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An effective energy management system for intensified grid-connected microgrids

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A R T I C L E I N F O

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A B S T R A C T

The utility's utilization of communication technology and renewable energy sources has paved the path for self-sustaining microgrids (MGs). However, the intermittency of solar and wind energies raises concerns about meeting demand effectively. To ensure optimal performance of distributed MGs, an efficient energy management system (EMS) is crucial to tackle this uncertainty. Historically, MGs have primarily achieved operational cost reduction through optimal functioning. Integrating demand response (DR) into the EMS could further enhance operational efficiency and peak reduction. This research work addresses this challenge by incorporating DR programs into grid-connected MGs' energy management. Stochastic programming is employed to account for the unpredictable solar and wind behaviours. Flexible price elasticity is used to calculate price elasticity coefficients, portraying customer responses effectively. The implemented research work compares the Dragon Fly Algorithm with other heuristic approaches, resulting in a 12.42 % reduction in overall operating costs and the efficacy of the proposed algorithm is shown.. Using the Analytic Hierarchy Process (AHP), the User Satisfaction Index is assessed, revealing that the CPP demand response initiative tops the satisfaction scale with a score of 0.92881.. Moreover, this research offers an exhaustive evaluation of techno-economic markers for each scenario, systematically ranked using the proposed AHP methodology..

CRediT authorship contribution statement

Abhishek Kumar, Arvind R. Singh and R. Seshu Kumar: Conceptualization, Methodology, Software, Visualization, Investigation, Writing – original draft. Yan Deng: Project administration, Supervision, Resources, Writing – review & editing. Xiangning He: Project administration, Supervision, Resources, Writing – review & editing. Praveen Kumar: Writing – review & editing. R.C. Bansal: Supervision, Writing – review & editing. R.M. Naidoo: Supervision, Writing – review & editing.

1. Introduction

Recently, electrical energy usage has been increasing rapidly due to the intensity of load demand for end-users. Some of the significant factors related to the distributed power system are overall operating cost, reliability, and quality of electrical power supply have gained more importance for obtaining the optimal power system operation. MGs are the alternative solution to operate the power system more healthily and satisfy the abovementioned factors. MGs have existed in some form or another in the power utility services toolkit for the past 30 years. MGs have become more efficient today because of the growth of software applications, economic reductions in renewable energy technologies, and increased consumer demand for sustainability, stability, resilience, and cost predictability. It consists of DERs, BES units, and critical and non-critical loads, which can be operated in grid-off and autonomous modes. Typically, the MG operates in grid-connected mode until any disturbances occur in the system. Under fault conditions, the disturbances occur in the upstream network; the MG disconnects from the primary grid and automatically operates the MG in autonomous mode. With the switch-over operations during grid-connected and islanded

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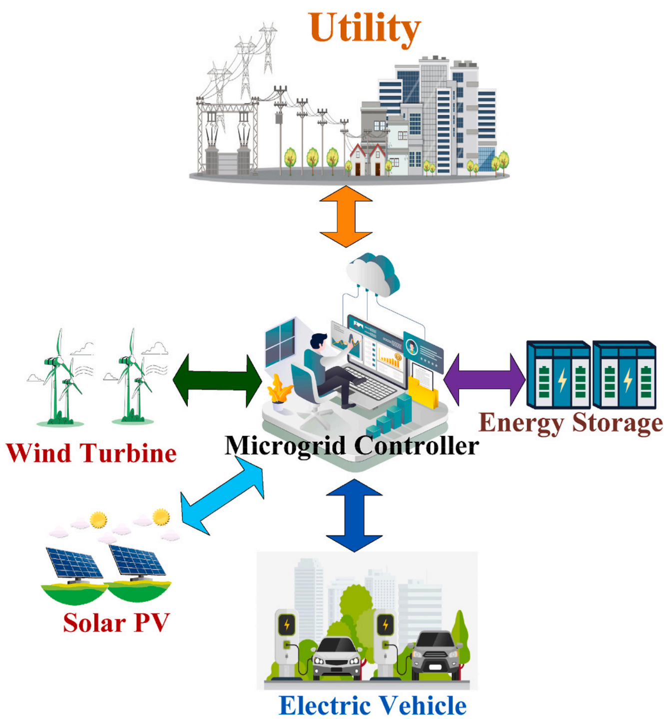

Fig. 1. Energy management system.

modes, the reliability of the MG is improved. Henceforth, a proper energy management system must determine whether each DG source can supply the necessary energy to the consumer to maintain grid reliability [1]. The typical MG energy management system is shown in Fig. 1.

