loss}, \lambda_{t}^{flow}, \lambda_{t}^{v}$ are dual variables associated with active power, reactive power, nodal voltage and branch current expressions, respectively; $\lambda_{n,t}, \lambda_{t}^{loss}, \lambda_{t}^{flow}, \lambda_{t}^{v}$ are dual variables of the voltage limits. From (26), we have to calculate $\lambda_{t}^{i,j}$ by solving KKT conditions of (26). The computation and interpretation of nodal prices by solving $dL/dP$ are complex due to non-linearity. Alternatively, nodal prices can be computed based on the concept of marginal loss [26], which are the sum of price at source node and a loss component associated in the connected line.

Once the nodal prices are calculated, the microgrid aggregator sends that information to all the nodes. The resources presented at that node will be scheduled based on the nodal price. The nodal price based resource scheduling can be expressed as:

$$\min_{P_{i}} \sum_{i=1}^{n} P_{i}$$  \hspace{1cm} (27)

where $\lambda_{n,t}$ is nodal price; and $P_{i}$ can be load, BESS or DG power.

III. SIMULATION RESULTS AND DISCUSSION

The proposed approach is tested with a 15-node radial distribution network integrated with solar PV, DG and BESS as shown in Fig. 3. The line resistance $R$ and reactance $X$ data are given in Table I. The base voltage rating of the system is 11 kV, and base current is considered as 200 kVA. The percentage share of load demand at node is tabulated in Table II. Two DGs are connected at node 2 and node 10, respectively, whereas two BESSs are connected at node 4 and node 8, respectively. Solar PV is connected at nodes 5, 13, and 15 with the capacity of 50 kW. The load power factor is considered as 0.9. The voltage limits are considered as 0.9 p.u. and 1.1 p.u. The details of BESS and DG parameters are given in Table III and Table IV, respectively. The optimization problem is modeled as a mixed integer non-linear programming (MINLP) and is solved by using GAMS software, KNITRO solver [27] on an Intel i5, 3.30 GHz processor with 4 GB of RAM.

Fig. 3. 15-node radial distribution network.

TABLE I

| From node | To node | $R$ (Ω) | $X$ (Ω) |
|-----------|---------|---------|---------|
| 1         | 2       | 1.35309 | 1.32349 |
| 2         | 3       | 1.17024 | 1.14464 |
| 3         | 4       | 0.84110 | 0.82271 |
| 4         | 5       | 1.52348 | 1.02760 |
| 2         | 9       | 2.01317 | 1.35790 |
| 9         | 10      | 1.68671 | 1.37700 |
| 2         | 6       | 2.55772 | 1.17249 |
| 6         | 7       | 1.08820 | 0.73400 |
| 6         | 8       | 1.25142 | 0.84410 |
| 3         | 11      | 1.79553 | 1.21110 |
| 11        | 12      | 2.44845 | 1.65150 |
| 12        | 13      | 2.01317 | 1.35790 |
| 4         | 14      | 2.23081 | 1.54047 |
| 4         | 15      | 1.19702 | 0.80740 |

TABLE II

| Node | Load (%) | Node | Load (%) | Node | Load (%) |
|------|----------|------|----------|------|----------|
| 1    | 0        | 6    | 6        | 11   | 8        |
| 2    | 8        | 7    | 6        | 12   | 5        |
| 3    | 6        | 8    | 6        | 13   | 8        |
| 4    | 8        | 9    | 7        | 14   | 8        |
| 5    | 8        | 10   | 7        | 15   | 8        |

The data of electricity price of November 1, 2018 with one hour resolution is from the ComEd [28] as shown in Fig. 4. Monte Carlo scenario generation technique is used to
generate thousands of scenarios for electricity price, and Kantorovich distance reduction technique is used to reduce them to six scenarios. The solar PV generation profiles and the load profiles are shown in Fig. 5 and Fig. 6, respectively. Both are taken for the same day (November 1, 2018) and assumed as forecasted information for this study.

The profiles are modeled via 500 scenarios, and they are further reduced to 3 scenarios in the cases of solar PV and load demand and to 6 scenarios for electricity price without losing their stochastic nature. The profiles of reduced scenarios are shown in Figs. 7, 8, and 9, respectively. The error variance for the generation of scenarios is considered to be 4% for load demand, 5% for electricity price and 8% for solar PV generation, respectively. The probabilities of reduced scenarios for electricity price, solar PV generation, and load demand are (0.214, 0.084, 0.054, 0.344, 0.235, 0.064), (0.34, 0.351, 0.309), (0.232, 0.511, 0.257), respectively.

Various cases are considered in the simulation study to show the effectiveness of the energy management framework for a microgrid with and without DR in nodal pricing scheme.

1) Case 1: the base case study without local generation and BESS. Case 1 is implemented with any local generation and BESS in the network. The power drawn from the grid is shown in Fig. 10 and voltage profile is shown in Fig. 11. The total energy cost per day is $1655 as show in Table V. In this case, the microgrid aggregator has to procure the energy to meet the load demand plus network losses. The maximum and minimum power is 11.16 p. u. and 6.94 p. u., respectively.

