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Original article

Energy management in microgrid using incentive-based demand response and reconfigured network considering uncertainties in renewable energy sources

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ABSTRACT

Demand response (DR) programs and reconfiguration of distribution networks are generally adopted in the energy management (EM) problem of microgrid to enhance the technical and economical features of microgrid. Assuming a fixed configuration of distribution network, DR programs usually optimize the generation cost by encouraging the consumers to reduce their energy demands. Whereas reconfiguration of network is done for a pre-defined generation schedule and energy demand. However, separate incorporation of these two operational techniques in the EM problem may lead to a non-optimal solution. In this paper, a joint framework is proposed to integrate a novel incentive-based DR program and reconfiguration method in the EM problem of microgrid on a day-ahead time frame. The objective of the work is to minimize the fuel cost of conventional distributed generation (DG) and the cost of power purchased from the grid, while maximizing the profit for microgrid operator (MGO). The efficacy of the proposed model is tested on a static model of grid-connected 33-bus microgrid which consists of renewable energy (RE) sources and a conventional DG. To account the uncertainties in RE sources, Hong's (2m+1) point estimation method (PEM) is considered in this work. The result confirms that the incorporation of DR program and reconfiguration method in the EM problem leads to an optimum energy schedule for the microgrid with a minimum lossy network. For the single-day operation of microgrid, it has been found that the power transfer from the grid and power lost in the network is reduced by 10.83% and 34.03% respectively.

Introduction

The growing awareness of environmental and energy challenges lead to diversify the energy autonomy, energy efficiency and energy sources. In order to confront these challenges, the penetration of RE sources in microgrid is rapidly increasing [1–3]. The merits of including RE sources in the microgrid are reduced operational cost, increased profit for investors, diminished greenhouse gas emission and decreased cost of power purchased from the grid [4]. To achieve the maximum welfare, microgrids with RE sources normally operate in the grid connected mode. When an alarming issue such as frequency or voltage collapse occurs in the system, the microgrids are capable of operating in autonomous mode to warrant the reliability during maintenance and/or emergency period [5,6]. However, these advantages can only be acquired by the proper coordination of various players such as MGO, grid operators and energy consumers in the various stages of investment, planning and operation of microgrid.

Energy management comes under the planning and operational stage of microgrid, which can be traditionally defined by the cost driven scheduling problem of conventional and non-conventional DGs with energy storage system to satisfy the energy demand of consumers along with specific constraints [7,8]. The main objective considered by the various researchers working on energy management problem in microgrid revolves around the optimization of some predetermined functions such as minimization of energy cost, regulation of peak load and reduction of electricity bill [9–11]. A robust dual dynamic method has been proposed in [12] for the energy management problem in grid-connected microgrid while considering the uncertainties in RE sources and load demands. A co-optimization scheme for planning of a microgrid has been proposed in [13] to determine the optimal size of distributed energy sources and to minimize the annual fuel cost. In order to determine the optimal size, location, type and economic benefits of microgrids with hybrid RE sources, a mathematical model for its planning and design has been discussed in [14]. In [15], an operating cost minimization problem has been formulated to estimate the optimal size

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Nomenclature

Indices and Sets

H	Total number of time intervals
J	Total number of consumers participating in DR program
N_c	Total number of consumers in microgrid
h	Index of time intervals
j	Index of consumers

Parameters

α^h	Market price of power purchased from the grid ($/MWh)
β_j	Factor representing inability of consumer j to handle the uncomfortable situations
$\gamma^{min/max}$	Minimum/Maximum value of incentive rate for the consumers ($/MWh)
$\mu^h_{solar/wind}$	Mean of solar irradiance or wind speed at h^{th} interval
$\sigma^h_{solar/wind}$	Standard deviation of solar irradiance or wind speed at h^{th} interval
ξ_j	Factor representing the attitude of consumer j towards DR program
a_1, a_2, a_3	Cost coefficients of conventional DG
FF	Fill Factor of PV module
K_v, K_i	Voltage and current temperature coefficients ($V/^\circ C$ or $A/^\circ C$)
MB	Daily budget of MGO ($)
N_{solar}	Total number of PV modules
$P_g^{min/max}$	Minimum/Maximum power output limit of conventional DG (kW)
$P_g^{up/down}$	Maximum upward/downward ramp-rate limits of conventional DG (kW)
P_j^h	Actual power demand of consumer j at h^{th} interval (kW)
P_r	Rated power output of wind-based DG (kW)
$f^h_{solar/wind}$	PDF of solar irradiance or wind speed at h^{th} interval
$P^h_{solar/wind}$	Power output of solar/wind-based DG at h^{th} interval (kW)
V_{MPP}, I_{MPP}	Voltage and current at maximum power point of a PV module
V_{OC}, I_{SC}	Open circuit voltage and short circuit current of a PV module
T_A	Ambient Temperature ($^\circ C$)
T_C	Cell Temperature ($^\circ C$)
T_{OT}	Nominal operating cell temperature ($^\circ C$)
v^h	Wind speed at h^{th} interval (m/s)
v_0	Nominal wind speed (m/s)
v_{cin}	Cut-in wind speed (m/s)
v_{coff}	Cut-off wind speed (m/s)
ψ_j^h	Cost of discomfort to consumer j at h^{th} interval ($)
x_j^h	Power curtailed by consumer j at h^{th} interval (kW)
γ^h	Incentive rate at h^{th} interval ($/MWh)
P^h_{Grid}	Power transferred from grid to microgrid at h^{th} interval (kW)
P_g^h	Power output of conventional DG at h^{th} interval (kW)
P^h_{loss}	Total power loss in distribution network at h^{th} interval (kW)
$x_j^{min/max}$	Minimum/Maximum power curtailment limit of consumer j (kW)
F_1	Cost of power transferred from grid to microgrid ($/day)
F_2	Fuel Cost of conventional DG ($/day)
F_3	Profit of MGO ($/day)

of energy storage systems in microgrid. To avail the techno-economic and environmental benefits from the solar-based microgrid, a microgrid model has been presented in [16] which seeks to achieve the maximum reliability. An optimal control strategy for autonomous microgrid containing RE sources has been investigated in [17], where the objective is to determine the optimal operational schedule and to minimize the cost of power generation while considering the uncertain nature of RE sources. With an aim to maximize the profit and energy consumption of solar-based DG, a grid-connected microgrid has been investigated in [18]. In [19,20], the economic benefit of microgrid consisting of RE sources with battery storage is maximized and the optimal generation schedule of energy sources is determined. Considering the hybrid microgrid involving diesel generators and solar-based DGs, cost of the diesel generators are minimized in [21] and optimal output for all the generating unit is determined for seasonal varied electrical loads. In [22–24], an energy management system for the microgrid has been modelled to provide the optimal operating points (voltage and power) of the microgrid. It can be seen from the above discussed works that the major researchers consider end-customers as a passive participant in the EM problem of microgrid. Introduction of strategies to relief the demand side of network can further optimize the EM problem of microgrid.