In [2], an energy management problem is solved by comprising distributed feeder reconfiguration and control of the reactive power dispatches to enhance the MG's technical and economic aspects. To control the real and reactive power dispatches among the interconnected distributed sources and RES, a novel optimization approach HBB-BC is implemented to solve the EMS problem. The techno-economic parameters are evaluated, which consist of operating cost, VSI, real& reactive power losses, and the MG's greenhouse emissions. Despite many advantages, MG operators run into issues while planning and running. However, it does not incorporate multi-objective operational planning, which is a crucial aspect of a conscious energy management system that holds considerable importance in accounting for the overall system emissions. In addition, it fails to account for the power network model and the reduction of transmission losses, which could significantly impact the efficiency and performance of microgrids. Further, some other essential aspects, including large-scale investments in renewable energy, ideal DER operation, control, market involvement, security, end-user privacy, and the creation of new policies, are a few examples that have not been incorporated exclusively. In the literature, artificial neural network-based algorithms have been very popular in developing methodologies to enhance MG performance and operation by incorporating optimization approaches such as PSO to enhance each artificial neural network to become a self-adaptable system. For example, in Ref. [3], the authors have proposed an energy management model which is implemented to operate the MG consisting of renewable energy sources, energy storage devices, and a generation set. The simulation results show that the implemented model reduces the deficiencies by percentages of fifty-nine and fifty-six for an individual and multi-step forecast of power constraint predictors. However, the present study fails to account for the model's performance under uncertain weather conditions or fluctuations in load demand profile, thereby constraining its practical implementation in a remote or grid-connected microgrid system. Moreover, the proposed model's applicability in a large-microgrid system that encompasses multiple and diverse energy resources and storage systems has not been taken into consideration.

Current practices of integrating renewable energy sources and storage systems with conventional generators mainly reduce fuel consumption and emissions have become popular worldwide for isolated MGs or unreliable grid systems in remote or underdeveloped regions such as Sub-Saharan Africa. But, the remote MGs based on renewables have a high peak-to-average ratio, and the conventional generators' capacity is dependable on the load demand conditions. Thus, traditional generators frequently run at minimal loading conditions, leading to insignificant fuel efficiency. Further, integrating multiple renewable energy sources and battery-based storage systems into the MG additionally decreases the load on the conventional generator and worsens the fuel efficacy. The other significant issues which were overlooked were the operating cost of MGs and the lifespan of the energy storage systems. Hence to overcome these issues, several EMS models for MGs having RES based on solar and conventional generator resources integrated with an energy storage device came into the picture, which somewhat considered of degradation models, hybrid optimization models etc. [4–6]. For example, in Ref. [4], a novel bi-layer EMS is implemented for remote MGs to enhance the BES lifespan and simultaneously aims to reduce the overall MG operating cost. Although the study introduces an innovative EMS algorithm that incorporates fuel consumption and battery lifetime in remote microgrids but, it neglects to account for the dynamic nature of electricity pricing and its influence on operational expenses of the MG. Also, the proposed framework is implemented only for an isolated microgrid system, and its efficacy is not verified for grid-connected MG systems. Another research related to the battery degradation model is proposed in Ref. [5] to find the influence of energy source ageing models on a grid-connected MG. Four models were considered and compared with combined Arrhenius peukert (CAPN) followed by NREL, PLET, and linear, respectively. But all four models considered in this study are based on single factor-based battery degradation without using real-time battery model data.

In [6] energy management problem of an off-grid MG is evaluated by implementing a novel hybrid optimization approach i.e., DE and chaos theory. The prime objective of this research is to minimise the overall operating cost and reduce MG's greenhouse emissions in both renewable and non-renewable energy sources. Both study [5,6] do not consider the variations and uncertainties which occur in real-time such as power demand fluctuations and RES generation, and how these variations will impact the efficacy of the proposed model and its energy management strategy. The authors in Ref. [7] aim for the optimal energy management and planning of MGs by incorporating DSM programs to control and schedule the generation and energy consumption for reducing the overall operating cost and emissions. Stochastic programming is implemented to handle the uncertainties associated with the proposed MG. The MOGA algorithm is proposed to solve the objectives and enhance MG's techno-economic aspects. The previous research study describes the optimal operation of the MG. However, the planning and operation of the MG indices have not been evaluated simultaneously. In Ref. [8], the study presents a promising approach to energy management in microgrids under environmental constraints, but it does not address the scalability of the proposed algorithm for larger microgrids. Additionally, the study assumes that the microgrid operates in an isolated mode without considering its connection to the primary grid. Finally, the study does not compare with other state-of-the-art EMS models or approaches in the literature. While [9] presents an optimal energy management strategy for multi-residential demand response utilizing self-produced renewable energy, it only assumes a centralised control approach without investigating the potential benefits of distributed control strategies. Finally, no account for battery degradation was considered, which could significantly impact the performance of the proposed energy management strategy. The studies outlined above only address the MG-EMS problem regarding battery ageing enhancement, MG operation and planning from different viewpoints

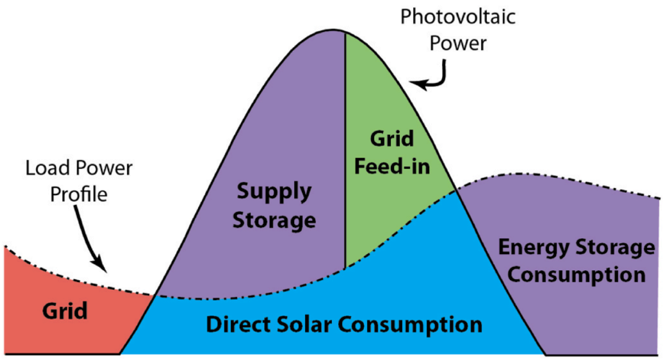

Fig. 2. Load demand management curve.

and goals. But, another significant research gap for energy management of MGs is the applications of utility-oriented and customer-oriented programs which is discussed further.