2) Case 2: the system study with local generation and BESS. Case 2 is simulated in presence of all the local generations and BESS. The power drawn from the grid and voltage is shown in Fig. 10 and Fig. 12, which is significantly different.
reduced in Case 2 compared with that of Case 1. Voltage profile is also improved in this case. BESS and DG schedules are shown in Fig. 13, where it is seen that both BESS systems are discharged/charged when the electricity price is high/low as expected. SOC is also shown in the Fig. 13(a) and the DG power generation is given in Fig. 13(b). In Fig. 13(a), $P_{c1}$, $P_{c2}$ are charging power of BESS1 and BESS2; $P_{d1}$, $P_{d2}$ are discharging power of BESS1 and BESS2; and $SOC_1$, and $SOC_2$ are SOC of BESS1 and BESS2. In Fig. 13 (b), $P_{dg1}$ and $P_{dg2}$ are power generation of DG1 and DG2. It is observed that the energy management platform schedules the DG generation during the time (e.g., hour 6 to hour 22) when the cost of DG power generation is cheaper compared to power purchased from the grid. In this case, the energy cost per day is $1503, which is less than that in Case 1. The voltage profiles are also improved as observed in Fig. 12 and satisfy the voltage constraints of ADN.

3) Case 3: Case 3 is an implementation of DR. For simulation, it is assumed that the demand at node 3 and node 11 has 50% flexible load which can be consumed at any time during a day. The flexible load demand limits are 0 and 1 p.u. for node 3, and 0.1 p.u. and 0.3 p.u. for node 11, respectively. Figure 14 shows that the flexible load is optimally scheduled during night hours only because the electricity price is low during that time. In this case, the energy cost per day is $1472, which is lower than that in Case 1 and Case 2. The power drawn from the grid is shown in Fig. 10 with a black line. It can be observed that in Case 3, most of the energy is consumed at night time (hour 1 to hour 6), whereas the energy consumption is less during the daytime due to the high price.

4) Case 4: the effect study of nodal prices without local generation and BESS. Case 4 represents the calculation of the nodal prices for the base case. The calculation of nodal price gains much attention nowadays. Nodal prices for 24 hours across all 15 nodes are shown in Table VI. From the

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**TABLE V**

| Case | Cost ($) |
|------|---------|
| 1    | 1655    |
| 2    | 1503    |
| 3    | 1472    |

---

Fig. 10. Power from grid connected at node 1 (Case 1 to Case 3).

Fig. 11. Node voltage for Case 1.

Fig. 12. Node voltage for Case 2.

Fig. 13. Schedules of BESS and DG. (a) Charging/discharging power of BESS and SOC. (b) Scheduled power of DG for Case 2.
table, it can be observed that the cost of energy increases as the sink node is being away from the source node as expected. The nodal price can be visualized as the function of the base energy cost and loss component.

5) Case 5: the effect study of nodal prices with local generation and BESS. Case 5 represents the calculation of nodal prices for the base case with the renewable generation and BESS. The nodal prices for this case are given in Table VII. The variation of nodal prices from node to node is well disturbed due to the local energy resources and charging/discharging cycles of the battery, as it differs compared with Case 4. The nodal price will not affect if the energy cost of all the nodes is the same. In the simulation, the energy cost of solar PV is not considered. The solar PV is connected at nodes 5, 13, and 15, respectively. Hence, the nodal price is reduced from its ancestor node. In this case, we schedule the load demand located at node 3 and node 11 (Case 3) as per the nodal prices calculated in Case 4 by solving the optimization problem given in (26). The load is optimally scheduled through energy management platform as shown in Fig. 14. Note that the energy cost of flexible load (at nodes 3 and 11) is $84 in the case of nodal price based energy management (Case 5). In the case of centralized scheduling, i.e., Case 3, the cost is $81. That is due to the marginal loss component in nodal price based scheduling.

| Hour | Node 3 | Node 11 |
|------|--------|---------|
| 1    | 2.490  | 2.539   |
| 2    | 2.581  | 2.632   |
| 3    | 2.453  | 2.495   |
| 4    | 2.607  | 2.653   |
| 5    | 2.283  | 2.323   |
| 6    | 2.845  | 2.899   |
| 7    | 3.845  | 3.932   |
| 8    | 4.197  | 4.307   |
| 9    | 4.798  | 4.916   |
| 10   | 3.936  | 4.041   |
| 11   | 4.108  | 4.224   |
| 12   | 3.963  | 4.062   |
| 13   | 4.032  | 4.139   |
| 14   | 4.144  | 4.257   |
| 15   | 4.409  | 4.521   |
| 16   | 4.319  | 4.430   |
| 17   | 3.799  | 3.895   |
| 18   | 4.588  | 4.717   |
| 19   | 5.024  | 5.163   |
| 20   | 4.917  | 5.059   |
| 21   | 4.412  | 4.533   |
| 22   | 3.786  | 3.879   |
| 23   | 3.152  | 3.226   |
| 24   | 2.868  | 2.932   |

**TABLE VI NODAL PRICES FOR CASE 4**

**IV. CONCLUSION**

In this paper, we have developed the stochastic energy management framework of a microgrid by considering uncertainties of solar PV generation, electricity price, and load demand. And the framework is tested on a 15-node radial distribution network. The effect of the flexible load is also examined. The energy cost and voltage profiles are improved in the case of local generation and BESS compared with that of the base case scenario. Economic benefit is observed with the integration of DR strategy in energy management. To improve the scheduling accuracy and minimize the financial risk of the microgrid aggregator, a nodal price based mi-
crogrid scheduling is also developed. It is implemented in two stages: firstly, the nodal prices are calculated based on the concept of marginal pricing, and thereafter, the flexible load demands and the local resources presented in the network are optimally scheduled. Further, the calculation and decomposition of nodal prices for unbalanced distribution network will be considered as the extended study.

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