Demand response (DR) is referred as the strategies to motivate the energy consumers to modify their normal electricity consumption patterns, so that there is a reduction in energy demand during the peak load period or when the system reliability is at risk. Different forms of DR problem were used in various literature [25–27], in which objective revolves around the optimal operation of microgrids. A multi-follower bi-level mathematical model has been formulated in [28], where the operational cost of microgrid is minimized in upper level and the profits for microgrid owner and DR aggregator are maximized in lower level. An approach to minimize the annual operational cost and maximize the customer satisfaction has been proposed in [29]. To achieve the optimization goal, the shift-able loads present in the microgrid has been coordinated. A novel contractual model has been proposed in [30] to establish a relationship between the utility companies and customers through a specific agreement. A multi-objective optimization problem has been proposed in [31–34], which simultaneously consider the energy scheduling problem and demand response in microgrid. A decentralised optimization problem for the energy trading between DGs and loads in smart microgrid has been discussed in [35]. In [36], a robust DR program is presented to fulfil the objective of energy management in the microgrid while guaranteeing the thermal benefits to the occupants. A price-based DR problem has been formulated in [37] to minimize the payment for energy lost in the system. An optimal planning of an energy hub has been formulated in [38,39] to satisfy the investment, reliability and emission constraints while considering the DR program and uncertainties in wind power, energy price and energy demand. With an objective to formulate a combined management of multiple virtual power plants (VPP), a price-based DR model has been incorporated in [40] to develop the VPPs scheduling problem. A leader–follower Stackelberg game model has been formulated in [41], where a real-time DR algorithm is used to optimally control the load in presence of continuously varying real-time pricing. In [42,43], an incentive-based DR model is incorporated in the energy management problem of grid-connected microgrid, with an objective to minimize the operational cost of microgrid by incentivizing the participation of customers in DR program. A framework to determine the optimal investment strategy and optimal pricing scheme for a microgrid has been presented in [44], which considers the integration of DR, storage systems and RE sources in microgrid. In the literature, it is quite evident that the energy consumers are reluctant to participate in the DR program. A suitable environment to motivate the energy consumers for their active participation in DR program is needed to be explored. In the present work, a novel incentive-based DR program is proposed where the participant will get more benefit if their degree of willingness to participate in the DR program is more. Thus, the incentives provided to the energy consumers will not only depends on their power curtailments, but also on their attitude towards DR program.

Reconfiguration of distribution network is another approach used by the researchers to optimise the energy schedule in the microgrid. It is referred as an optimization problem to modify the structure of network by changing the on/off status of sectional and tie switches, with the aim to improve the overall performance of distribution network. The inclusion of reconfigured network in the energy management problem of microgrid is a complex optimization problem. But it has the tendency to further decrease the operational cost of microgrid by improving the overall performance of distribution network. In numerous literatures, reconfiguration of distribution network has been introduced for reducing network losses [45], optimum load shedding [46], enhancing reliability [47], improving voltage deviation [48] and energy balance [49]. A multi objective energy management problem based on distribution feeder reconfiguration has been introduced in [50], with an aim to find an optimum location and size of RE-based DGs. The work in [51] proposed a methodology to reconfigure an autonomous microgrid during fault operation, with an aim to reduce the power loss in the system and to enhance the loading capacity of microgrid. In [52], a day ahead stochastic model has been proposed for a microgrid in order to determine the optimal reconfiguration and power schedule of generating units considering the electricity market. The uncertainty in the load demand and wind power generation is also accounted using Monte-Carlo method. A two-stage approach for the coordination of generation from RE-based DGs with hourly network reconfiguration in real time scenario has been proposed in [53]. The problem of energy management and reconfiguration has been linked in [54,55], with an objective to minimize the energy losses, cost of operation and greenhouse gas emissions. It also includes the objective to maximize the voltage stability index in microgrid. In [56,57], an optimal reconfiguration is performed while accounting the uncertain nature of RE-based DGs and load demand. The objective of the defined problem is the maximization of voltage stability index and minimization of line losses.

To the best of authors knowledge, there is no such reference which focus on the suitable coordination of the two approach (DR program and reconfiguration) in the EM problem of microgrid. It is quite relevant from the discussed works that the DR programs are implemented in the problem while considering a fixed configuration of the distribution network. Whereas reconfiguration method is applied to the network with pre-defined generation schedule and load demands. This gap in the EM problem of microgrid may lead to a non-optimal solution. A joint framework is proposed in this paper to incorporate the DR program and reconfiguration method in the EM problem of grid-connected microgrid. In a grid-connected microgrid, it is quite often that the power exchange between the main grid and microgrid is scheduled to a contracted value. The contracted value of power exchange is dependent on the technical and economic requirements of the microgrid. The conventional DGs in microgrid can operate in unit power output control (UPC) and feeder flow control (FFC) mode [58]. To maintain a fixed amount of power exchange between the grid and microgrid, it is important for a DG in microgrid to operate in FFC mode. The EM problem in microgrid has been explored in numerous literatures, but none of the work deals with the situation where constant power is being scheduled for an exchange between grid and microgrid. In the proposed work, a conventional DG is made to operate in FFC mode so that a pre-calculated power exchange can be scheduled between grid and microgrid.

The inclusion of RE sources in microgrid reduces the environmental concern and fossil fuel consumption, but it troubled the power system researchers because of its stochastic nature. There are several techniques to deal with the problem of uncertainty, which is broadly classified into analytical, simulation and approximate methods [59]. State of the art methods such as model prediction control [60] and support vector machines [61,62] are the analytical models which provides the sufficient information to MGO for making an optimal decision. However, analytical approach considers some mathematical assumptions to simplify the complex power system problems. Simulation methods like Monte Carlo simulation predicts the uncertainty by imitating the actual process and random behavior of the system. The limitation of the simulation approach is its large computational time to reach convergence. Approximate methods such as point estimate method (PEM) provides a good balance between accuracy and computational speed [63,64]. PEM uses the deterministic methods to solve the probabilistic problem and overcomes the problems arises due to insufficient knowledge of probability functions of random variables. PEM was first proposed by Rosenblueth in 1975 [65] and was later modified by various researchers to obviate the issues related to its efficiency and computational time [66–69]. Hong's 2m PEM has been mostly used in power system problems [70,71], but it fails to provide satisfactory output in presence of large number of input random variables [72]. In this work, Hong's $(2m+1)$ PEM is considered to handle the uncertainties in solar irradiance and wind speed.

To summarize the proposed work with respect to the identified gaps in the literature, the main contributions of the work are listed as follows:

1. A joint framework is introduced to incorporate the DR program and reconfiguration method in the EM problem of microgrid.
2. A novel incentive-based DR program is proposed to enhance the participation of energy consumers in operation and planning of microgrid.
3. UPC and FFC modes of operation is incorporated in the EM problem of grid-connected microgrid.
4. Stochastic nature of RE-based DGs is considered using Hong's $(2m+1)$ PEM.

Mathematical representation of microgrid

The grid-connected microgrid considered in this work is shown in Fig. 1, which consists of conventional DG (diesel generator) and RE-based DGs (solar and wind) for the energy supply. At the load side, demand response model is considered for the energy consumers (C1–C5) who are participating in DR program.

For the proposed work, dynamic information such as day-ahead forecast of solar irradiance, wind speed, electricity price and energy demand of consumers are assumed to be communicated to MGO on a daily basis. So, it is reasonable to consider a static model of microgrid for the day-ahead operation in this work. The mathematical models of RE-based DGs and DR program are presented in the subsequent subsections.