In [10], authors perform optimal scheduling of a holistic bidirectional energy DN by incorporating demand-side management programs for greater power sharing and improving the performance of the distribution network. A multi-objective genetic approach is implemented in the energy distribution network to handle the optimum scheduling problem intelligently and sustainably. However, it does not consider the effect of demand elasticity and customer behaviour. Additionally, the study assumes that the distribution network is static without considering the potential impact of network topology changes. Further, it does not consider the impact of communication delays on the performance of the proposed strategy. That's why the DSM and DR programs have gained more attention while solving MG energy management, operation, and planning problems, as reported in the literature. Fig. 2 demonstrates how the peak load demand is shifted by implementing demand response programs.

The study [11] proposes an integrated energy and reserve management strategy for microgrids with demand response. Yet, it fails to address the impact of renewable energy source uncertainty and does not investigate the benefits of distributed control. In Ref. [12], an optimization based on building internal design was employed to investigate the MG scheduling problem. The scope of this study is primarily limited to individual apartment buildings, without considering the potential synergies and interplay that may arise in a broader microgrid context, which includes larger communities or multiple buildings. Furthermore, it does not explore the potential contribution of demand response programmes (DRPs) that may play a pivotal role in regulating energy distribution within microgrids.

The drawback of the conventional power system in contrast with networked MG during the day ahead scheduling process is appropriately addressed in Ref. [13]. The day-ahead scheduling of a networked MG is investigated, and the conventional power system's negative aspects are also discussed in Ref. [13]. Although the study has significant implications, it did not consider using more advanced optimization algorithms for scheduling. Also, there were no fair comparisons illustrated with other metaheuristic techniques to explore and suggest which method could considerably be more efficient in terms of computational time and response. Additionally, incorporating factors such as power demand variations, market price fluctuations, and customer behaviour would result in a more comprehensive approach to microgrid operation and planning.

The impact of DRPs on different MGs was studied [14]. The authors evaluated several technical parameters, including efficiency, voltage profile, and system reliability. To maximize the financial gains for the MG operator [15], pairs the incentive-driven DRP with EMS. The numerical findings of the above research work, which used the Whale Optimization Algorithm (WOA), revealed an 11 % & 7 % reduction in daily energy usage in two cases, respectively. The incorporation of DR into the EMS problem will be an add-on to both supply and demand sides of the M.G. The DG output powers and battery charging and discharging process during the day ahead scheduling operation of the MG is effectively and economically evaluated using WOA. However, in these studies usages of static values of consumer load profile has been done to determine the price elasticity coefficients which does not provide a real-time solution with integration of DR program.

The authors in Ref. [16] investigate the optimal power solution of the DC MG system consisting of RES, DGs and ESS. This research investigates the coordination among the interconnected DGs for optimal power sharing to meet the required load demand. To plan a hybrid energy system [17], develops a two-stage robust optimization technique with a RES penetration of 65 %. In a aggressive vigour and reserve promote, lowering day-ahead energy prices is the primary goal of the research effort outlined above. The second stage of the research effort is focused on reducing worst-case dispatch costs. The system's demand response scheme was credited with a 7.48 % to boost the revenue of the system. The CHP dispatch difficulty is one of the highly predominant EMS issues in MGs. But, these studies have only considered the load demand shape during an individual period only that also without periodic alters and for a limited number of operational scenarios.

The most recent initiatives have focused on implementing DRPs towards effective planning of MG. In Ref. [18] examined how customer oriented DRPs affected MG operating costs. The stochastic approach suggested in the previous study associates the intermittent parameters related to Solar PV, WT, MP, and load demand are evaluated effectively. In Ref. [19], a hybrid stochastic robust approach is implemented for the optimal scheduling of MG tested and verified under normal and resiliency operations. Because of this, load adjustable and interruptible DR programs resiliency of the MG is improved effectively. A hybrid robust-stochastic optimization technique to deal with the uncertainties related to RES, active, and reactive loads were used. A new energy management strategy is adopted to balance supply and load for an isolated rural MG in the presence of dispatchable and non-dispatchable energy resources [20]. To maintain the balance between supply and load by incorporating a pumped storage unit and an IBDR program. Similar research work in Ref. [21] explores the effects of an IBDR program on the day-ahead and intraday markets. These studies did not address the techno-economic aspects to determine the efficacy of the demand response programs for reducing the overall operating cost of the grid-connected microgrids.

Enhancing the resiliency of the MG [22] is expressed in terms of users' convenience to water and energy after environmental calamities. A stochastic EMS program is implemented in the proposed MG to determine the required energy delivered to the distributed system with DR programs. The simulation results are verified and validated on a standard IEEE-33bus distribution network. In Ref. [23], stochastic energy management of an MG in the presence of DGs, RES and tidal, respectively. The uncertainty parameters are handled by using the Monte Carlo simulation approach. The implemented paradigm is linear multi-objective which primarily focuses on reducing the operating cost and later aims to reduce greenhouse emissions under the GAMS environment. Most of the time, MG customers are composed of several policymakers who do not always have the exclusive authority to control energy-utilizing machinery. This research suggests a unique small-scale market-supported DSM approach in Ref. [24] to influence those policymakers for dynamic power pricing by providing extra rewards to the consumers. Another application of the DSM approach for domestic MG is proposed in Ref. [25] and formulated as an NCMI issue. The challenge was handled using a multi-agent-based decentralised approach because of the high computational cost of centralised approaches. The viability of incorporating a utility-induced DSM approach based on variable load shaping into an MG EMS was investigated in Ref. [26]. A QPSO method was used to resolve the intended research problem. A two-level optimization problem for a smart MG is given in Ref. [27], utilizing an IoT-based DSM. The appropriate scheduling of load appliances is the focus of the first level of the issue and later focuses on the reliability control of frequency and voltage. Although this work provided new insight into DSM strategy, its application to larger MGs or networked Mgs is questionable. Similarly, these studies did not consider the utilization of their proposed approaches for optimal scheduling of grid-connected MGs in consideration of real-time price elasticity coefficients based on end users load profile characterization.

