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Multi-objective energy management in microgrids with hybrid energy sources and battery energy storage systems

V. V. S. N. Murty* and Ashwani Kumar

Abstract

Microgrid with hybrid renewable energy sources is a promising solution where the distribution network expansion is unfeasible or not economical. Integration of renewable energy sources provides energy security, substantial cost savings and reduction in greenhouse gas emissions, enabling nation to meet emission targets. Microgrid energy management is a challenging task for microgrid operator (MGO) for optimal energy utilization in microgrid with penetration of renewable energy sources, energy storage devices and demand response. In this paper, optimal energy dispatch strategy is established for grid connected and standalone microgrids integrated with photovoltaic (PV), wind turbine (WT), fuel cell (FC), micro turbine (MT), diesel generator (DG) and battery energy storage system (ESS). Techno-economic benefits are demonstrated for the hybrid power system. So far, microgrid energy management problem has been addressed with the aim of minimizing operating cost only. However, the issues of power losses and environment i.e., emission-related objectives need to be addressed for effective energy management of microgrid system. In this paper, microgrid energy management (MGEM) is formulated as mixed-integer linear programming and a new multi-objective solution is proposed for MGEM along with demand response program. Demand response is included in the optimization problem to demonstrate it's impact on optimal energy dispatch and techno-commercial benefits. Fuzzy interface has been developed for optimal scheduling of ESS. Simulation results are obtained for the optimal capacity of PV, WT, DG, MT, FC, converter, BES, charging/discharging scheduling, state of charge of battery, power exchange with grid, annual net present cost, cost of energy, initial cost, operational cost, fuel cost and penalty of greenhouse gases emissions. The results show that CO_2 emissions in standalone hybrid microgrid system is reduced by 51.60% compared to traditional system with grid only. Simulation results obtained with the proposed method is compared with various evolutionary algorithms to verify it's effectiveness.

Keywords: Microgrid energy management, Renewable energy sources, Storage system, Demand response

1 Introduction

For several decades the conventional power generation was transferred to the load centers over long distances. There was huge cost involved for infrastructure development of longer transmission lines. The longer lines have the issues of stability and voltage profile management with reliable and flexible operation. Renewable sources based distribution generation penetration into the grid has the advantages of deferring the construction of new transmission lines and there by the reduction in cost of infrastructure and reduced network losses. With the smart grid technology, the microgrid (MG) model was suggested to coordinate distributed generators with conventional power grid. Establishment of MGs by integrating local renewable energy sources, conventional generators and loads, is a significant step towards Smart Grids [1]. Despite significant benefits, there are some challenges in terms of system configuration, adequate energy storage capacity requirement, energy management, reserve power allocation, and control. One of the critical issues is optimal coordination of hybrid energy sources in MG with the main grid. The economic dispatching of microgrids will affect the operating efficiency [1]. Energy management module of the central controller

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is responsible for ensuring an optimal energy generation in a MG. A novel power scheduling methodology is presented in [2] for economic dispatch in microgrid with integration of renewable energy sources to operation cost of microgrid. The problem of MGEM encompasses both supply and demand side management, unit commitment (UC), while satisfying system constraints, to realize an economical, sustainable, and reliable operation of microgrid. MGEM provides many benefits from generation dispatch to energy savings, support to frequency regulation, reliability to loss cost-reduction, energy balance to reduced greenhouse gas emissions, and customer participation to customer privacy. Generally, the objective is to minimize total microgrid operating cost, but other important objectives such as minimizing gaseous emissions and line losses can be taken into account. Figures 1 and 2 illustrate the architecture of the MGEM system. Usually in such system, some information such as the DG parameters, availability of ESS, the forecasted load demand, RES generations and market electricity price for all hours of day ahead should be known in advance. These data are sent as input parameters to the MGEM optimization algorithm, and the outputs show the best generation schedule for all hours of day ahead. A comprehensive review of energy management and control with hybrid energy sources have been discussed in [3]. A typical framework of microgrid with its key components is shown in Fig. 2. The microgrid is connected to main utility grid through the point of common coupling (PCC) which is under control of MGO. Microgrid agents are assigned the responsibility of energy management of individual microgrid units. Bi-directional communication link is mandatory for optimal energy management in microgrid. Each microgrid unit comprising of battery energy storage device, diesel generator set, PV and wind turbines etc. Each microgrid agent communicates to MGO in real time for optimal energy dispatch. In microgrids, battery energy storage systems are mandatory to deliver power instantaneously, store surplus energy from RES, load curve smoothing, reserve support and optimal energy dispatch etc. with adequate battery ESS the microgrid network become strong and stable grid. It is recommended to run PV and WT units at maximum operating points to maximize objective function. Capacity of BES shall be selected suitable to maintain energy balance in the microgrid and to store excessive surplus energy of renewable energy sources. Diesel generator set in microgrid serves as reserve. DG sets shall be sized adequately to fed emergency loads i.e., critical loads during emergency situation i.e., main grid and renewable energy sources are not available. Microgrid operator needs to compute load and generation uncertainties accurately for optimal dispatch of energy in microgrids. In the MGEM model, the ESS state of charge (SOC) in each hour depends on the SOC in the previous hour. Therefore, the ESS SOC in each two consecutive hours is correlated and the optimization problem is subjected by a dynamic constraint. Up to now, two main methods, namely centralized energy management (CEM) and decentralized energy management (DEM) have been proposed in various literatures to solve MGEM problem. The structure of a CEM system includes a central controller which solves a global optimization problem with regard to selected objectives and constraints, but DEM system is based on multi-agent systems. Various optimization formulations have been proposed for CEM of MG [4]. These formulations are often aimed at minimizing operating costs [5–13] or at minimizing both the operating cost and emissions [14–18]. Sometimes objectives such as load curtailment index [19], voltage deviation [20], power losses [21], fuel consumption [22], and grid power profile fluctuations [23] are also considered as the objective function of MGEM problem. Although the objective function of the energy management problem in [24] includes several objectives, such as minimizing grid voltage deviations, power losses, security margins and energy imported from the main grid; and the objective function presented in [25], includes four objectives of minimizing customer's costs, emissions, load peak and load curve fluctuations, but the proposed MG configuration only consist of renewable sources and electrical vehicles, and controllable DGs or ESS are not considered. Furthermore, the main objective function is formulated in the