Solar-based DG

Solar irradiance model

The uncertain behaviour of solar irradiance (s^h) in time interval 'h' is considered to follow beta probability distribution function (PDF), which is mathematically expressed as [73],

$$f^h_{solar} = \frac{\Gamma\left(k^h_s + c^h_s\right)}{\Gamma\left(k^h_s\right) + \Gamma\left(c^h_s\right)} \left(s^h\right)^{k^h_s - 1} \left(1 - s^h\right)^{c^h_s - 1} \quad for\ k^h_s > 0;\ \ c^h_s > 0 \tag{1}$$

where Γ symbolizes gamma function; and k^h_s & c^h_s denotes the shape parameters at time interval 'h', which is calculated using μ^h_{solar} and σ^h_{solar} in the corresponding time interval.

$$c^h_s = \left(1 - \mu^h_{solar}\right)\left(\frac{\mu^h_{solar}\left(1 + \mu^h_{solar}\right)}{\left(\sigma^h_{solar}\right)^2} - 1\right) \tag{2}$$

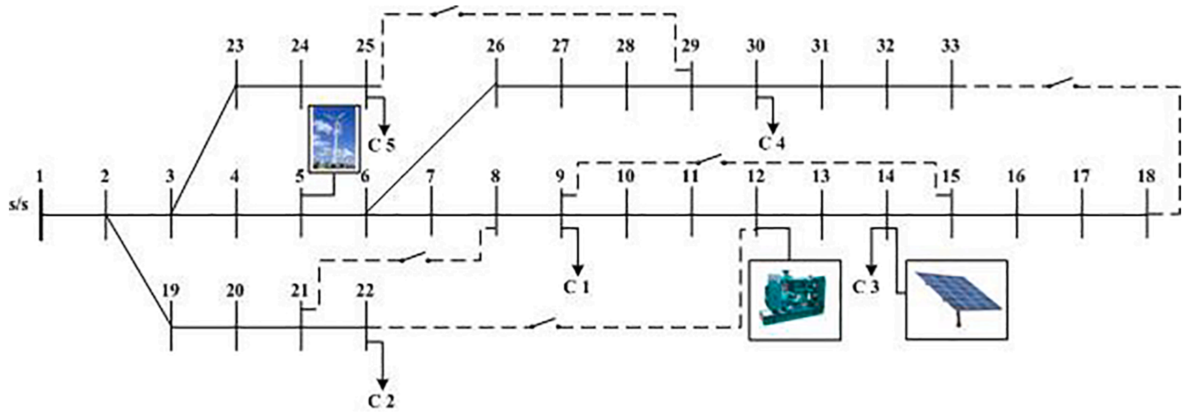

Fig. 1. 33 bus distribution network with DGs and loads participating in DR program.

$$k_s^h = \frac{\mu_{solar}^h c_s^h}{(1-\mu_{solar}^h)} \tag{3}$$

Solar power output model

At each time interval, Hong's $(2m+1)$ PEM is used to consider the uncertainty in solar irradiance by determining its concentration, which is discussed in section "Hong's (2m+1) point estimation method". For the given solar irradiance s^h, the power output from solar-based DG is determined by [73],

$$P_{solar}(s^h) = N_{solar} \times FF \times V_s \times I_s \tag{4}$$

where

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{SC}} \tag{5}$$

$$V_s = V_{OC} - K_v T_C \tag{6}$$

$$I_s = s^h[I_{SC} + K_i(T_C - 25)] \tag{7}$$

$$T_C = T_A + s^h\left(\frac{T_{OT}-20}{0.8}\right) \tag{8}$$

Wind-based DG

Wind speed model

The probabilistic nature of wind speed (v^h) in pre-defined time period is determined using Weibull PDF, which is mathematically expressed as [73],

$$f_{wind}^h = \frac{k_w^h}{c_w^h}\left(\frac{v^h}{c_w^h}\right)^{k_w^h-1} e^{-\left(\frac{v^h}{c_w^h}\right)^{k_w^h-1}} \tag{9}$$

The shape parameters (k_w^h and c_w^h) at the time interval 'h' is dependent on μ_{wind}^h and σ_{wind}^h in the corresponding time interval and is calculated as,

$$k_w^h = \left(\frac{\sigma_{wind}^h}{\mu_{wind}^h}\right)^{-1.086} \tag{10}$$

$$c_w^h = \frac{\mu_{wind}^h}{\Gamma(1+1/k_w^h)} \tag{11}$$

Wind power output model

At the given wind speed (v^h), the output power of wind-based DG is dependent on its performance curve and is calculated as [73],

$$P_{wind}(v^h) = \begin{cases} \left(a(v^h)^3 + bP_r\right) & v_{cin} \leqslant v^h \leqslant v_0 \\ P_r & v_0 \leqslant v^h \leqslant v_{coff} \\ 0 & otherwise \end{cases} \tag{12}$$

where constants a and b are dependent quantities which is obtained as,

$$a = \frac{P_r}{(v_o)^3 - (v_{cin})^3} \tag{13}$$

$$b = \frac{(v_{cin})^3}{(v_o)^3 - (v_{cin})^3} \tag{14}$$

Hong's $(2m+1)$ PEM is used to determine the expected power output of wind-based DG for the particular hour, which is discussed in Section "Hong's (2m+1) point estimation method".

Demand response model

DR programs encourage the energy consumers to curtail their energy demand for the reliable operation of microgrid. However, the reduction of energy demand can result in discomfort for the consumers, which is modelled in terms of cost as [41]

$$\psi_j^h = e^{\beta_j\left(\frac{x_j^h}{P_j^h}\right)} - 1 \tag{15}$$

Eq. (15) shows that the discomfort of the consumers increases exponentially as the amount of power curtailment increases. Here, β_j indicates the inability of consumers to handle the uncomfortable situations, which means that the consumers with less ability to handle the uncomfortable situation will have higher value of β_j.

The participation of consumers in DR program will result in profit for MGO. The role of MGO in DR program is to decide an optimal incentive rates (γ^h) for the consumers participating in DR program. For the given α^h, the profit for the MGO can be decided by

$$C = \sum_{j=1}^{J}\left(\alpha^h x_j^h - \gamma^h x_j^h\right) \tag{16}$$

The first term of Eq. (16) shows the amount of money saved by not buying x_j^h kW from the grid and second term is the total amount of money provided to the consumers as an incentive to take part in DR program.

However, the consumers will participate in DR program only if they will be compensated sufficiently. The benefit for each consumer can be shown by

$$B_j = \gamma^h x_j^h - \psi_j^h \tag{17}$$

It is more obvious to say that the consumers will participate in DR program only if the value of benefit is in positive side.