In contrast to the previous research [28], offered studies concentrating on offline and online DSM techniques. The work mentioned above considers a two-stage real-time DSM approach. The first stage is reducing MG operating costs, while the second involves online power scheduling to account for real-time variability. The opportunities for implementing many DR efforts on total operational costs and rapid correlative analysis of significant technical and economic quantities are not significantly focused. A few researches works focused on incorporating demand response programs on traditional microgrids and hybrid microgrids, respectively [29,30]. In Ref. [31] utility-oriented DSM programs are incorporated to reduce the peak load burdens for the optimal scheduling of grid-connected microgrids. The same aforementioned problem is evaluated by incorporating demand response programs for the optimal operation of LV microgrid [32]. Similarly, some works were focused on minimising the operating cost of the microgrids without implementing demand side management programs [33–35].

Authors in Ref. [35] aim to address the concerns and considerations of market players, such as electricity suppliers and consumers, in order to optimize their bidding decisions. Their objective was to develop a strategy that considers various factors, such as market prices, demand elasticity, and participants' preferences, to enhance their overall profitability and satisfaction in the electricity market. In Ref. [36] aims to design a bidding strategy that can enhance their decision-making process and optimize their outcomes. The novelty of this work lies in the development of a reconfigured bidding strategy that considers the concerns of the players in the electricity market. The authors likely consider various concerns that players may have, such as market power, risk management, profit maximization, and fairness. Whereas in Ref. [37] investigated economic analysis of microgrids based on renewable energy uncertainty and demand response in the electricity market. In addition to the above-mentioned research work one more similar work [38] analysing the performance and economic viability of the microgrid system under different scenarios and conditions. The authors likely investigate the optimal operation and control strategies that can maximize the utilization of renewable energy resources, minimise costs, and ensure grid reliability. Another research work focuses on day ahead scheduling for the best scheduling process of RES based microgrid. To regulate the demand side energy management price and load driven programs were incorporated in which changing the end user load profile for the reduction operational cost of the microgrid. The simulation results were carried out on a standard IEEE -24 node distributed test system respectively [39]. Regarding energy management one more research work is concentrated on transactive energy management of a cluster microgrids to manage energy transition among the interconnected microgrids [40]. Another transactive energy technology is adopted in Ref. [41] to create a free energy trading environment for microgrids that soley rely on renewable energy resources for local energy trading. To achieve this proposed objective the hybrid version of stochastic programming and information gap theory is incorporated with the implementation of risk averse and risk seekers strategy in a deregulated circumstance. The recommended model's validity is demonstrated by applying it to the enhanced version of IEEE 14-bus test system. A novel optimizer is incorporated to solve the proposed complex engineering problem and for the first time to evaluate the corresponding technical indices by using AHP method [33].

In the realm of microgrid energy management, the principle of flexible price elasticity takes center stage. Microgrids are defined as localized energy systems, distinguishable by their small scale. They possess the capability to operate both independently and in tandem with the primary grid framework. Typically, microgrids house an assortment of distributed energy resources (DERs), which span from solar panels and wind turbines to energy storage mechanisms and traditional generators. Skillful management of these diverse resources is pivotal to optimize energy efficiency, guarantee reliability, and ensure economic viability within a microgrid. Flexible price elasticity revolves around the responsiveness of energy consumption or production in the face of energy price variations. Within microgrid settings, it's evident that a mix of consumers and prosumers – those involved in both energy consumption and generation – display varied extents of price elasticity. Grasping these elasticity nuances is instrumental in formulating demand response strategies. Such strategies empower consumers to adapt their energy utilization in accordance with price cues. For example, highly price-elastic consumers might adjust their energy habits, favouring times when prices are comparatively lower. This adjustment in behaviour plays a crucial role in curtailing peak demand and the related financial burdens.

For instance [42–47] research works related to incorporation of demand response programs on microgrid energy management for reducing the overall operating costs in which satisfies all equality, inequality, and network constraints respectively. In Ref. [48] authors tackle an energy management problem for a hybrid system without incorporating demand response programs by implementing robust optimization approach called information gap decision theory. The concept under consideration is implemented using the dataset from the municipality of Espoo, located in Finland. The numerical results demonstrate the suggested architecture's effectiveness in generating resilient economic planning for the hybrid system under consideration. The hybrid solution method has superior computational efficiency to non-hybrid solvers, attaining the optimal solution at a reduced time-frame. Additionally, the algorithm exhibits a minimal standard deviation of around 0.94 % in the outcome. In Ref. [49] authors focuses on multiobjective flexible power management in a Software-Defined Networking (SDN) framework, incorporating Renewable Energy Sources (RESs) and Electric Vehicle Power Loads (EVPLs). The formulation of this model is rooted on the hybrid ε-constraint and fuzzy decision-making methodologies, which together create a multiobjective approach. The suggested method including electric vehicle (EV) energy management has demonstrated notable enhancements in energy costs, energy losses, and voltage profiles in comparison to the network flow distribution. Specifically, there has been an approximate improvement of 11 % in energy costs, 28 % in energy losses, and 10 % in voltage profiles. In the given circumstances, the system's adaptability is enhanced by up to 30. It is worth noting that the aforementioned outcomes and functionalities may be effectively attained in practical networks through the implementation of the suggested approach to this particular power system.