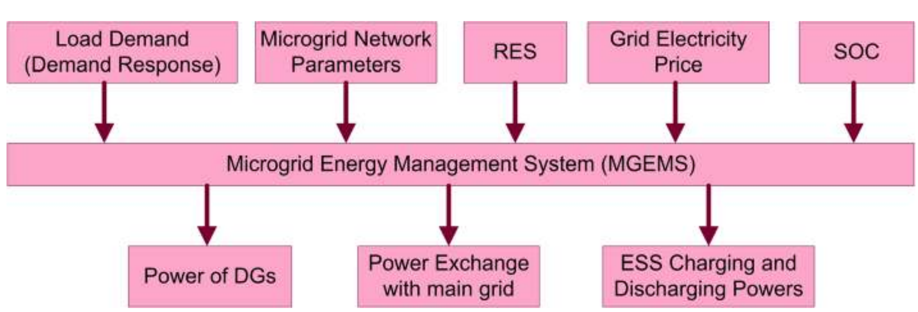

Fig. 1 Microgrid energy management system

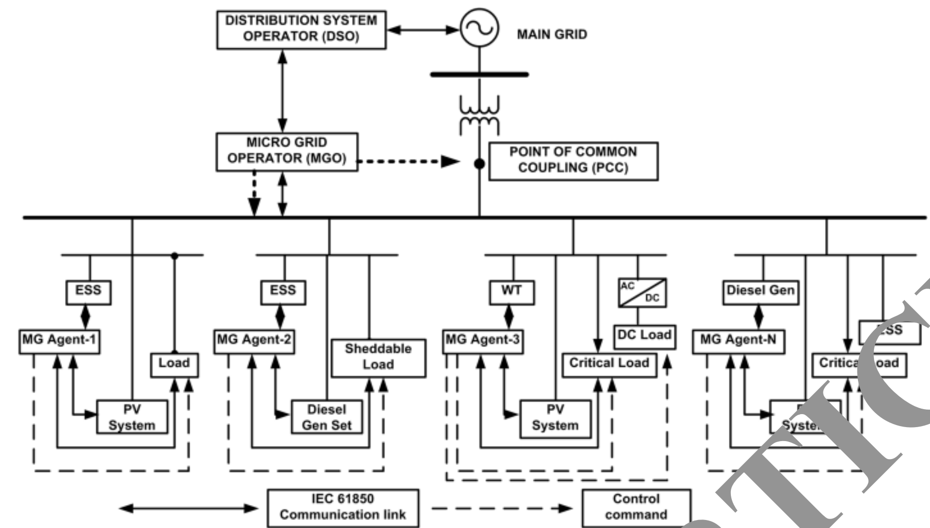

Fig. 2 Typical framework of microgrid

simplest form, i.e., in the form of a weighted sum of objectives, as well as the MG configuration is also ignored. The inadequacy of objective functions and constraints in most existing models affects the accuracy and effectiveness of the MGEM results, and, despite the computational effort, the results are not efficient [1]. Additionally, these models do not specify how to deal with the ESS and the dynamic mode of MGEM problem as well as the unit commitment of controllable DGs have not been identified in them and only addressed the economic dispatch problem. Therefore, a more comprehensive model for MGEM is needed [1, 12]. Different optimization techniques have been used to solve the CEM problem in MGs [4]. These techniques include classical methods (linear programming [illegible], 18, 22, 26, 27], nonlinear programming [20, 24, 25], dynamic programming [3] and stochastic programming [16, 28, 29], Heuristic approach [17, 30], evolutionary approach [6, 7, 14, 19, 31], model predictive control approach [9, 12, 29], and robust optimization [10, 11, 15]. A generalized architecture proposed for energy management in microgrids [6] based on multi agent system. Multi period imperialist competition method used in [8] for energy management in microgrids to minimize cost of generation. Optimal power dispatch in islanded microgrid presented in [32] considering distributed energy sources and storage systems. In hybrid power system with PV and wind based energy sources, ESS used to smoothing the load and generation curve. In [33], smoothing control approach proposed to regulate power fluctuations in hybrid power system. Economic dispatch problem among multiple microgrid clusters was presented in [34]. In each microgrid, energy management problem solved and simultaneously co-operate with adjacent microgrid clusters. The problem of economic scheduling on multi-time scale with PV and wind based renewable energy sources considering deferrable loads were discussed in [35] for energy exchange and reserve allocation. Scheduling of energy among wind, nuclear, gas based DG, and hydro sources along with reserve management problem is solved using MATPOWER tool [36]. Energy management among multiple microgrids having heat and electricity energy systems was discussed in [37] using distributed optimization algorithm. Demand response program also included in the optimization problem. Economic strategy for power dispatch to reduce operating cost in AC-DC hybrid microgrid presented in [38] considering uncertainty of load demand and renewable energy sources. Uncertainties were modeled using Hong's two- point estimate approach. The economic dispatch problem was solved using combination of PSO and fuzzy logic system. Energy management in community microgrids was presented in [39] considering distribution generation and electrical load demand to minimize total cost. Photovoltaic and battery storage system integrated to grid connected microgrid [40]. Authors have formulated the dispatch problem as MILP with an objective of maximization of PV production. Genetic algorithm used in [41], for power dispatching in grid connected microgrid for minimizing operating cost of PV, WT, FC, MT and grid. Economic dispatch problem was formulated as a quadratic programming problem in grid connected microgrid [42] with an objective of minimization of cost of grid, DG and battery storage system. Dynamic programming based economic dispatch in grid connected microgrid was presented in [43] for minimization total operation cost. Economic schedule of grid connected microgrid with hybrid energy sources was carried out based on distributed model predictive control algorithm and solved using mixed integer linear programming [44]. In [45], power dispatch in grid connected microgrid with

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PV/BES was obtained using quadratic programming to minimize grid cost. Power dispatch strategy of island microgrid consists of diesel generator, PV and battery energy storage system presented in [46] to minimize operation cost and optimization problem was formulated as MINLP. Capacity of PV/WT/DG/FC/BES in island hybrid system was determined using particle swarm optimisation to minimise net present cost [47]. Dispatch of PV/DG/BES in isolated microgrid was presented in [48] to minimise annual system cost. Two-stage min-max-min robust optimal dispatch model presented in [49] for island hybrid microgrid considering uncertainties of renewable energy generation and customer loads. The first stage of the model determines the startup/shutdown state of the diesel engine generator and the operating state of the bidirectional converter of the microgrid. Then, the second stage optimizes the power dispatch of individual units in the microgrid. The column-and-constraint generation algorithm was implemented to obtain dispatching plan for the microgrid, which minimizes the daily operating cost. A decomposition-based approach was proposed to solve the problem of stochastic planning of battery energy storage system under uncertainty to minimize net present value [50]. Cutting-plane algorithm used to solve unit commitment problem in isolated microgrid [51]. Simulation results were compared with deterministic and stochastic formulations. In [52], chaotic group search optimizer with multiple producer used to solve dispatch problem in island microgrid to minimise energy cost and voltage deviation. Authors have considered uncertain power output of wind turbine and photovoltaic cell in the optimization problem as interval variables. Two stage methodology proposed in [53] for dynamic power dispatch in isolated microgrids with micro turbines and energy storage devices considering demand side management. In first stage, dominance based evolutionary algorithm used to find pareto-optimal solutions of the problem. The best solution was obtained using decision analysis in the second stage. Probabilistic nature of load demand and renewable energy sources were taken care in energy scheduling problem of isolated microgrid [54], which was solved using mixed integer linear programming. Authors have considered objective function as minimization of fuel cost of micro turbines, spinning reserve cost, and BES.

Application of robust optimization methods to energy management in microgrids have been addressed on grid connected systems. The critical issues in this type of microgrid: power balance and reserve power allocation. Further, many researchers have solved energy management problem considering objective function of total operation cost minimization. It can be deduced from the comprehensive review on the most recent literature that a great deal of studies have mainly focused on energy scheduling implementation and operation cost minimization for the purpose of improving microgrid performance.

In summary of above research gaps, intent of this paper is development of optimal energy dispatch model for microgrid in grid connected and off-grid modes with hybrid energy sources and energy storage devices. In order to investigate the impact of the flexible loads on system operation, the collaboration of demand response strategies are evaluated in detail. In this paper, a multi-objective solution is formulated as mixed integer linear programming for optimal energy management of microgrid. The multi-objective function consists of minimizing the total operating cost, cost of emissions and cost of power loss. The large number of decision variables and the dynamic model of the MGEM problem dramatically increase the execution time of multi-objective optimization algorithms. Therefore, in this work a global criterion method is proposed and new single objective problem obtained from this method. The main contribution of this paper work is given as below:

The main contributions of this paper are as follows:

i) A multi-objective optimization solution is proposed for microgrid energy management problem with hybrid energy sources and battery storage system.
ii) Hybrid energy sources such as photovoltaic (PV), wind turbine (WT), diesel generator (DG), micro turbine (MT), fuel cell (FC) and energy storage system (ESS) are integrated into to the microgrid.
iii) The multi-objective function proposed in this paper for determining the best optimal capacity of energy sources and storage system.
iv) Two modes of microgrids i.e., grid connected and standalone microgrid are studied in this work.
v) Proposed a fuzzy inference system for optimal scheduling of charging/discharging of ESS.
vi) Techno-economic benefits of microgrid operation is further enhanced through demand response program.
vii) The proposed method is scalable and can be implemented in real systems interconnected with distribution network.
viii) The proposed scheme provides end user flexibility.
ix) Optimization algorithms: PSO, GA, DE, TS, TLBO, ICA, BBO and ABC have not been reported in the literature for energy dispatch in microgrids. A comprehensive comparison among these algorithms has been reported in this work. Further, performance of the proposed methodology is compared with evolutionary optimization algorithms.
x) Simulation results are obtained for optimal capacity of PV, WT, DG, MT, FC, BES, converter, state of charge of BES, grid power exchange, levelized COE,

NPC, capital cost, replacement cost, O&M cost, fuel cost, power loss cost and emission penalty.

2 Modeling of hybrid energy sources in microgrid

Hybrid power system comprise of PV/WT/DG/MT/FC/BES could be an economic solution to produce clean energy to match with time varying realistic load demand and therefore unmet energy demand shall be zero at any instant of time. Modelling of each component is explained in this section.

2.1 Modelling of PV system

Output power of PV array can be calculated as follows:

$$P_{pv} = P_{pv}^{r} f_{pv}\left(\frac{\overline{G_T}}{\overline{G_{T,\ STC}}}\right)\left[1+\alpha_p\left(T_c - T_{c,STC}\right)\right] \tag{1}$$

$$T_c = T_{a+}\left(T_{c,NOCT} - T_{a,NOCT}\right)\left(\frac{G_T}{G_{T,NOCT}}\right) \times \left(1 - \frac{\eta_{mp}}{0.9}\right) \tag{2}$$

2.2 Modelling of wind power

Power output from wind turbine is calculated using following equations:

$$P_w = P_r \begin{cases} 0, v \le v_{ci} \\ P_n(v), v_{ci} < v < v_r \\ 1, v_r < v < v_{co} \\ 0, v > v_{co} \end{cases} \tag{3}$$

$$P_{wt} = \eta_{wt} P_w \tag{4}$$

2.3 Modelling of BES

Integration of renewable generation and electric vehicles to the grid makes it more difficult to maintain energy balance and can result in large frequency deviations on a microgrid. Ancillary services provide the supplementary resources required to maintain the instantaneous and ongoing balance between sources and load. ESS can provide regulating reserve, a type of ancillary service, by modulating active power for frequency control, to reduce frequency deviations caused by sudden changes in renewable generation. The rating of ESS is affected by battery configuration, back-up period, temperature, battery life time, depth of discharge, reserve power requirement and renewable energy sources etc. Charging and discharging schedule of battery is expressed in eqs. (5–6).

$$P_{BES}(t) = P_{ch}(t) \quad if\ P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + P_{FC}(t) + P_{MT}(t) + P_g(t) - P_d(t) \ge 0 \tag{5}$$

$$P_{BES}(t) = P_{dch}(t) \quad if\ P_{PV}(t) + P_{WT}(t) + P_{DG}(t) + P_{FC}(t) + P_{MT}(t) + P_g(t) - P_d(t) < 0 \tag{6}$$

At particular instant BES can be operate in one mode only i.e. charging or discharging state. Charging and discharging power of battery is calculated as below:

Charging mode:

$$E_{ch}(t) = \left(\frac{P_{DG}(t)+P_{WT}(t)+P_{FC}(t)+P_{MT}(t)-P_d(t)}{\eta_{Conv}} + P_{pv}(t)\right) * \Delta t * \eta_{ch} \tag{7}$$

$$SOC(t) = SOC(t-1)(1-\sigma) + E_{ch}(t) \tag{8}$$

Discharging mode:

$$E_{dch}(t) = \left(\frac{-P_{DG}(t)-P_{WT}(t)-P_{FC}(t)-P_{MT}(t)+P_d(t)}{\eta_{Conv}} - P_{pv}(t)\right) * \Delta t * \eta_{dch} \tag{9}$$

$$SOC(t) = SOC(t-1)(1-\sigma) - E_{ch}(t) \tag{10}$$

$SOC(t)$: battery state of charge at time "t".