Problem formulation

Objective function

For the grid-connected microgrid, there are two broad objectives of MGO. First objective deals with the minimization of cost of power supplied to the consumers through grid and conventional DG. The other objective focus on the maximization of MGO's profit obtained from consumers participating in DR program. Mathematically, it is represented as,

$$Min.\ F = w_1(F_1 + F_2) - w_2(F_3) \tag{18}$$

Here, w_1 and w_2 are the weights defined for the two different objectives and the condition needed to be fulfilled before deciding its values is

$$w_1 + w_2 = 1 \tag{19}$$

In this work, the energy trading scheme between grid and microgrid is considered to be unidirectional i.e. from grid to microgrid and the cost of power transferred from grid to microgrid is given by

$$F_1 = \sum_{h=1}^{H} \alpha^h P^h_{Grid} \tag{20}$$

The fuel cost of conventional DG is taken as a quadratic function of its output power, which is presented as

$$F_2 = \sum_{h=1}^{H} \left(a_1 \left(P^h_g \right)^2 + a_2 P^h_g + a_3 \right) \tag{21}$$

The profit function of MGO for the total time interval can be written as

$$F_3 = \sum_{h=1}^{H} \sum_{j=1}^{J} \left(\alpha^h x^h_j - \gamma^h x^h_j \right) \tag{22}$$

Since the objective of MGO is to maximize the profit function, it is logically introduced in the minimizing function given in Eq. (18) with a negative sign.

Operating constraints

1. **Power Balance Equation:** This constraint ensures that in every time interval 'h', the total power output from DGs and power transferred from grid to MG balances the total power demand of microgrid.

$$P^h_{Grid} + P^h_g + P^h_{solar} + P^h_{wind} = \sum_{j=1}^{N_c} P^h_j - \sum_{j=1}^{J} x^h_j + P^h_{loss} \quad \forall h = 1,2,\dots,H \tag{23}$$

2. **Generation Limit:** This constraint defines a generating limit for conventional DG by defining a boundary for its power output.

$$P^{min}_g \leqslant P^h_g \leqslant P^{max}_g \qquad \forall\ h = 1,2,\dots,H \tag{24}$$

3. **Ramp Rate Limit:** It will ensure that the ramp-up and ramp-down rate of conventional DG is within its limit.

$$-P^{down}_g \leqslant \left(P^h_g - P^{h-1}_g \right) \leqslant P^{up}_g \qquad \forall\ h = 2,3,\dots,H \tag{25}$$

4. **Power Curtailment Limit:** This limit will ensure that the power curtailment of each consumer is within the allowable range of power curtailment limit.

$$x^{min,h}_j \leqslant x^h_j \leqslant x^{max,h}_j \qquad \forall\ h = 1,2,\dots.,H \tag{26}$$

Here, $x^{min,h}_j$ and $x^{max,h}_j$ is set as the fraction of actual power demand of consumer 'j' in corresponding time interval and it is given by

$$x^{min,h}_j = \mu_1 P^h_j; \qquad x^{max,h}_j = \mu_2 P^h_j \tag{27}$$

The necessary conditions which is needed to be satisfied before finalizing the values for μ_1 and μ_2 are

$$0 \leqslant \mu_1 < \mu_2; \qquad 0 < \mu_2 \leq 1 \tag{28}$$

The upper limit of μ_2 will ensure that the power curtailment does not exceed the actual demand of consumer. For this work, μ_1 and μ_2 are set to 0 and 0.6 respectively.

5. **Daily Power Curtailment Limit:** To ensure that the consumers should not have to face the higher level of discomfort by participating in DR program, it is necessary to limit the daily interruptible power of the consumers which is given by

$$\sum_{h=1}^{H} x^h_j \leqslant \lambda \sum_{h=1}^{H} P^h_j \qquad \forall\ j = 1,2,\dots,J \tag{29}$$

It is important to mention that the value of λ should be in range of (μ_1, μ_2), so that the presence of this constraint in the problem is justified. Here, λ is taken as 0.4.

6. **Individual Consumer Benefit:** It is necessary for each consumer to get enough incentives, so that the amount of discomfort caused by reducing the power demand can be overcome. This can be ensured by

$$\sum_{h=1}^{H} \left(\xi_j \gamma^h x^h_j - (1 - \xi_j) \psi^h_j \right) > 0 \qquad \forall\ j = 1,2,\dots,J \tag{30}$$

Here, ξ_j is the weighting factor which represents the attitude of consumers towards DR program. It is set in the range of $[0,1]$. Higher value of ξ_j shows that in spite of discomfort caused to consumer 'j', their willingness to participate in DR program is more.

7. **Individual Consumer Benefit Limit:** For more active participation of consumers in DR program, a competitive environment is introduced among the consumers. All the participating consumers have been sorted on the basis of their willingness to participate in DR program, which indicates that the consumer with high value of ξ_j will be ranked first. Then, accordingly their benefits have been restricted by

$$\sum_{h=1}^{H} \left(\xi_j \gamma^h . x^h_j - (1 - \xi_j) \psi^h_j \right) < \sum_{h=1}^{H} \left(\xi_{j-1} \gamma^h . x^h_{j-1} - (1 - \xi_{j-1}) \psi^h_{j-1} \right) \quad \forall\ j = 2,3,..,J \tag{31}$$

This warrants that the consumer with higher value of ξ_j will have more benefit as compared to other consumers.

8. **Incentive Rate Limit:** This is to ensure that the incentive rate defined by MGO is within the prescribed limit.

$$\gamma^{min} \leqslant \gamma^h \leqslant \gamma^{max} \qquad \forall\ h = 1,2,\dots.,H \tag{32}$$

Here, maximum and minimum value of incentive rate is defined by

$$\begin{aligned} \gamma^{max} &= min.\left(\alpha^h\right) \\ \gamma^{min} &= \eta . min.\left(\alpha^h\right) \end{aligned} \tag{33}$$

For this work, the value η is set to 0.4.

9. **MGO Budget Limit:** To ensure that the total incentives paid to consumers should be in the daily budget of MGO, following constraint is introduced in the problem.

$$\sum_{j=1}^{J}\sum_{h=1}^{H}\gamma_j^h x_j^h \leqslant MB \tag{34}$$

Proposed strategy

To integrate the incentive-based DR program (discussed in Section "Demand response model") and reconfiguration method (discussed in Section "Reconfiguration through circular mechanism") in the EM problem, a strategy is proposed in this section to inter-connect the optimisation method, PEM, reconfiguration technique and power flow method. The objective of proposed strategy is to find the optimal value of decision variables in such a way that the operational cost of microgrid can be minimized. The minimized operational cost will lead to the optimal generation schedule of all the DGs present in the microgrid. The decision variables considered for this work are the incentive rate (γ^h) set by the MGO and the power curtailed (x_j^h) by each consumer in the simulation period. To achieve the desired objective, the well-developed methods are adopted in this paper with slight modifications.

Particle Swarm Optimization (PSO) method

The particle swarm optimization method has been developed in 1995 and its various versions are being widely used in the power system problem [74–76]. In this paper, PSO is used as an optimization tool to minimize the objective function given in Eq. (18). Algorithm 1 shows the steps taken to incorporate PSO in the work.