The above-mentioned research works [35–49] primarily focused on renewable based microgrid models with grid connected and islanded modes respectively. The integration of demand side management programs was incorporated to characterize the end user load profiles with only static coefficient values for the optimal operation of the typical low voltage levels microgrid system. But, due to lack of real time characterization of end user load profiles the obtained simulated results in these studies are pre-deterministic in nature and not close to real time values. Similarly, majority of the works which have been discussed thoroughly above were mainly focused on the scheduling, electricity markets, operation, and planning domains respectively. Only, a limited number of the research works were focused on the integration of demand side management programs on the IEEE standard distributed test systems with static coefficients for characterization of consumer load profiles. Thus, there is a lot scope to evaluate the real time flexible price elasticity coefficients for true characterization of the end user load profile to enhance the grid reliability.

Hence, in this research paper we have incorporated first-time customer-oriented demand response systems that examine the technical and financial improvements and benefit the grid operator by employing DR programs. Further, in the literature, no effort has been made to use customer-induced DSM approaches, such as price-based DRPs, in MG EMS under the presence of IEEE-34 node network configuration circumstances. Also, most studies' characterisation of pricing elasticities lacks actual modelling of consumer response to price variations in the market and to determine customer satisfaction, the technical aspects have not been extensively covered so far. Therefore, the FPE approach [33] is employed in this research, and the real-time load [31] is used instead of normal loads. AHP method is implemented to evaluate the techno-economic indicators for each DR program based on the obtained weights [34]. To summarize, we have primarily focused on the above-mentioned research gaps with novelty measures:

1. To handle the suggested EMS issue of grid-connected MGs in the context of a price-driven demand response program. The prospects for different techno-economic indicators to benefit the MG network operator are investigated.
2. The FPE method is used to analyse price flexibility quantities of customer oriented DRPs. In addition, a real-time 24-h day ahead load is utilized to ensure network reliability.
3. The recommended EMS problem is resolved using the Dragon Fly Algorithm, a special kind of nature-inspired metaheuristic optimization technique. And also, investigate the solutions' quality and the powerful optimizer's computing efficiency in addressing the problem with both discrete and continuous variables. Finally, the decision-making analysis is done by implementing the AHP process concerning each technical indices of the MG test system.

The remaining sections are structured as follows: Section 2 presents the problem formulation of the proposed microgrid energy management problem and its mathematical representation. Section 3 discusses the mathematical representation of the DG units and the handling of uncertainty parameters. In Section 4, we employ the stochastic framework based on the Dragon Fly optimizer. Section 5 focuses on integrating the AHP method to evaluate the Users' satisfaction index and other techno-economic indices. Finally, in Section 6, we present the simulation results, analyse them in detail, and discuss the research findings.

2. Problem formulation

This section outlines how the improved IEEE-34 node distributed feeder network optimization problem was formulated to minimise operational costs while considering various economic factors. MATLAB software is used to solve the EMS issue. The Dragon Fly Algorithm is implemented and compared with heuristic, meta-heuristic, and quantum-inspired optimization approaches for the first time in a MATLAB environment. In addition, a stochastic optimization method is created to forecast the degree of uncertainty in the price of energy using historical data and a probabilistic density function.

2.1. Objective function

The primary goal of the objective function in (1) is to reduce the overall operating expenses over a period of 24 h T. The MG consists regarding operating costs of dispatchable, non-dispatchable, energy storage unit and utility power exchange costs, respectively. The decision variables of the optimization problem are evaluated and stored in the vector A respectively, represented in (2). The startup/shutdown of the respective DG units associated with discrete variables decides and enables the status of each unit is represented in (3). The terms itemized in (4) are power output, market prices, and startup/shutdown costs of BES units, respectively.

$$\mathscr{F}(\mathscr{A}) = \sum_{t=1}^{T} OPC = \sum_{t=1}^{T}\left\{\sum_{i=1}^{NDG}[\mathrm{DSG}._{i}] + \sum_{j=1}^{NBS}[\mathrm{BS}_{i}] + P_{ue}^{t}\mathscr{M}P_{u}^{t}\right\} \tag{1}$$

$$\mathscr{A} = \left[P_{DSG1}^{t}, P_{DSG2}^{t}, ..P_{NDG}^{T}, P_{BS1,}^{t} P_{BS2,}^{t} ..P_{NBS}^{T}, P_{ue}^{1}, P_{ue}^{2}, P_{ue}^{3}, \ldots, P_{ue}^{T}\right] \tag{2}$$

$$DSG_{i} = \left[\psi_{i}^{t} P_{DSGi}^{t} \mathscr{M}_{DSGi}^{t} + \mathscr{S}_{DSGi}^{on} mx\left\{0, \psi_{i}^{t} - \psi_{i}^{t-1}\right\} + \mathscr{S}_{DSGi}^{off} mx\left\{0, \psi_{i}^{t-1} - \psi_{i}^{t}\right\}\right] \tag{3}$$

$$BS_{i} = \left[\psi_{j}^{t} P_{BSj}^{t} \mathscr{M} P_{BSj}^{t} + \mathscr{S}_{BSj}^{on} mx\left\{0, \psi_{j}^{t} - \psi_{j}^{t-1}\right\} + \mathscr{S}_{BSj}^{off} mx\left\{0, \psi_{j}^{t-1} - u_{j}^{t}\right\}\right] \tag{4}$$