$SOC(t-1)$: battery state of charge at time "t-1".

Two independent factors may limit the lifetime of the storage bank: the lifetime throughput ($Q_{lifetime}$) and the storage float life ($R_{batt,\ f}$). While selecting storage system, operator can choose whether the storage lifetime is limited by time, throughput, or both. If the storage properties indicate that the storage life is limited by throughput, operator need to replace storage bank when its total throughput equals to it's lifetime throughput. The storage bank life is determined using the following equation:

$$R_{batt} = \begin{cases} \dfrac{N_{batt} Q_{lifetime}}{Q_{thrpt}} & if\ limited\ by\ throughput \\ R_{batt,f} & if\ limited\ by\ time \\ \min\left[\dfrac{N_{batt} Q_{lifetime}}{Q_{thrpt}}, R_{batt,f}\right] & if limited\ by\ throughput\ and\ time \end{cases} \tag{11}$$

The float life of the storage system is the length of time it will last before it needs replacement. When you create a storage system you can choose whether to limit its life by time, by throughput, or by both. The float life does not apply if you have chosen to limit the storage lifetime by throughput only. The battery wear cost can be determined using the following equation:

$$C_{bw} = \frac{C_{rep,batt}}{N_{batt} Q_{lifetime} \sqrt{\eta rt}} \tag{12}$$

2.4 Modelling of power converter

Converter is required in hybrid systems contains AC and DC elements. Rating of inverter is determined using eq. (13) [30].

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$$INV_{cap} = (3L_{ind}) + L_0 \tag{13}$$

2.5 Generator capacity

The output power of each controllable unit must satisfy its upper and lower limits as follows.

$$P_{DG}^{min} \le P_{DG}(t) \le P_{DG}^{max} \tag{14}$$

$$P_{MT}^{min} \le P_{MT}(t) \le P_{MT}^{max} \tag{15}$$

$$P_{FC}^{min} \le P_{FC}(t) \le P_{FC}^{max} \tag{16}$$

2.6 Demand response

Microgrid operator offers incentive to consumers against participation in demand response program. Incentive cost for demand response is given below:

$$IC_t^{DR} = \sum\nolimits_{b \in nb} k_{DR} P_{b,t}^{DR} \tag{17}$$

3 MGEM problem modeling

Optimization model for microgrid energy management problem is presented in this section with multi-objective as defined in eq. (18) and constraints as follows.

3.1 Objective function

Decision problems with several conflicting objectives, or multi-objective optimization, unlike standard optimization problems, do not have a single solution; rather, all the optimal possible points that satisfy the constraints can be accepted as an optimal. The choice of a single point from these optimal points (the Pareto Front) is the responsibility of the so-called decision-maker. For the proposed MGEM, the solution of the MO process comes to find the unit commitment and output power generation of each controllable DGs, the power exchanged with the main grid, and the charging and discharging power of the ESS for all hours of day ahead to ensure that the certain objectives are achieved while satisfying the constraints [55]. Although, due to the presence of RES, the environmental issue of the micro-grid is less than traditional power generation systems, it cannot be ignored in the definition of the objective function. Also, due to low voltage and high resistance of MG lines, power losses cannot be ignored. This work aims to define, implement and validate energy management in microgrids with hybrid energy sources. The power dispatch strategy is formulated as mixed integer linear programing problem and implemented in GAMS using CPLEXS solver. The proposed multi-objective function of the MGEM problem is given in eq. (18).

$$min\{F_1(P_g), F_2(P_{DG}), F_3(C_{RES,i}(P_{RES,i}(t))), F_4(CE), F_5(DR), F_6(P_{loss})\} \tag{18}$$

$$F_1(P_g) = \sum\nolimits_{t=1}^{n} \{C_g(t) P_g(t)\} \tag{19}$$

$$F_2(P_i) = \sum\nolimits_{t=1}^{n} \left\{ \sum\nolimits_{i=1}^{NDG} FC_i(P_i(t)) + S_i(t) \right\} \tag{20}$$

$$F_3(C_{RES,i}(P_{RES,i}(t))) = (a_{RES,i} P_{RES,i}(t)^2 + b_{RES,i} P_{RES,i}(t) + C_{RES,i}) \tag{21}$$

$$F_4(CE_i) = \sum\nolimits_{t=1}^{n} \left\{ \sum\nolimits_{i=1}^{N} \sum\nolimits_{j=1}^{M} (EF_{ij}.P_i(t)) ce_{dg} + \sum_{j=1}^{M} (EF_{gj}.P_g(t)) ce_g \right\} \tag{22}$$

$$F_5(DR) = IC_t^{DR} \tag{23}$$

$$F_6(P_{loss}) = K_e TPL \tag{24}$$

$$FC_i(P_i(t)) = (a_i P_i(t)^2 + b_i P_i(t) + C_i) \tag{25}$$

$$S_i(t) = SC_i \ if \ \theta_i(t) - \theta_i(t-1) = 1 \tag{26}$$

Where, $F_1(P_g)$ is cost of main grid, $F_2(P_i)$ is fuel cost and start-up cost of controllable generators, $F_3(C_{RES,\ i})$ is cost of renewable based distribution generation, $F_4(CE_i)$ is cost of green house gas emissions, $F_5(DR)$ is incentive cost of demand response and $F_6(P_{loss})$ is cost of real power loss in microgrid. $P_g(t) = 0$, if the MG operates in island mode, $P_g(t) > 0$ if the power is purchased from the main grid, and $P_g(t) < 0$ if the power is sold to the main grid. $\theta_i(t) = 1$, if the ith unit is on and $\theta_i(t) = 0$, if it is off at time t.

3.2 Constraints

The microgrid energy management system is affected by a number of constraints as follows.

Power balance constraint: The balance between generation and demand is maintained as mentioned in eq. (27). Net power generation shall be equal to total load demand and losses. Therefore, unmet energy at any time shall be zero.

$$\begin{aligned} P_D(t) + P^{DR}(t) + P_{loss}(t) + P_{ch}(t) \\ = P_{grid}(t) + P_{DG}(t) + P_{WT}(t) + P_{PV}(t) \\ + P_{MT}(t) + P_{FC}(t) + P_{dc}(t) \end{aligned} \tag{27}$$

Generation capacity constraint: The output power of each controllable generator unit must satisfy its upper and lower limits as specified in eqs. (14)–(16).

Consumer Loads: Based on process/operation requirements loads are categorized as critical loads, non-critical loads, transferrable, sheddable and non-sheddable loads etc.

$$0 \le P_{L,t}^{shed} \le P_{L,t}^{shed,\ max} \tag{28}$$

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$$0 \le P_{L,t}^{trans} \le P_{L,t}^{trans,\,max} \tag{29}$$

$$0 \le P_{b,t}^{DR} \le \propto P_{D\ b,t} \tag{30}$$

Charging-discharging constraints:

Charging and discharge power of BES shall be less than nominal capacity of BES.

$$0 \le P_{ch}(t) \le P_{BES}^{r} \tag{31}$$

$$0 \le P_{dch}(t) \le P_{BES}^{r} \tag{32}$$

The output power of each energy storage unit must satisfy charge-discharge limits as follows.

$$ES_i^{min} \le ES_i(t) \le ES_i^{max} \tag{33}$$

Where, ES_i^{min} and ES_i^{max} represent the minimum and maximum exchanged power of energy storage unit i, respectively.

$ES_i(t) > 0$ *energy storage unit is discharging mode*

$ES_i(t) < 0$ *energy storage unit is charging mode*

Dynamic performance of the energy storage units:

$$SOC_i(t+1) = SOC_i(t) - \frac{\eta_i ES_i(t)}{C_i} \tag{34}$$

$$SOC_i^{min} \le SOC_i(t) \le SOC_i^{max} \tag{35}$$

Where, SOC_i, η_i and C_i represent the state of charge, charging or discharging efficiency and capacity of the energy storage unit i, respectively. Battery life time shall be limited as given in eq. (11).