Algorithm 1 Particle Swarm Optimization

```
Obtain the input data of microgrid.
Initialize the position (decision variables) and velocity of N number of particles
  with random feasible solution.
for iteration = 1, 2, ..., iter_max do
    for particle_counter = 1, 2, ..., N do
        Update the position (X) and velocity (V_X) of particle using equation.
            V_X = ω.V_X + c_1.rand.(P^best − X) + c_2.rand.(G^best − X)
            X = X + V_X
        for h = 1, 2, ..., H do
            Perform PEM using Algorithm 2.
        end for
        Check for the violations in the operating constraints and penalize each
          violations by multiplying square of the violations with a suitably high value of
          penalty factor.
        Evaluate the fitness function which includes the objective function, F and
          the penalties.
    end for
    Update the positions of particle best (P^best) and global best (G^best).
end for
Save the optimal values of decision variables.
```

Hong's $(2m+1)$ point estimation method

The basic form of Hong's PEM to account the probabilistic nature of input random variable is Hong's $(K\times m)$ PEM. Using Hong's $(K\times m)$ PEM, the probabilistic information extracted from the central moments of m number of input random variable is concentrated on K points for each variable, named concentrations. With the use of these concentrations and the function F relating input and output variables, an information about the uncertainty associated with the output variables can be estimated. The detailed procedure of basic Hong's $(K\times m)$ PEM is given in Algorithm 2 [72].

Algorithm 2. Hong's $K\times m$ Point Estimation Method

```
Obtain the mean and standard deviation of solar irradiance (s^h) and wind speed
  (v^h) for the corresponding interval h.
Evaluate PDF for solar irradiance and wind speed using Eqs. (1) and (9)
  respectively.
Initialize the raw moments E[(F^h)^j] = 0
for l = 1, 2, ..., m do
    Calculate the central moment using Eq. (38).
    Calculate the standard location using Eq. (37).
    Calculate the weight using Eq. (36).
    for k = 1, 2, ..., K do
        Determine the location p_{l,k} using Eq. (35).
        Using Eq. (4) and Eq. (12), calculate the power output of RE-based DGs
          considering the input random variables as (μ_p1, μ_p2, ...p_{l,k}, ..., μ_pm).
        Calculate the power exchange between grid and microgrid using Eqs.
          (42) and (43).
        Perform reconfiguration, discussed in section 4.3, to get the power output
          of conventional DG in the reconfigured network.
        Calculate the objective function (F^h_{l,k}) using Eq. (18).
        Update the raw moments using Eq. (41).
    end for
end for
With the use of raw moments, compute the mean and standard deviation of
  objective function F at the interval h.
```

A pair of location $p_{l,k}$ and weight $\omega_{l,k}$ defines the k^{th} concentration of a random input variable p_l. The k^{th} value of input variable at which the function F is to be evaluated is known as location. The weight $\omega_{l,k}$ accounts the importance of this evaluation in the final estimation of output variables. For the present work, the $K=2$ number of concentrations $(p_{l,k},\omega_{l,k})$ of the $m=2$ input random variables $p_l \in \{s^h, v^h\}$ are obtained for every time interval 'h'. The location $p_{l,k}$ and weight $\omega_{l,k}$ is determined by

$$p_{l,k} = \mu_{pl} + \xi_{l,k}\sigma_{pl} \qquad \forall\ l = 1,\ldots,m;\ k = 1,\ldots,K \tag{35}$$

$$\omega_{l,k} = \begin{cases} \dfrac{(-1)^{3-k}}{\xi_{l,k}\cdot(\xi_{l,1}-\xi_{l,2})} & k = 1,2 \\[2ex] \dfrac{1}{m} - \dfrac{1}{\lambda_{l,4} - (\lambda_{l,3})^2} & k = 3 \end{cases} \tag{36}$$

where $\mu_{pl} \in \{\mu^h_{solar}, \mu^h_{wind}\}$ and $\sigma_{pl} \in \{\sigma^h_{solar}, \sigma^h_{wind}\}$ are the mean and standard deviation of random variable p_l; and $\xi_{l,k}$ is the standard location. For the $(2m+1)$ scheme of PEM, the standard location is obtained from

$$\xi_{l,k} = \begin{cases} \dfrac{\lambda_{l,3}}{2} + (-1)^{3-k}\sqrt{\lambda_{l,4} - \dfrac{3}{4}(\lambda_{l,3})^2} & k = 1,2 \\[2ex] 0 & k = 3 \end{cases} \tag{37}$$

where $\lambda_{l,j}$ denote the j^{th} standard central moment of the random variable p_l with its corresponding PDF f_{pl}, and is calculated by

$$\lambda_{l,j} = \frac{M_j(p_l)}{(\sigma_{pl})^j} \qquad \forall\ j = 1,\ldots,2K-1 \tag{38}$$

$$M_j(p_l) = \int_{-\infty}^{\infty}(p_l - \mu_{pl})^j f_{pl}\,dp_l \qquad \forall\ j = 1,\ldots,2K-1 \tag{39}$$

In Hong's $(2\times m)$ PEM, the objective function $F^h(l,k)$ has to be evaluated for $K=2$ times for each 'm' input uncertain variable p_l. The point of evaluation includes the k^{th} location $p_{l,k}$ of variable p_l and the mean of remaining (m-1) variables i.e. at the points $(\mu_{p,1}, \mu_{p,2}, \ldots, p_{l,k}, \ldots, \mu_{p,m})$.

In a specific Hong's $(2m+1)$ PEM, the number of evaluation is increased by one. Putting $\xi_{l,3}=0$ in Eq. (35) will yield $p_{l,k}=\mu_{pl}$. So, it is enough to do the evaluation at this location for once, provided that the respective weight is updated by

$$\omega_0 = \sum_{l=1}^{m} \omega_{l,3} = 1 - \sum_{l=1}^{m} \frac{1}{\lambda_{l,4} - (\lambda_{l,3})^2} \tag{40}$$

Finally, by using the weighting factors $\omega_{l,k}$ and the values of $F^h(l,k)$, the j^{th} raw moment of objective function at h^{th} time interval is evaluated as

$$E\left[\left(F^h\right)^j\right] \cong \sum_{l=1}^{m}\sum_{k=1}^{K} \omega_{l,k}\left(F^h(l,k)\right)^j \tag{41}$$

Then, the desired statistical information is evaluated using the estimated raw moments of objective function for the time interval 'h'. Besides calculating the mean and standard deviation, this work also considers the Gram–Charlier expansion [77] to compute the PDF and the cumulative density function (CDF) of the uncertain output.

Reconfiguration through circular mechanism

To achieve the optimal generation schedule, it is important to minimize the power lost in the network. In order to minimize the power lost, an optimal switching schedule is prepared using the minimum-current circular-updating mechanism for reconfiguration [78]. The flow chart of the mechanism is shown in Fig. 2.

In this mechanism, a list of tie-switches is created and a switch is arbitrarily selected from the list for the closing operation. The selected tie-switch is removed from the list. After the closing of selected tie-switch, a network loop will be formed in the original radially configured network. Then, a list of lateral switches and tie-switch present in the loop is created and the best switch in the list is selected for the opening operation. The current flowing through each switch is found by performing the power flow analysis and the best switch is selected as the one through which minimum current is flowing. The list of tie-switches is updated by including the best switch in the list.

This mechanism is repeated till the convergence point is reached. When a negligible change in power loss of network is observed for consecutive n number of iterations and the bus voltages are within the limits, then the point of convergence is achieved.