2.2. Operational constraints

A power system's principal function is to maintain a proper balance between supply and demand during time intervals. As a result, the required power balance produced by the RES, BES, DG sources and utility power exchange is envisioned as an equality limitation, exemplified in (5). The minimum and maximum power constraints of DGs, BES, and the utility can be derived (6). In the occurrence of a violation, the quantities of the controller parameters are limited within the power limit constraints to achieve a viable solution. The battery storage restrictions of BES units are stated in terms of the extreme allowable recharge and discharge rates is stated (7). The parameters related to BES indicate the acceptable quantity of charging and discharging and its related efficiency. The energy storage limitations for any hour t are stated in (8).

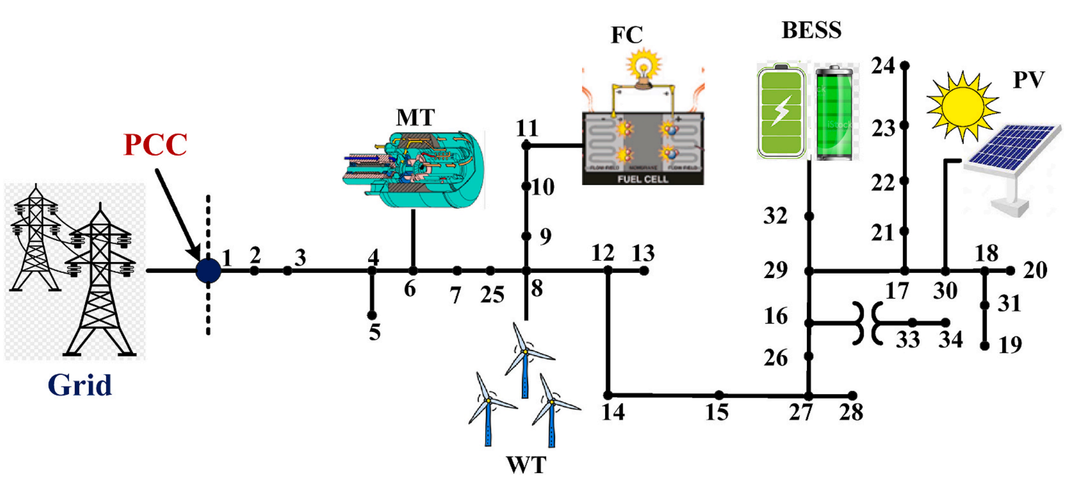

Fig. 3. Enhanced version of IEEE-34 node network.

$$\sum_{x=1}^{t} \dot{P}^{t}_{DSG\mathcal{x}} + \sum_{y=1}^{t} \dot{P}^{t}_{BS\mathcal{y}} + \dot{P}^{t}_{ue} = \sum_{l=1}^{t} \dot{P}^{t}_{demand} \tag{5}$$

$$\begin{cases} \dot{P}^{t}_{DSG\mathcal{x},mnm} \le \dot{P}^{t}_{DSG\mathcal{x}} \le \dot{P}^{t}_{DSG\mathcal{x},mxm} \\ \dot{P}^{t}_{BS\mathcal{y},mnm} \le \dot{P}^{t}_{BS\mathcal{y}} \le \dot{P}^{t}_{BS\mathcal{y},mxm} \\ \dot{P}^{t}_{ue,mnm} \le \dot{P}^{t}_{ue} \le \dot{P}^{t}_{ue,mxm} \end{cases} \tag{6}$$

$$\dot{E}_{BS,t} = \dot{E}_{BS,t-1} + \eta_c \dot{P}_c \Delta t - \frac{1}{\eta_{dc}} \dot{P}_d \Delta t \tag{7}$$

$$\begin{cases} \dot{E}_{BS,mnm} \le \dot{E}_{BS,t} \le \dot{E}_{BS,mxm} \\ P_{c,t} \le P_{ch,mxm}; P_{dch,t} \le P_{d,mxm} \end{cases} \tag{8}$$

2.3. Flexible price elasticity (FPE)

The traditional power generating model governs the energy consistency from the demand and supply by maintaining that consumer requirement is insignificant and unresponsive to variations in electricity pricing. DRPs, on the other hand, promote consumers to shift from inelastic to elastic demand. The term "price elasticity," defined as the proportion of a variation in power demand to a shift in market price, is the foundation for these DRPs. The flexible pricing elasticity is used in this work to generate the E (i,j) matrix for the TOU, CPP, and RTP programs. Depending on their responsiveness to fluctuations in the market price, end users are split into two different load categories according to the basic idea of price elasticity. The essential and non-essential loads, which are responsive to specific and multiperiods, correspondingly, are taken into account while adjusting the coefficients of the self- and cross-elasticity matrices. The overall price elasticity matrix for a 24-h period, which shows how demand changes in relation to price changes, is taken from Ref. [31].