4 Scheduling of ESS

Energy storage is needed to overcome the intermittent nature of RES power output, enhance the power quality and improve the controllability of power flow. Since in a MG, the coordination of the energy storage system with the generating units can improve the energy efficiency and the voltage and frequency stability of the system, the attention to these systems is significantly increasing. A fact appears in MGEM problem that the SOC of battery in each hour depends on the SOC in the previous hour. Hence this problem is constrained by a dynamic programming [3]. Therefore, if we can determine the amount of charging and discharging power of the ESS before optimizing the MGEM problem, the computational burden of problem solving will be greatly reduced. Smart decision about the amount of charge and discharge of the energy storage units should be such that they are allowed to discharge only when there is no very big load predicted within the future periods. In order to minimize energy costs and improve MG operation indices, the central controller must find the best pattern for charging and discharging the ESS using some information about the forecasted main grid power prices, load demand and RES generation levels. Fuzzy logic is used for optimal scheduling of BES.

4.1 Fuzzy logic based ESS scheduling

In fact, ESS scheduling as a part of MGEM problem is a decision-making process in which, due to the combination of many scenarios, it seems inevitable to use a fuzzy inference system that is able to decide whether the ESS should be charged or discharged and at which rates.

4.2 Fuzzification process

The fuzzy inference system used in ESS scheduling is based on the following parameters as inputs.

- ESS State of Charge (SOC)
- Normalized Electricity Prices (NEP)
- Normalized Remaining Load (NRL) - As the difference between load demand and RES generations

The following membership functions specify the degree of membership for the input and output patterns sent to the fuzzy inference engine. The terms VL, L, M and H in input membership functions are very low, low, medium and high, respectively. Furthermore, the terms HC, MC and LC, in output membership function respectively mean high, medium and low charging; the terms HD, MD and LD, respectively mean high, medium and low discharging and the term ZR indicates that the BES is neither charged nor discharged.

4.3 Inference engine

After determining the fuzzy rules, inference engine using these rules converts the fuzzy input to the fuzzy output. The fuzzy rules applied in the inference engine are shown in Table 1 of the appendix. In the fuzzy rule set, charging priority relates to the low NRL and NEP periods and discharging priority relates to the high NRL and NEP periods to avoid expensive energy purchases from main grid.

4.4 Defuzzification

After calculating the fuzzy output by the inference engine, the next step is the defuzzification into an output signal of charging or discharging of the ESS and its rate. Here, the defuzzification is done by the center of mass of the fuzzy outputs.

5 Implementation of demand response

Demand side participation is an important tool for scheduling generation and consumption at lower cost and higher security [28]. Demand response (DR) is one

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of the most popular methods of demand side participation that encourages the customers to adjust their elastic loads in accordance with the operator's request or price signals. Usually, the elastic loads are classified into shiftable and curtailable loads. The benefits of DR for customers are the financial benefits and the continuity of electricity. It also has benefits for MG operator such as cost savings, optimal operation, reducing the use of costly generators, reduced purchases of expensive power from the main grid and load curve flattening. In general, DR programs are classified into two main categories of time-based rate (TBR) and incentive-based (IB) programs. In TBR programs, the motivation to change customer demand is related to the difference in electricity prices at different times, but in IB programs, incentive and penalty options are the motivation behind the change in customer demand.

5.1 Load control in the time-based rate DR programs

In this DR program, customer load demands change with respect to the electricity price signals. The modified load demand at i^{th} and j^{th} hours due to the implementation of time-based rate DR program can be obtained using the following equation.

$$d(i) = d_o(i)\left\{1 + \frac{E(i)\left[\rho(i) - \rho_o(i)\right]}{\rho_o(i)} + \sum\nolimits_{j=1, j\neq i}^{24} E(i,j)\frac{\left[\rho(j) - \rho_o(j)\right]}{\rho_o(j)}\right\} \tag{36}$$

5.2 Load control in the incentive-based DR programs

In this DR program, the changes in electric usage are based on incentive and penalty options in certain periods, such as peak load times. The modified load demand due to the implementation of incentive-based DR programs is obtained as follows.

$$\mathrm{d(i)} = \mathrm{d_o(i)}\left\{1 + \frac{\mathrm{E(i)}\left[\rho(\mathrm{i}) - \rho_\mathrm{o}(\mathrm{i}) - \mathrm{A(i)} + \mathrm{pen(i)}\right]}{\rho_\mathrm{o}(\mathrm{i})} + \sum\nolimits_{\mathrm{j=1, j\neq i}}^{24} \mathrm{E(i,j)}\frac{\left[\rho(\mathrm{j}) - \rho_\mathrm{o}(\mathrm{j}) - \mathrm{A(j)} + \mathrm{pen(j)}\right]}{\rho_\mathrm{o}(\mathrm{j})}\right\} \tag{37}$$

Table 1 Fuzzy rules for ESS scheduling

I/P-1	SOC	VL	VL	VL	VL	VL	VL	VL	VL	VL
I/P-2	NRL	L	L	[illegible]	[illegible]	M	M	H	H	H
I/P-3	NEP	L	M	H	L	M	H	L	M	H
O/P	C&D	HC	[illegible]	HC	HC	MC	MC	HC	MC	LC
I/P-1	SOC	L	L	L	L	L	L	L	L	L
I/P-2	NRL	[illegible]	L	L	M	M	M	H	H	H
I/P-3	NEP	[illegible]	M	H	L	M	H	L	M	H
O/P	C&D	HC	MC	MC	MC	LC	ZR	MC	LC	ZR
I/P-1	SOC	M	M	M	M	M	M	M	M	M
I/P-2	NRL	L	L	L	M	M	M	H	H	H
I/P-3	NEP	L	M	H	L	M	H	L	M	H
O/P	C&D	LC	LC	LD	LC	ZR	LD	ZR	LD	MD
I/P-1	SOC	H	H	H	H	H	H	H	H	H
I/P-2	NRL	L	L	L	M	M	M	H	H	H
I/P-3	NEP	L	M	H	L	M	H	L	M	H
O/P	C&D	ZR	LD	MD	MD	MD	HD	MD	HD	HD

6 General framework for MGEM problem solving

Figure 3 illustrates the implementation flowchart of the proposed multi-objective MGEM problem in two cases without using the fuzzy scheduling system of BES and with the presence of this system. According to this flowchart, the forecasted values of load demand and electricity prices, along with the self and cross elasticity parameters and incentive and penalty tariffs for controllable loads, are sent to the load control system to provide the modified load demand values resulting from the implementation of DR programs.

Then, in the case of the presence of the fuzzy scheduling system of ESS, the values of the modified load demand along with the forecasted RES generations and electricity prices and the characteristics of ESS and its SOC are sent to the fuzzy scheduling system, and the output of this system and the load control system along with the characteristics of the MG system and its controllable DGs are forwarded to the optimization algorithm to calculate the set points of the resources and the amount of power exchange with the main grid for each hour of day ahead. In the case of the absence of scheduling system of BES, the MGEM problem has a dynamic nature, and the optimization algorithm should calculate the set points of the controllable DGs, power exchange with the main grid and the charging and discharging power of the BES, for all hours of day ahead altogether.

6.1 Solution methods

Since in the MGEM problem, several objectives have to be optimized simultaneously, this is called a multi-objective optimization, which does not have a single answer, but all the non-dominate points that meet the constraints can be considered as optimal. This set of points is called the Pareto front. There are various methods to select the final optimal point, the most common of which is the replacement of objective functions with a weighted combination of all objectives, but these methods are highly dependent on the information the analyst receives from the decision maker. Therefore, in the following, two methods of fuzzy membership rule and global criterion have been proposed that require the least information from the decision-maker and their performance will also be compared.

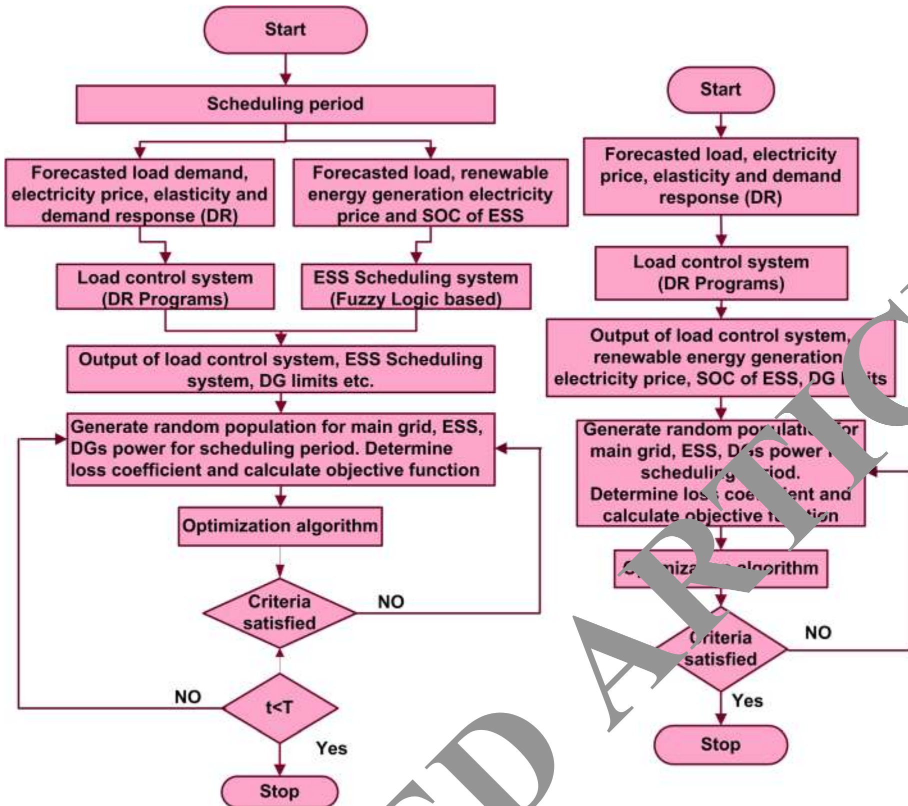

Fig. 3 Flow chart for microgrid energy management system

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6.1.1 Fuzzy membership rule

In this method, after determining the points of the Pareto front by the multi-objective optimization algorithms, since each point k has a specified value for the objective function i, its fuzzy membership value is determined as follows.