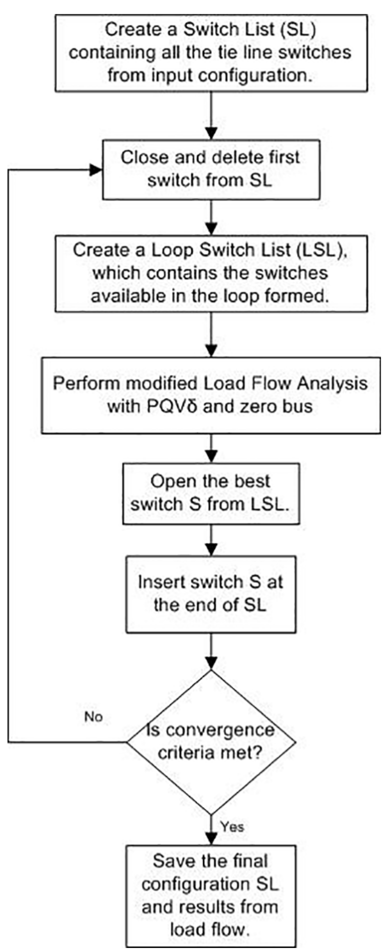

Fig. 2. Reconfiguration with minimum-current circular mechanism method [78].

Power flow method

In a conventional power flow method, the voltage magnitude and angle of slack bus is known; whereas the active and reactive power injections in the bus is unknown. However, in the case of microgrid, a scheduled amount of active and reactive power is injected to microgrid from the main grid. Thus, all the four quantities of bus through which grid is transferring power to microgrid is known and therefore, it will not act as conventional slack bus. To avoid this problem in power flow analysis, two different types of bus is defined as follows [79]:

1. ***PQVδ* Bus**: The bus through which grid and microgrid is exchanging power is denoted as *PQVδ* bus or UPC bus. The active and reactive power transferred to microgrid from the grid is scheduled as

$$P^h_{Grid} = \sum_{j=1}^{N_c} P^h_j - \sum_{j=1}^{J} x^h_j - P^h_{solar} - P^h_{wind} \qquad \forall\ h = 1,2,\ldots.,H \tag{42}$$

$$Q^h_{Grid} = P^h_{Grid}\tan\varphi \qquad \forall\ h = 1,2,\ldots.,H \tag{43}$$

Here, φ is fixed at some angle so that the grid can operate at constant power factor.

2. **Zero Bus:** The bus to which conventional DG is connected is termed as zero bus or FFC bus. The power output through DG connected to zero bus is controlled, so that the power transfer from *PQVδ* bus remains equal to the scheduled power. From Eqs. (23) and (42), it can be seen that

$$P^h_g = P^h_{loss} \qquad \forall\ h = 1,2,\ldots.,H \tag{44}$$

Since, the network loss is unknown prior to analysis, the power injection at this bus are unknown. Thus, all the four quantities of zero bus are unknown.

Therefore, depending on the number of unknown variables in microgrid, the size of Jacobian matrix is modified and then, conventional Newton–Raphson power flow method is carried out. The details of modified Jacobian matrix with the inclusion of *PQVδ* and zero bus is presented in [79].

Simulation results

Input data

The proposed work is investigated on 33-bus 12.66 kV distribution network [80], the single line diagram of which is shown in Fig. 1. The network consists of 32 sectional switches (shown by solid lines) and five tie switches (shown by dashed lines). Since bus 1 is the connection point between grid and microgrid, it is considered as *PQVδ* bus in this work. A conventional DG is connected to bus 12 (zero bus) and is operated in FFC mode to ensure the scheduled power transfer between grid and microgrid through *PQVδ* bus. The parameters of conventional DG (diesel generator) are taken from [79] and is tabulated in Table 1.

Table 1
Attributes of DGs connected to Microgrid.

Type of DGs	Attributes	Values
Solar-based DG [73]	Bus Location	14
	$V_{MPP}(V)$	31.0
	$I_{MPP}(A)$	8.40
	$V_{OC}(V)$	37.8
	$I_{SC}(A)$	8.95
	$T_A(^\circ C)$	25
	$T_{OT}(^\circ C)$	45
	$K_v(V/^\circ C)$	0.1278
	$K_i(A/^\circ C)$	0.00545
	N_{solar}	4231
Wind-based DG [73]	Bus Location	5
	$P^r(kW)$	500
	$v_0(m/s)$	12
	$v_{cin}(m/s)$	3
	$v_{cout}(m/s)$	25
Conventional DG [79]	Bus Location	12
	$P_g^{min}(kW)$	35
	$P_g^{max}(kW)$	300
	$P_g^{up}(kW)$	70
	$P_g^{down}(kW)$	50
	$a_1(\$/kW^2)$	0.0001
	$a_2(\$/kW)$	0.1032
	$a_3(\$)$	14.5216

Table 2
Statistical Data of solar irradiance and wind speed

Hour	Solar Irradiance		Wind Speed [73]	
	$\mu_{solar}(kW/m^2)$	$\sigma_{solar}(kW/m^2)$	$\mu_{wind}(m/s)$	$\sigma_{wind}(m/s)$
1	0	0	9.9000	0.7937
2	0	0	9.3667	0.8021
3	0	0	9.1667	0.8505
4	0	0	9.0000	0.8185
5	0	0	8.7000	0.7550
6	0.0983	0.0307	8.6000	1.0583
7	0.2380	0.1264	9.0000	1.1533
8	0.4094	0.1700	9.0333	1.1504
9	0.5607	0.1923	9.3333	0.9504
10	0.6636	0.2203	9.6000	1.1533
11	0.6949	0.2216	10.1333	1.0066
12	0.6841	0.2128	10.2667	0.8622
13	0.5894	0.1838	7.9667	0.3786
14	0.4349	0.1564	8.0000	0.4583
15	0.2596	0.1103	8.0000	0.5000
16	0.1039	0.0316	7.7333	0.4509
17	0.1030	0.0300	6.9667	0.2309
18	0	0	5.9667	0.3786
19	0	0	4.8333	0.3215
20	0	0	4.4333	0.3215
21	0	0	4.3333	0.4163
22	0	0	4.1000	0.2646
23	0	0	4.0667	0.2082
24	0	0	4.0000	0.1732

Two RE-based DGs are integrated in the microgrid and their attributes are given in Table 1 [73]. To consider the uncertainty in solar-based DG, the historical data of solar irradiance is collected from 100 kWp solar PV plant at IIT Kharagpur, West Bengal, India and is utilized to calculate its mean and standard deviation. The mean and standard deviation of wind speed is taken from [73]. Statistical data of uncertain variables are tabulated in Table 2 and are used to generate their respective PDFs for each hour. The discrete probability distribution of solar irradiance and wind speed at hour 9, 12 and 15 is shown in Fig. 3.

At the peak hours, the total active and reactive power demands of the microgrid are 3715 kW and 2300 kVAr respectively and the total power loss in the system is accounted to be 202.67 kW. The hourly load profile and market price considered for this work is shown in Fig. 4 [37,81]. Considering the reluctant attitude of energy consumers towards DR program, only five consumers are considered for the participation in DR program and their details are given in Table 3.