3. System configuration

Fig. 3 depicts a modified IEEE-34 node distributed network based a grid-connected MG. Dispatchable, non-dispatchable and storage units are linked to the external grid through PCC. A central controller typically controls the energy flow inside the MG (MGCC). MGCC's primary goal is to transmit best possible dispatch signals to LC for stabilizing supply and demand. The energy stream is controlled by the MC controller installed corresponding DER unit, and load management is provided by the load supervisor installed at every controllable load [31]. The following section is provided with the required information of modelling DERs as follows.

3.1. PV solar

Deploying solar PV cells is an alternative solution for green energy with zero emissions. Apart from the advantage, PV power output is limited due to intermittent characteristic exhibits that cannot be predicted accurately. The solar output power is generated concerning solar irradiance and module temperature of the cell. The complete PV power output with each parameter description is considered from Ref. [31], and it is mathematically represented in (9) and (10), respectively.

$$\mathscr{P}_{pv} = \mathscr{P}_{STC} \frac{I_{rad}}{1000} (1 + \sigma(T_c - 25)) \tag{9}$$

$$T_c = T_a + \frac{I_{rad}}{800} . (T_n - 20) \tag{10}$$

3.2. Wind turbine

Wind energy has been extremely employed to generate clean energy with zero emissions, and it can be contemplated as the first developed renewable energy. Due to several mechanical and generator constraints, and the power output is generated within the range of wind speeds from cut-in to cut-out. The information regarding wind power generation is considered from Ref. [32] and mathematically represented in (11).

$$P_{wind} = \begin{cases} 0 \quad 0 \le \mathscr{V} \le \mathscr{V}_{ci} \ or \ \mathscr{V} \ge \mathscr{V}_{co} \\ \dfrac{\mathscr{V}^2 - \mathscr{V}_{ci}^2}{e_r^2 - e_{ci}^2} \times P_r \mathscr{V}_{ci} \le \mathscr{V} \le \mathscr{V}_r \\ P_r \mathscr{V}_r \le \mathscr{V} \le \mathscr{V}_{co} \end{cases} \tag{11}$$

Table 1
DG unit bid costs and utility prices (hourly) [31].

DG Type	P^{min}_{DG} (kW)	P^{max}_{DG} (kW)	$S^{on}_{DGi,}$ S^{off}_{DGi} ($)
MT	6	30	0.14
FC	3	30	0.12
PV	0	25	–
WT	0	15	–
Battery	−30	30	–
Utility	−30	30	–

3.3. Bid prices of distributed generators

FC is one type of green energy generator which includes anode and cathode chemical reactions. MT is integrated with MG to improve reliability, power quality, and reduce the peak load demands. These two DG units are considered non-linear functions represented in (12) and (13). The overall operating costs of these DG sources, including investment expenses, downgrading charges and manufacture expenses, are taken from Ref. [31] and it is tabulated in Table 1 respectively. The corresponding mathematical representation is mentioned in (14).

$$F_{MT} = aP_{MCT}^2 + bP_{MCT} + c \tag{12}$$

$$F_{FC} = aP_{FUC}^2 + bP_{FUC} + c \tag{13}$$

$$\begin{cases} \mathscr{B}_{DG} = C_f \dfrac{\mathscr{P}_{DSG}}{\eta_{DSG}} + \mathscr{A}_c \\ \mathscr{A}_c = \mathscr{D}_c \dfrac{\mathscr{P}_{DSG,n}}{\mathscr{P}_c} \end{cases} \tag{14}$$

3.4. Uncertainty assessment with scenario based strategy

In most of the actual engineering optimization problems, some of the technical parameters cannot be directly measurable and are uncertain. The MG scheduling issue considers several unpredictable variables, including solar radiation, wind velocity, market rate, and demand. The scenario-based approach is among the most popular methods for estimating these unknown components. The PDF for each parameter is examined using the historical data that is currently available. The resulting PDF is then divided into numerous subdivisions based on the likelihood values. As a result, the limited number of possibilities will affect each stochastic variable. Most research investigations use the Weibull PDF and the Beta PDF to simulate the uncertainty quantity of solar irradiance [32]. The standard PDF simulates the market pricing and load demand uncertainty [5]. Each stochastic variable will thus rely on a limited number of possible outcomes [4]. In most research studies, wind variations are simulated using the Weibull PDF, while solar power is evaluated using the Beta PDF. The standard PDF calculates the degree of market pricing and load demand uncertainty [5]. The comprehensive scenario generation and reduction features can be derived from Ref. [32]. Figs. 4 and 5 indicate the generated solar irradiance and wind speed scenarios, respectively.

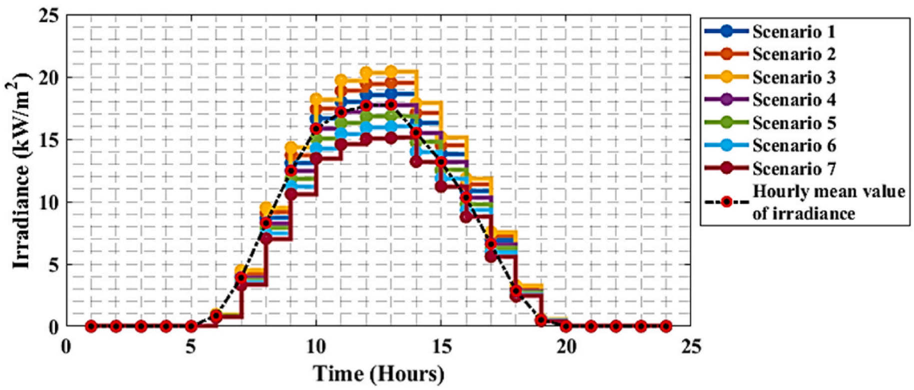

Fig. 4. Solar PV power (kW/m2).