$$\mu_i^k = \frac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} \tag{38}$$

Where, μ_i^k is the fuzzy membership value of the point k for the objective function i, and F_i^{min} and F_i^{max} are respectively the lowest and highest value of the objective function in all points of the Pareto front. After calculating the fuzzy membership values μ_i^k for all points of the Pareto front, the overall fuzzy membership value of each point k for all objective functions are defined as follows.

$$\mu_k = \frac{\sum_{i=1}^{nobj} \mu_i^k}{\sum_{k=1}^{Np} \sum_{i=1}^{nobj} \mu_i^k} \tag{39}$$

Where, μ_k is the overall fuzzy membership value for point k, nobj is the total number of objectives, and Np is the total number of Pareto front points. Finally, the point with the highest fuzzy membership value μ_k is selected as the final optimal point. Since the Pareto front must first be determined in this method and this is very time-consuming, it is reasonable to use other methods, such as methods for converting a multi-objective problem into a single objective.

6.1.1.1 Global criterion method

In this method, the sum of the relative deviations of objectives from their global optimum is minimized. Therefore, a single objective optimization problem is defined as follows.

$$\min Z = \sum_{k=1}^{n} \left(\frac{F_k - F_k^*}{F_k^*} \right)^p \tag{40}$$

Where, F_k and F_k^* are the kth objective function and its unique optimum value, respectively. Different metrics can be used, e.g. Lp metric where $1 \leq p \leq \infty$, but here p is assumed to be equal to 1. Global criterion method has attracted much attention because of the ease of use and the little need for information from the decision maker. In this paper, population-based evolutionary algorithms are also used to optimize the MGEM problem; but since the evolutionary algorithms do not guarantee a global optimal solution. MGEM problem is formulated as MILP and implemented in GAMS 23.4 environment and solved using CPLEX solver.

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7 Results and discussions

Figure 4 shows microgrid network considered for the simulation study [56]. The cost and emissions information of the controllable DGs and the flat rate price and the average emissions of the main grid are shown in Table 2. The penalty rate for CO_2, SO_2 and NOx emission is set at 0.03, 2.18 and 9.26 \$/kg, respectively. Maximum capacity of diesel generator is 60 kW and minimum output is 20 kW. Micro turbine and fuel cell have max and minimum capacity of 30 kW and 10 kW respectively. Limit on power import and export to main grid is 100 kW. The total energy storage devices have a maximum charging and discharging power of 50 kW and a capacity of 100 kWh. In order to increase the life of the ESS, the minimum and maximum SOC is set to 20% and 95%, respectively.

7.1 MGEM without using the fuzzy scheduling of ESS

In this case, it is assumed that the fuzzy scheduling system of BES is not available and the energy management problem has a dynamic nature. Initially, total loads are considered uncontrollable, and then different demand response programs are implemented in the MG, and in each case, the optimization results of MGEM problem are presented and compared.

7.2 Use the global criterion method to find the final optimum

7.2.1 MGEM without demand response program

Simulation results are shown in Fig. 5 using global criterion approach. The optimal value of the general single objective function (Eq. 40) is equal to 0.567. The total operating costs, emission penalties, and power losses for all hours of day ahead are 280.48 \$, 81.51 \$, and 62.88 kWh, respectively. Although the cost and emission of a microturbine unit is lower than a diesel unit, due to the high impedance of the microturbine feeder, this unit is given priority to shutdown when the load is low. The performance of various evolutionary optimization algorithms in solving the energy management problem (Eq. 40) has been compared in Table 3. In all evolutionary algorithms, the population is considered as 50 and max iteration as 1000. Due to the large number of decision variables, in spite of changing the parameters of crossover and mutation, algorithms such as GA and DE failed to converge to the optimum. Despite the initial fast convergence of the ISA algorithm, the optimum was not achieved at maximum allowed iteration. Among all the evolutionary algorithms, the PSO algorithm and then the TLBO algorithm provided the best performance.

7.2.2 MGEM with demand response program

In this paper, from time-based rate programs, real time pricing (RTP) and from incentive-based programs, direct load control (DLC) has been implemented. Figure 6 illustrates the change in load demand after implementation of demand response programs. It is assumed that 20% of total load demand would participate in DR programs. The self and cross elasticity and flat rate price are considered to be 0.2, 0.01 and 12.5 \$/kWh, respectively. The incentive rate to reduce load in peak hours is set at 2 \$/kWh and the peak period is from 12:00 to 18:00. Optimization results of the objective function of the energy management problem (Eq. 40) with DR programs are illustrated in Fig. 7 and Fig. 8, respectively. The

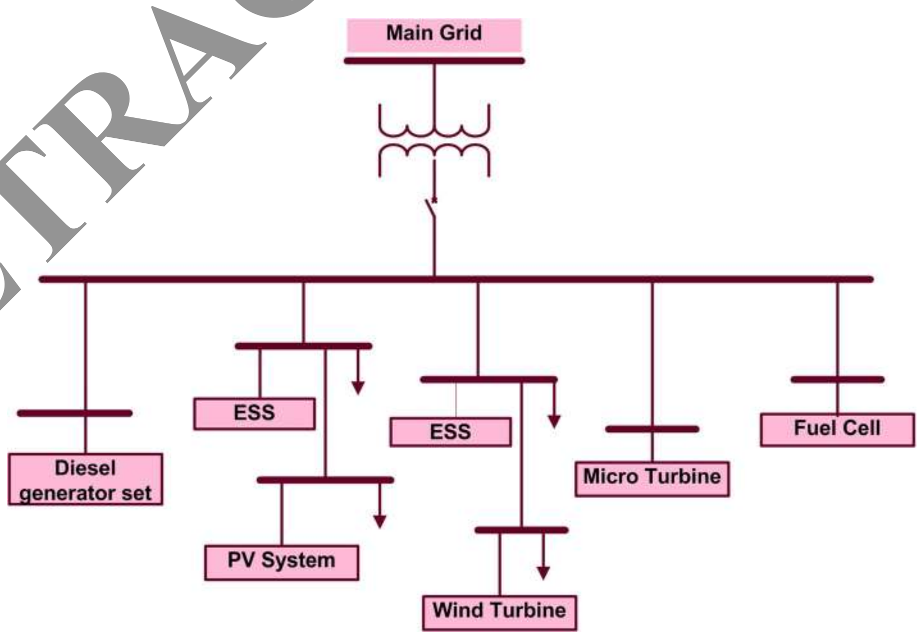

Fig. 4 Typical microgrid system

Table 2 Power cost and emission rate

DG type	Si ($)	Operating cost			Emission rate (g/kwh)		
		a_i	b_i	Ci	CO_2	SO_2	NOx
Diesel Generator	3	0.00104	0.0304	1.3	697	0.22	0.5
Micro turbine	2	0.00051	0.0397	0.4	670	0.0036	0.186
Fuel cell	1.5	0.00024	0.0267	0.38	441	0.0022	0.0136
Main grid	–	–	–	–	889	1.8	[illegible]

amount of operating costs, emission penalties, and power losses after the implementation of RTP program throughout the scheduling period are 271.19 $, 79.38 $, and 62.49 kWh, respectively; which represents a 3.31% reduction in operating costs, 2.61% reduction in emission penalties and 0.62% reduction in power losses compared to MGEM without DR implementation. On the other hand, the operating costs, emission penalties, and power losses after the implementation of DLC program are 274.18 $, 79.80 $, and 60.64 kWh, respectively; which represents a 2.25% reduction in operating costs, 2.1% reduction in emission penalties and 5.56% reduction in power losses compared to MGEM without DR implementation. Obviously, the impact of demand response programs will increase with increasing the participation percentage and the incentive rate.