Results and discussions

The main aim of the proposed work is to demonstrate the benefit of optimized energy management model, when the economically viable incentive-based DR program is incorporated in the optimally configured network of microgrid. To show the impact of DR program and reconfiguration on energy management problem, the proposed model is implemented with and without DR program in original and reconfigured network. The optimal values of various components in the objective function is given in Table 4. The result shows that the inclusion of DR program brings a huge decrement in the power transferred from grid and therefore, the cost of purchasing power from grid is saved considerably.

The hourly power outputs from the supply side of microgrid is shown in Fig. 5. It is clear from the power output of DGs that the dependency of energy consumers on grid is reduced due to the presence of RE-based DGs in the microgrid. However, due to the uncertainties in solar irradiance and wind speed, the power output of RE-based DGs are expected to vary throughout the simulation period. The uncertainties introduced by RE-based DGs in the evaluation of objective function is represented in form of PDF and CDF, which is shown in Fig. 6. The mean and standard deviation in the total operating cost of microgrid comes out to be 2286.38 $/day and 19.5985 $/day respectively.

In addition to the power outputs, Fig. 5 also shows the reduction in hourly power demand after implementation of DR program. The reduction in power demand is due to the energy consumers participating in DR program. Fig. 7 sheds light on the power demand of each consumers participating in DR program. The positive bar of the figure shows the actual power demand and the negative bar depicts the power curtailed by the consumers. It can be seen in the figure that the amount of curtailment is high during the period of peak power demand. This peak shaving of load profile helps the operator by reducing the operational expenses and market price.

The motivation for the energy consumers to curtail their energy demand comes from the incentives offered by MGO. The total energy curtailed by each consumers and the incentives received by them is given in Table 5. The incentives offered to the consumers is proportional to the amount of energy curtailed by them, but the benefit received by them for their participation in DR program is dependent on energy curtailment and their attitude towards the DR program. Thus, the consumer C1, who actively participated in DR program, is benefited more as compared to consumer C5 whose willingness to participate in DR program is least. From the prospect of MGO, the incentives offered to the consumers for overcoming their discomfort should not exceed the cost of purchasing power from grid. Thus, the profit for MGO is decided by the difference between market price of purchasing power from grid and the optimal incentive rate (shown in Fig. 4).

Implementation of DR program in the reconfigured network gives an advantage in terms of minimum power lost in network of microgrid. The improvement in power loss of microgrid can be seen from Fig. 8. During the early hours of day, the minimum energy curtailment of consumers and negligible power output from RE-based DGs resulted in more power loss in the original network. It means that the upstream grid has to supply the maximum of energy demand, which increases the current flowing through network and thus, increases the losses in the network. In the reconfigured network, the power loss is minimized by modifying the structure of network with the help of sectionalizing and tie switches. The optimal switching schedule for the implementation of DR program in microgrid is given in Table 6. As the energy demand of consumers is

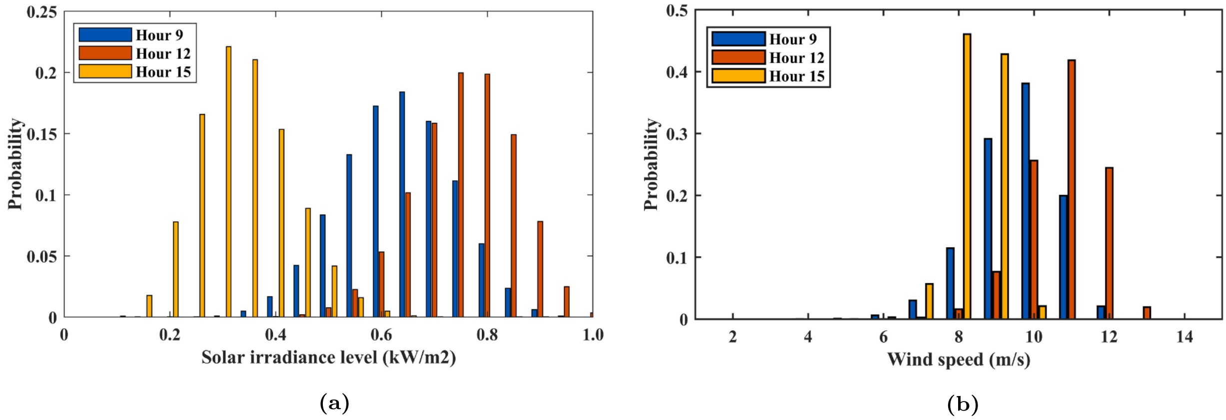

Fig. 3. Probability distribution of (a) solar irradiance and (b) wind speed, at different hours.

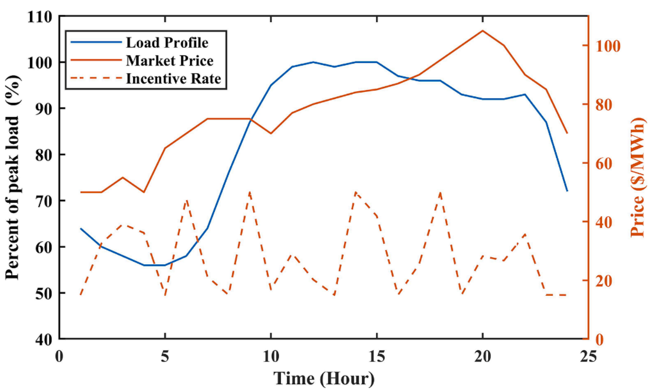

Fig. 4. Hourly load profile [81], market price [37] and optimum. incentive rate.

Table 3
Details of consumers participating in DR program

Consumer	Bus Location	β	ξ
C1	9	1	1.0
C2	22	2	0.9
C3	14	2	0.7
C4	30	3	0.6
C5	25	3	0.4

fulfilled by grid and RE-based DGs, the minimized power loss of the reconfigured network is reflected in the generation of conventional DG and thus, its fuel cost (presented in Table 4) is reduced remarkably.

For the proper operation of microgrid, it is important for an operator to maintain the voltage within the limits. Fig. 9 shows the voltage profile of all the bus in microgrid at every hour. The voltage profile shows the improvement in bus voltages after implementation of DR program in reconfigured network.

Conclusion

In this work, the energy management of microgrid has been performed while incorporating the DR program in a reconfigured distribution network.The PSO method has been used to solve the optimization problem and the obtained result shows that the incorporation of DR program and reconfiguration in the EM problem of microgrid brings optimality at its supply, distribution and load side. For the scheduling interval of 24 h, the proposed optimization model determines the optimal power curtailed by the consumers participating in the DR

Table 4
Effect of proposed work on objective function and energy from different sources

	Before implementation of DR program in original network	After implementation of DR program in original network	After implementation of DR program in reconfigured network
Cost of power transferred from grid to microgrid ($/*day*)	5003.00	4432.30	4429.50
Fuel cost of conventional DG ($/*day*)	621.52	594.74	521.77
Profit for MGO ($/*day*)	0	374.61	374.40
Total energy generated by conventional DG (MWh/day)	2.38	2.18	1.57
Total energy transferred from grid to microgrid (MWh/day)	65.34	58.26	58.26

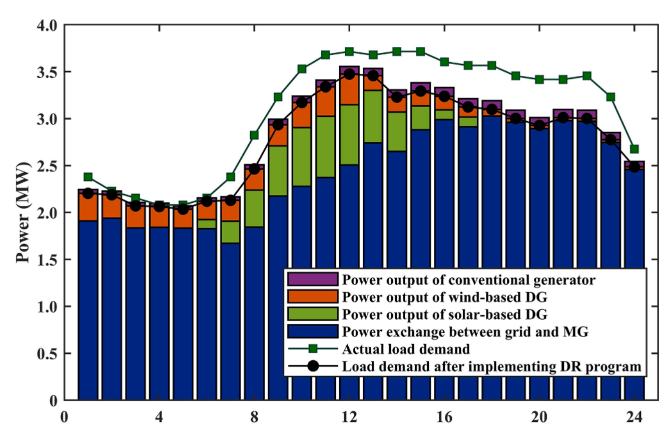

Fig. 5. Power outputs of DGs and grid.