7.3 MGEM using fuzzy scheduling of ESS

Figures 9 and 10 illustrates the output results of the fuzzy storage scheduling system for the initial load demand, which includes charging and discharging decisions, and the SOC of the ESS. With the availability of such

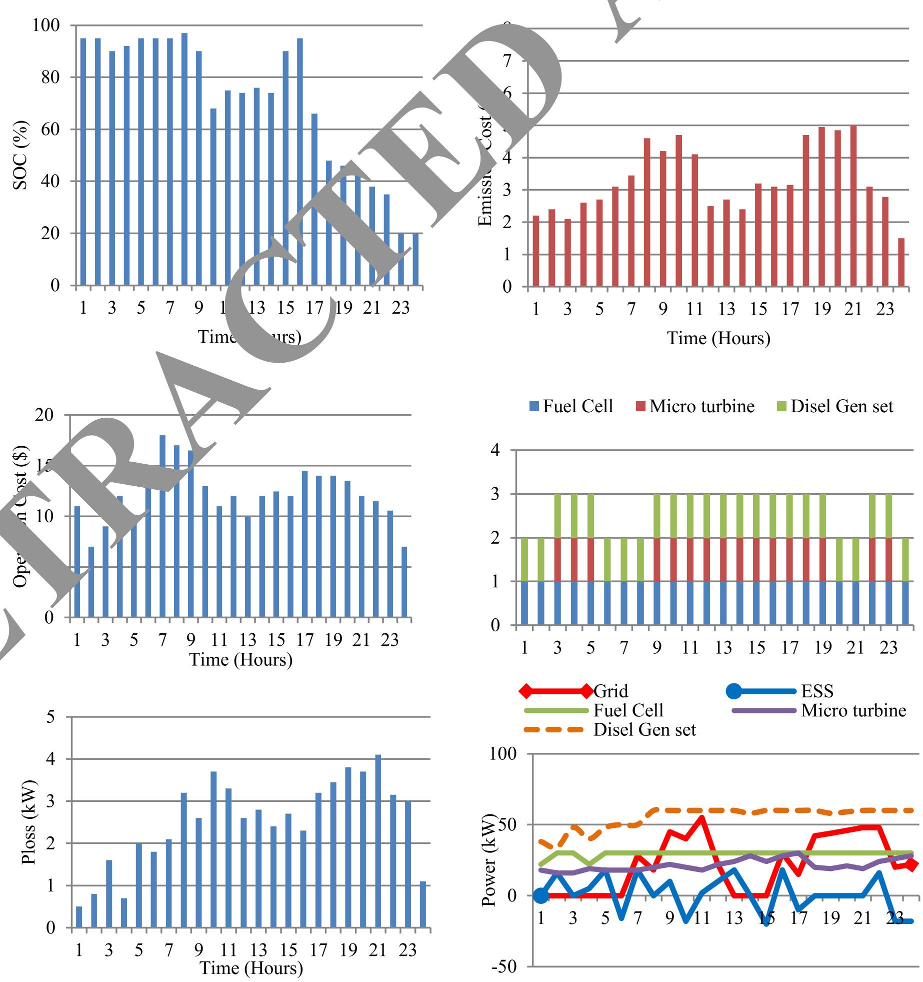

Fig. 5 Simulation results for MGEM in using global criterion

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Table 3 Comparison of evolutionary algorithms for MGEM

Optimization method	Objective function value	Total cost ($)	Total emission penalty ($)	Total power loss (kwh)	Convergence (Iterations)	Execution time
PSO (Particle Swarm Optimization)	0.5944	284.28	78.23	65.75	930	6 min
GA (Genetic Algorithm)	1.1324	–	–	–	1000	7 min
DE (Differential Evaluation)	1.752	–	–	–	1000	6 min
TS (Tabu Search)	0.6069	289.35	83.08	61.86	810	[illegible] min
TLBO (Reaching Learning Based Optimization)	0.5937	283.84	81.90	63.38	970	10 min
ICA (Imperialist Competitive Algorithm)	1.769	–	–	–	1000	6 min
BBO (Biogeography)	5.89	–	–	–	1000	15 min
ABC (Artificial Bee Colony)	0.7926	290.60	84.07	65.08	760	13 min
GAMS	0.567	280.48	81.51	62.88	–	12 s

information prior to optimization, the energy management problem goes out of dynamic mode and can be optimized for each hour of the scheduling period separately. Fig. 11 illustrate the optimization results of the MGEM problem using the fuzzy inference system for ESS scheduling. The operating costs, emission penalties, and power losses throughout the scheduling period are 283.05 $, 81.93 $, and 64.06 kWh, respectively; which compared with the results of dynamic MGEM problem, represents an increase of 0.92%, 0.52% and 1.88%, respectively; however, due to reduced decision variables and consequently the significant reduction in the runtime of optimization algorithms, the effectiveness of the use of fuzzy storage scheduling system in the MG energy management is confirmed.

7.4 Optimal power dispatch in standalone microgrid with hybrid energy sources

Peak load demand on the system is 195 kW, daily average consumption is 4001kWh/day, and annual load consumption is 1,459,899 kWh/year. Hourly optimal power dispatch of the hybrid system is illustrated in Fig. 12 and noted that there is no unmet energy at any point of time. Annual power production in the hybrid power system is as follows: PV power is 740,873 kWh/year, WT power is 87,951 kWh/year, DG power is 153,302 kWh/year, MT power is 486,857 kWh/year and FC power is 57,333 kWh/year to cater the load demand. Optimal hybrid system consists of 25 kW fuel cell, 70 kW micro turbine, 180 kW PV, 50 kW diesel generator set, 200 kW wind turbine, 142 battery strings and 200 kW converter. Levelized COE and NPC of hybrid system is 0.2347$/kWh and 4,429,333$ respectively. Scheduling of hybrid energy sources for a typical day is shown in Fig. 13. Figure 14 shows state of charge of battery throughout the year. Detailed cost summary of standalone hybrid microgrid system is given in Fig. 15. As specified in Table 4, capital cost is low for FC and high for PV. Also, greenhouse gas emissions in standalone hybrid system and

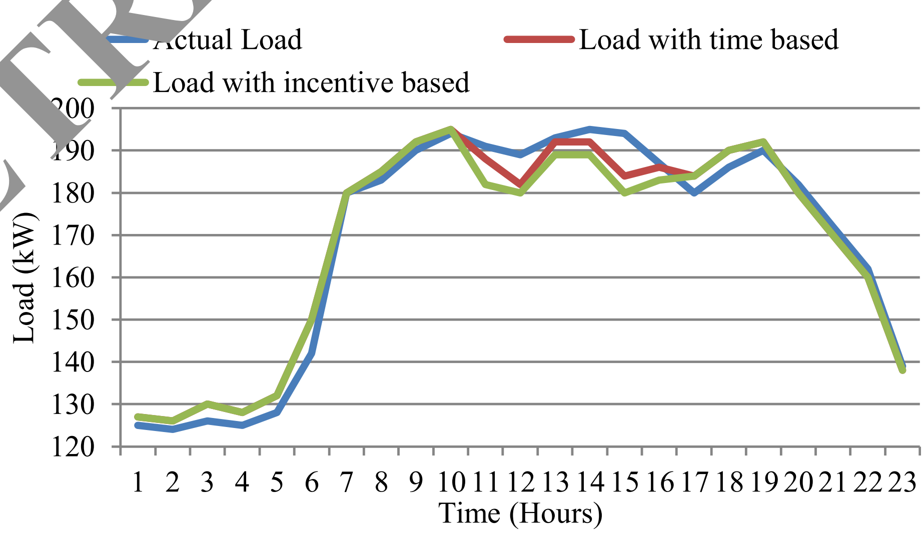

Fig. 6 Impact of demand response on load demand

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Fig. 7 Energy management considering DR real time pricing

with grid only is given in Table 5. Greenhouse gases emissions in microgrid with hybrid energy sources is lower than conventional grid.

8 Conclusion

In this paper, a new multi-objective optimization problem for microgrid energy management is formulated as MILP in GAMS environment. Energy dispatch and techno-economic analysis has been presented for standalone and grid connected microgrids with hybrid energy sources and storage devices. Capital cost, operational cost, fuel cost, cost of energy, emission penalty and total cost are determined for the test system. From the simulation results it is observed that fuel cost of diesel generator and micro turbines has significant impact on cost of energy. The presence of the energy storage system in the microgrid, raises the complexity of solving the energy management problem, and increases the time and computational burden of optimization algorithms. Therefore, in this paper, the fuzzy inference system is used to decide on the amount of charging and discharging power of the storage system in MGEM problem solving. The results confirm the effectiveness of using such a system in the MGEM optimizing. Simulation results obtained with the proposed method is compared with various evolutionary algorithms to verify it's effectiveness. In this study, demand response programs were integrated into the energy management system for better operation of microgrids. Accordingly, the impact of different demand response programs on optimal energy dispatch, techno-economic and environment benefit has been investigated. Capital, replacement and O&M cost of the system is low after implementation of demand response. After implementation of RTP based DR program, operating cost, emission penalty and power losses reduced by

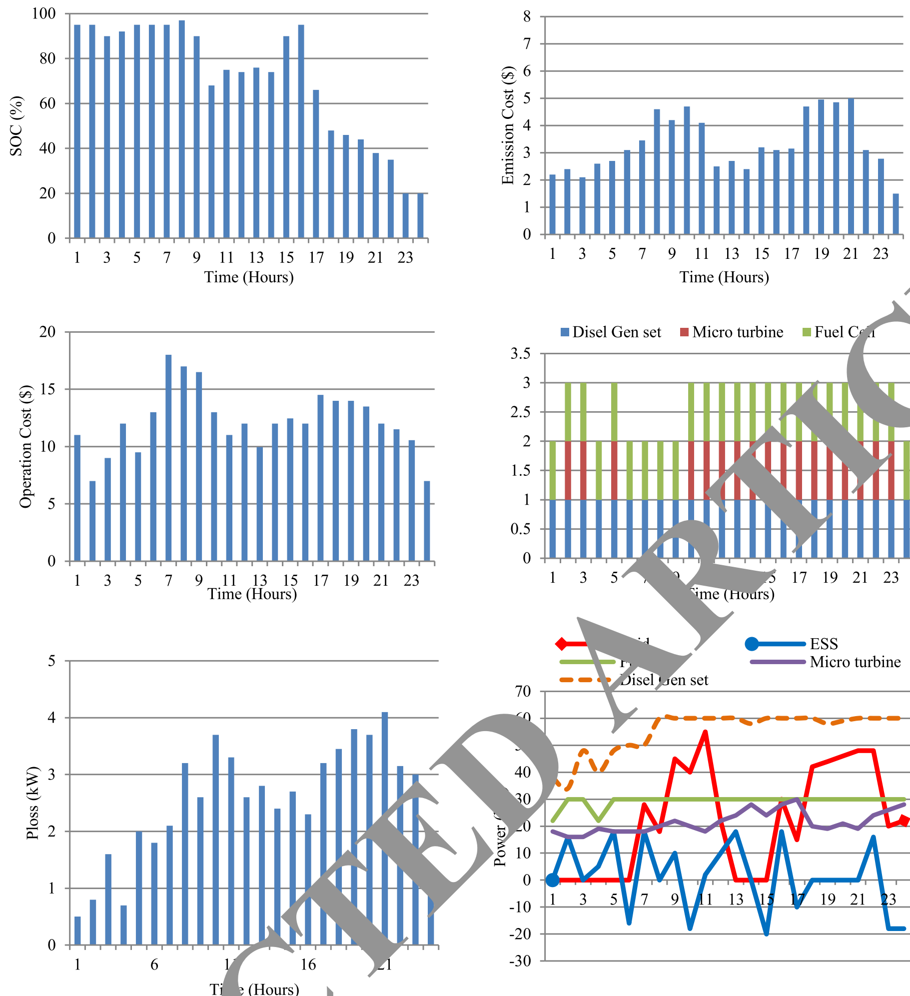

Fig. 8 Energy management considering indirect load control

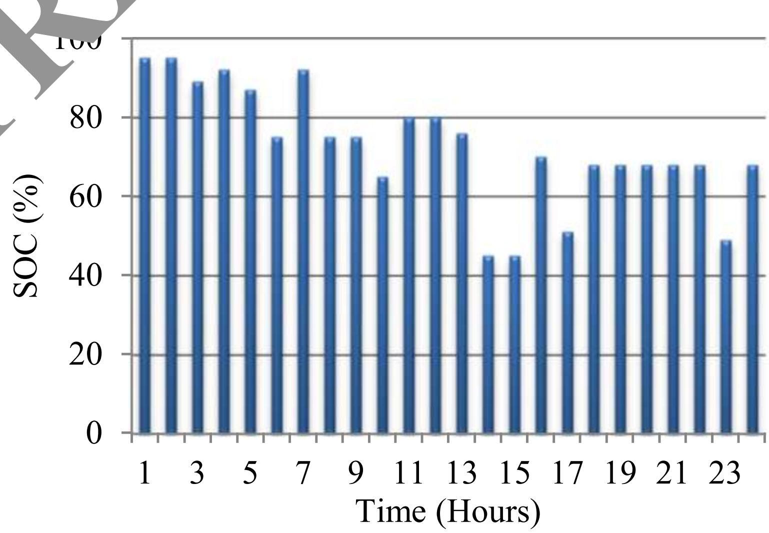

Fig. 9 State of charge of ESS

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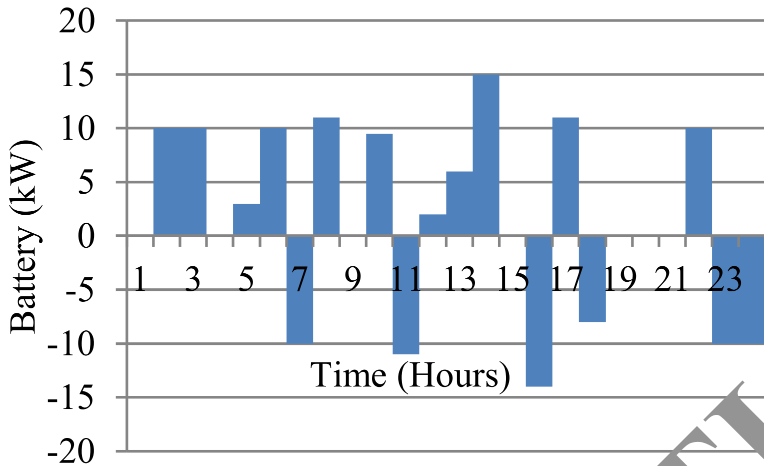

Fig. 10 Charging and discharging of ESS

3.31%, 2.61% and 0.62% respectively. On the other hand, after implementation of DLC based DR program, operating cost, emission penalty and power losses reduced by 2.25%, 2.1% and 3.56% respectively. In standalone microgrid with hybrid energy sources, CO_2 emissions reduced by 51.60% per year as compared to conventional grid.

This paper can be useful to microgrid operator for decision making, solid investment towards rural electrification, design a competitive hybrid micro grid and optimal energy dispatch strategy. Further, this study facilitates microgrid system engineers during preliminary design phase and project cost estimation.

9 Nomenclature

$\overline{G_{T,STC}}$ Solar radiation at standard test conditions(1 kW/m^2)

$\overline{G_T}$ Solar radiation on PV array (kW/m^2)

C_{bw} Battery wear cost ($/kWh)

$C_g(t)$ Main grid power price

C Capacity of energy storage system

$C_{rep,\ batt}$ Replacement cost of storage bank ($)

EF_{gj} Average emission factor of the main grid related to emission type j (SO_2, CO_2, NO_x)

EF_{ij} Emission factor of unit i related to emission type j (SO_2, CO_2, NO_x)

$E_{ch}(t)$ Battery charging energy

$E_{dch}(t)$ Battery discharging energy

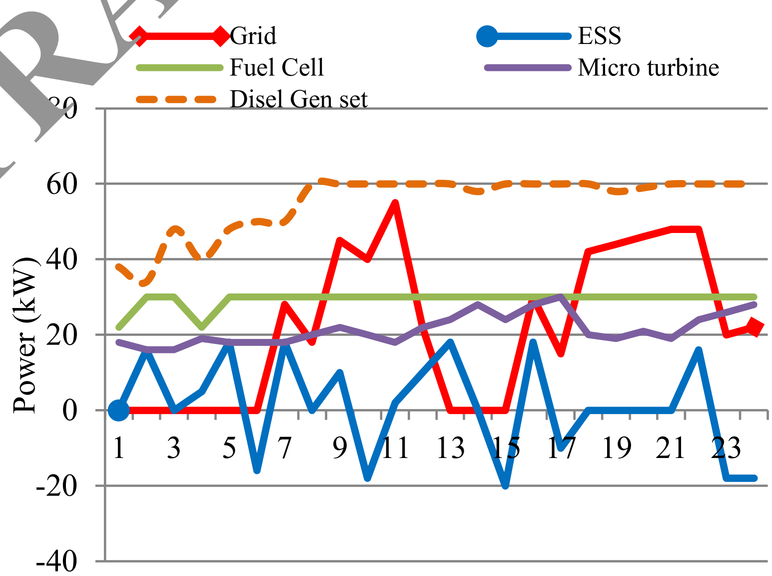

Fig. 11 Results for energy management using fuzzy interface

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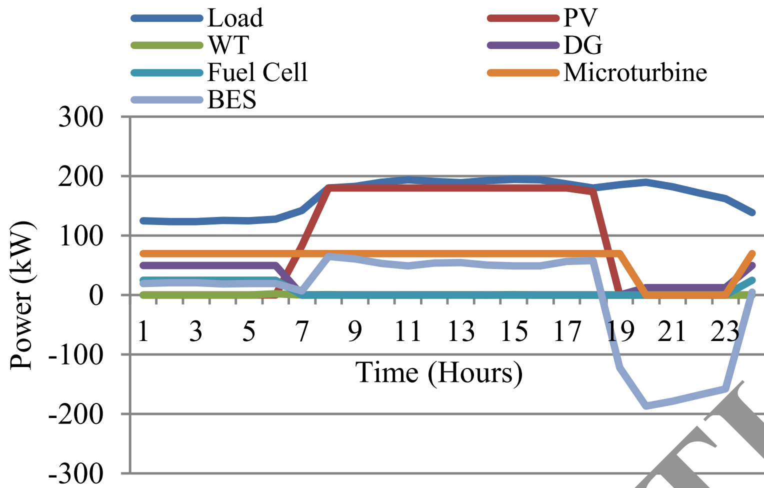