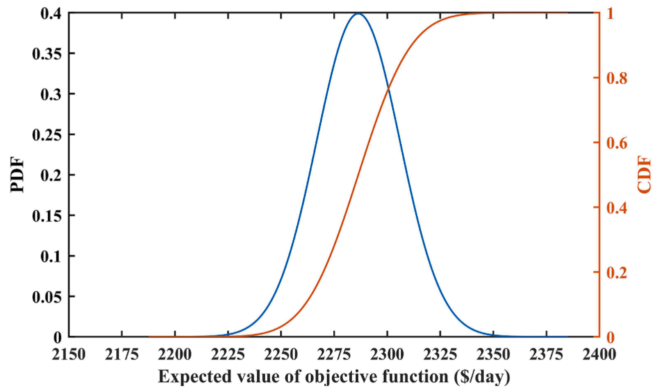

Fig. 6. PDF and CDF of expected operational cost.

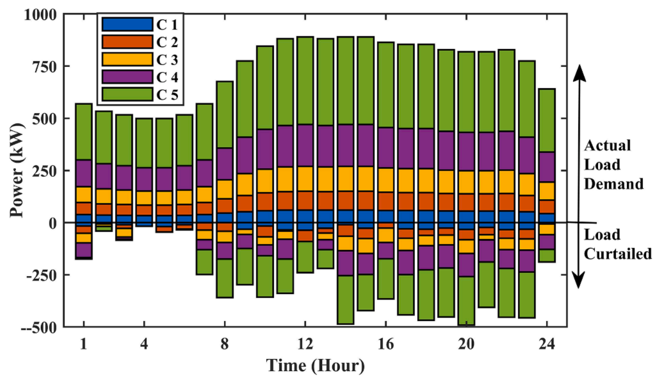

Fig. 7. Impact of DR on load demand.

Table 5
Total energy curtailed and incentives & benefits received by consumers

Consumer	Energy Curtailed (MWh/day)	Percentage of energy curtailed with respect to its actual energy demand (%)	Incentives received ($/day)	Benefit ($/day)
C1	0.4776	40.00	13.9474	13.9474
C2	0.7164	37.66	19.1613	13.5464
C3	0.9552	30.10	26.3694	8.5824
C4	1.5920	25.70	45.0094	0.8827
C5	3.3432	23.24	94.6148	0.3059

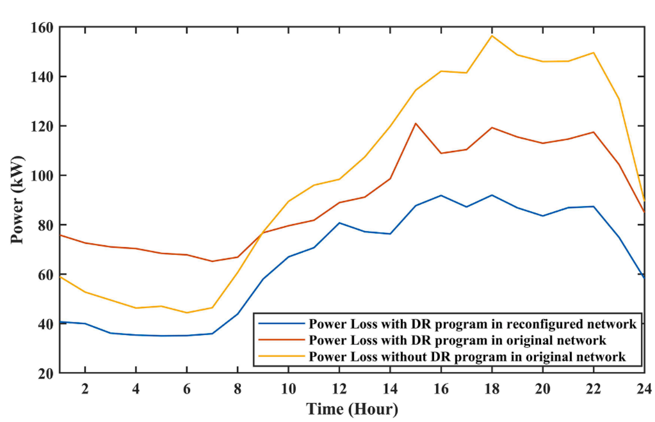

Fig. 8. Effect of DR program and reconfiguration in power loss of microgrid.

Table 6
Optimal switching schedule of reconfigured network

Hour	Branches opened in reconfigured network	Minimum Voltage (p. u.)	Hour	Branches opened in reconfigured network	Minimum Voltage (p. u.)
1	34,10,32,37,7	0.9665	13	35,9,37,6,34	0.9581
2	37,7,14,9,32	0.9677	14	10,28,7,34,35	0.9605
3	37,7,14,9,32	0.9694	15	37,6,34,11,35	0.9556
4	37,7,14,9,32	0.9698	16	10,32,28,7,34	0.9498
5	37,7,14,9,32	0.9699	17	10,32,28,7,34	0.9513
6	34,10,32,37,7	0.9675	18	7,14,9,32,28	0.9585
7	35,32,28,33,34	0.9671	19	7,14,9,32,28	0.9594
8	35,31,28,33,34	0.9693	20	7,14,9,32,28	0.9609
9	34,35,31,37,33	0.9645	21	7,14,9,32,28	0.9591
10	34,35,31,37,33	0.9616	22	7,14,9,32,28	0.9598
11	34,35,31,37,33	0.9612	23	7,14,9,32,28	0.9628
12	34,35,31,37,33	0.9574	24	37,7,14,9,32	0.9610

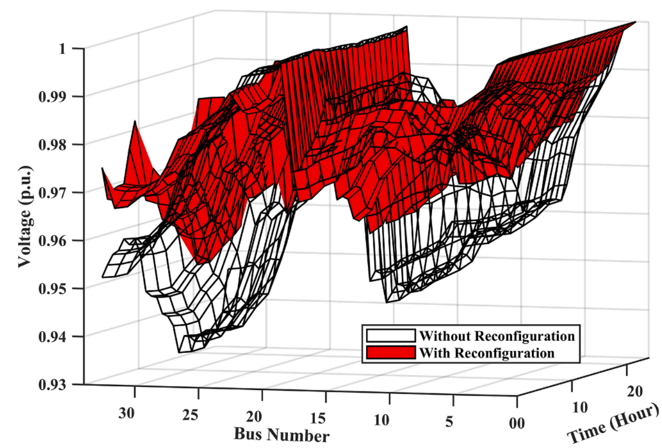

Fig. 9. Effect of reconfiguration on voltage profile.

program and the optimal incentive rate set by the MGO. Introduction of DR program resulted in the reduction of energy demand and thus, the optimality at the load side of microgrid is obtained. Furthermore, the proposed incentive-based DR program maximizes the profit for MGO by encouraging the consumers to participate more actively in DR program and curtail more load during the peak demand period. As the conventional DG present in the microgrid is made to operate in the FFC mode, it is forced to deliver power equal to the power loss in the network. Reconfiguration of distribution network leads to a network with minimum power loss, which can be concluded from the reduced generation of conventional DG. Further analysis reveals that the technical and operating constraints considered in this work has also been satisfied. However, the proposed work can be extended to test its feasibility in the islanded microgrid.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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