Fig. 12 Optimal power dispatch in standalone microgrid

FC_iFuel cost of unit i
F_i^{max}Highest value of the objective function
F_i^{min}Lowest value of the objective function
$G_{T,\ NOCT}$Solar radiation at which NOCT defined (0.8 kW/m^2)
INV_{cap}Rating of inverter (kVA)
L_0Total non-inductive load (kW)
L_{ind}Total inductive load (kW)
N_{batt}Number of batteries
P_{BES}^rNominal capacity of BES
$P_{D\ b,\ t}$Load at bus 'b' and time 't'
P_DLoad demand
P_{DG}Rated capacity of diesel generator (kW)
P_{DG}^{max}Maximum capacity of diesel generator (kW)
P_{DG}^{min}Minimum capacity of diesel generator (kW)
P_{FC}Fuel cell power output
P_{FC}Rated capacity of fuel cell (kW)
P_{FC}^{max}Maximum capacity of fuel cell (kW)
P_{FC}^{min}Minimum capacity of fuel cell (kW)
$P_{L,t}^{shed,\ max}$Maximum sheddable load (kW)
$P_{L,t}^{shed}$Sheddable load (kW)
$P_{L,t}^{trans,\ max}$Maximum transferrable load (kW)
$P_{L,t}^{trans}$Transferrable load (kW)
P_{MT}Micro turbine power output
P_{MT}Rated capacity of micro turbine (kW)

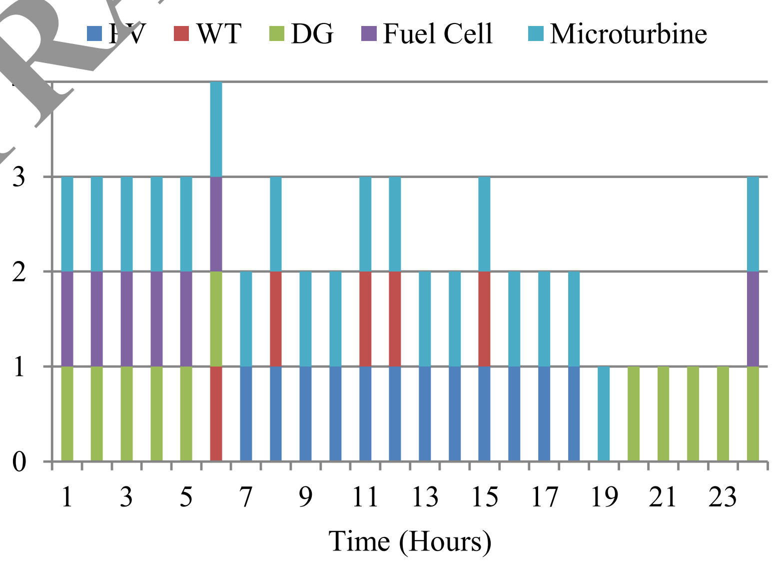

Fig. 13 Scheduling of hybrid energy in standalone microgrid

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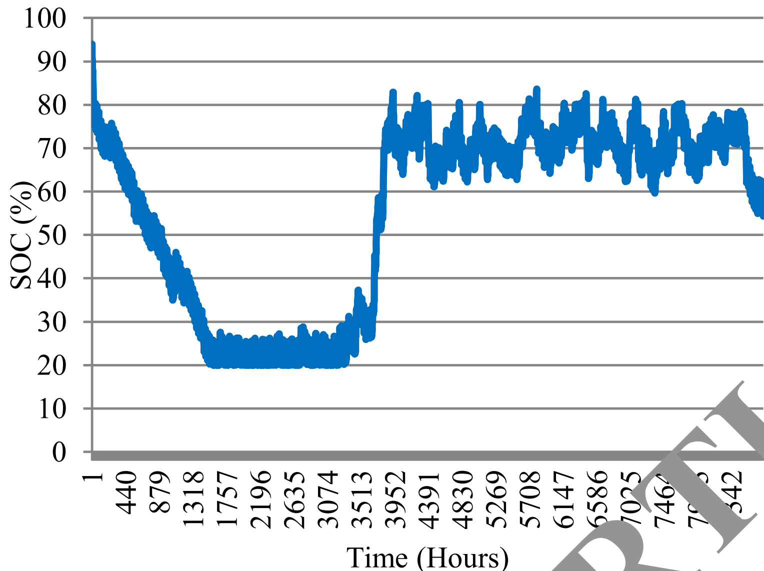

Fig. 14 Annual state of charge of BES

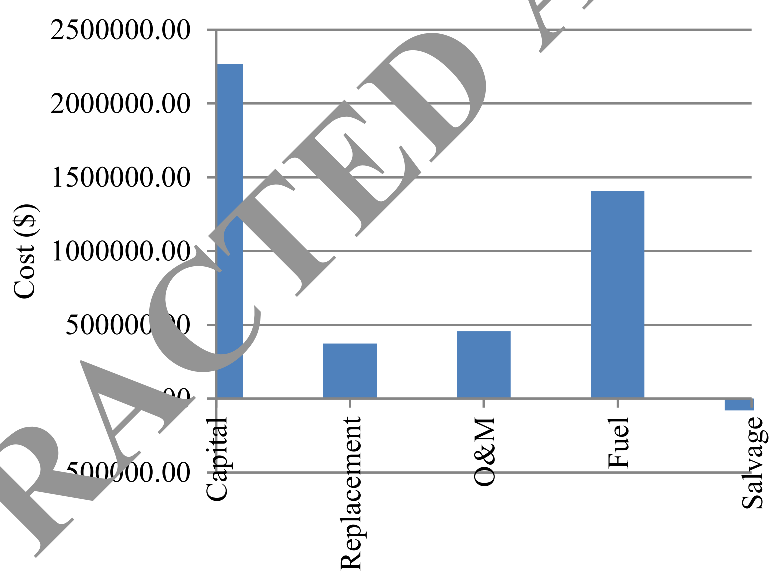

Fig. 15 Cost summary of standalone microgrid

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Table [illegible] Detailed cost summary of standalone microgrid

	Capital	Replacement	O&M	Fuel	Salvage
FC	12,500.0	12,259.1	22,377.5	226,955.1	− 344.3
WT	300,000.0	95,642.2	19,391.2	0.00	−53,900.5
BES	56,800.0	24,098.7	18,357.0	0.00	− 4535.6
DG	25,000.0	85,073.0	83,130.4	632,478.3	− 5120.5
MT	70,000.0	131,694.3	63,028.1	547,565.1	−10,847.4
PV	1,746,237.9	0.0	250,828.0	0.00	0.00
Converter	60,000.0	25,456.4	0.0	0.00	− 4791.1

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Table 5 Greenhouse gases emissions summary

Emission (kg/yr)	Off-grid system	Grid only
Carbon Dioxide	446,628	922,950
Carbon Monoxide	1993	–
Unburned Hydrocarbons	47.9	–
Particulate Matter	32.1	–
Sulfur Dioxide	426	4001
Nitrogen Oxides	2923	1957

P_{MT}^{max}Maximum capacity of micro turbine (kW)
P_{MT}^{min}Minimum capacity of micro turbine (kW)
P_{PV}Photo voltaic system power output
P_{WT}Wind turbine power output
$P_{b,t}^{DR}$Load shifted at bus 'b' and time 't'
P_{ch}Battery charging power
P_{dc}Battery discharging power
$P_g(t)$Power import from main grid at time t
$P_i(t)$Output power of the controllable unit i at time t,
P_{pv}Power output of PV array (kW)
P_{pv}^rRated capacity of PV array (kW)
P_wRated power output of wind turbine (kW)
P_{wt}Power output of wind turbine (kW)
$Q_{lifetime}$Battery lifetime throughput (kWh)
Q_{thrpt}Annual storage throughput (kWh/yr)
$R_{batt,\ f}$Battery float life (years)
R_{batt}Battery storage system life (years)
S_iStart-up cost of unit i
$T_{a,\ NOCT}$Ambient temperature at which NOCT is defined
T_aAmbient temperature ($^{\circ}C$)
$T_{c,\ NOCT}$Nominal operating PV cell temperature ($^{\circ}C$)
$T_{c,\ STC}$PV cell temperature at STC (25 °C)
T_cPV cell temperature ($^{\circ}C$)
$d_o(i)$Initial load demand (kW)
f_{pv}PV derating factor (%)
k_{DR}Incentive rate ($/kW)
α_pTemperature coefficient of power (%/$^{\circ}C$)
η_{Conv}Efficiency of converter
η_iCharging and discharging efficiency
η_{mp}Efficiency of PV array at MPP (%)
η_{wt}Efficiency of wind turbine (%)
μ_i^k Fuzzy membership value of the point k for the objective function i
μ_kOverall fuzzy membership value
$\rho_o(i)$Initial electricity price
∝Reduction factor of load
NTotal number of controllable units
nTotal number of scheduling time intervals
$A(i)$Incentive amount at ith hour
$E(i,j)$Cross-elasticity
$E(i)$Self-elasticity
NpTotal number of Pareto front points
TPLTotal real power loss
$d(i)$Modified load demand due to demand response (kW)
ngTotal number of PV buses in the micro-grid network in addition to the slack bus
$nobj$Total number of objectives
$pen(i)$Penalty amount at ith hour
ηrtStorage roundtrip efficiency
$\rho(i)$Spot electricity price
σBattery self-discharge rate

Abbreviations
DG: Diesel generator; DLC: Direct load control; DR: Demand response; ESS: Energy storage system; MGEM: Microgrid energy management; MGO: Micro grid operator; RTP: Real time pricing

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Authors' contributions
VVSNM carried out basic design, simulation work and prepared draft paper. AK participated in checking simulation work, results & discussions, sequence of paper and helped to prepare the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

Competing interests
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