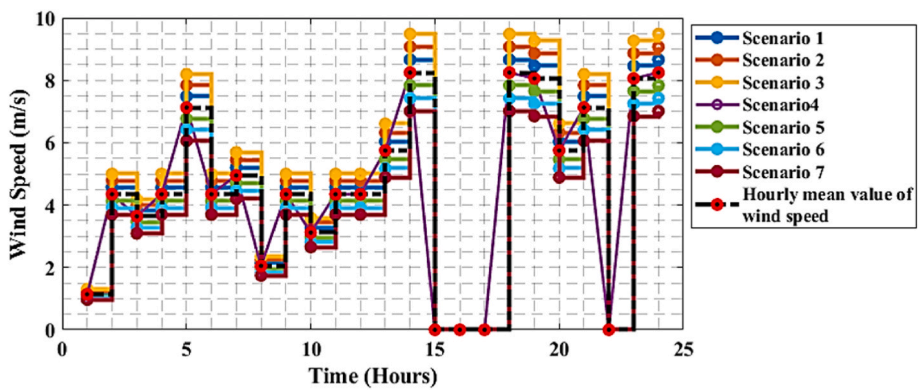

Fig. 5. Wind velocity (m/s).

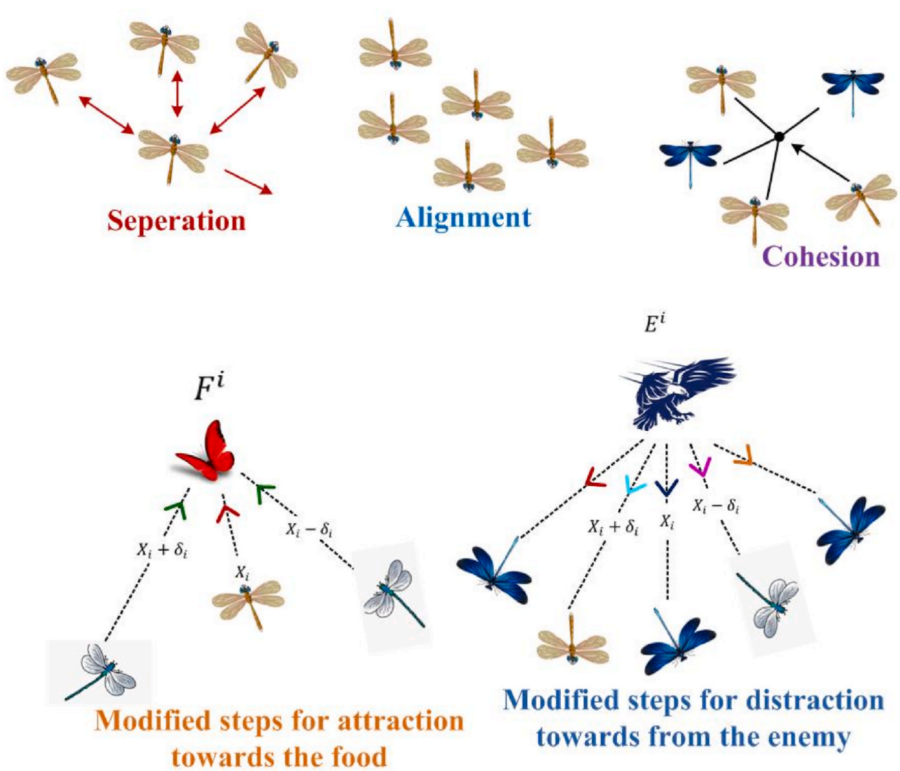

Fig. 6. Dragon fly algorithm.

4. Dragon Fly Algorithm

A meta-heuristic method known as a swarm-based algorithm is based on the behaviour of many animal groupings that compete for life in the wild, including dragonflies, ants, ducks, and other creatures. Practically all areas of research, engineering, and business, including data mining and strategic planning, use computational intelligence techniques called swarm intelligence to tackle non-linear model issues. This approach was developed in 1989 for developing cellular robotic systems by Gerardo Berni and Jing Wang. Swarm intelligence is used for optimization in various ways, such as the real-ant adoption Ant-Colony Optimization (ACO), fish colony-based AFSO, flashing behaviour (FFA), and more. Inspired by dragonflies' static and dynamic swarming, Seyedali Mirjalili created the Dragonfly Algorithm (DA) in 2015. The Dragonfly algorithm is a similar kind of swarm optimization algorithm. It has dual swarming behaviours: static swarming, in which many dragonflies fly in a single direction across a considerable distance after forming a packed configuration locally, and dynamic swarming. These static and dynamic swarming shows the Dragonfly Algorithm's exploration and exploitation behaviour. Five kinds of dragonfly swarm movements have been identified: separation, alignment, cohesion, attraction to a food source, and diversion from hostile sources [33]. Real-world nonlinear engineering problems are currently being addressed with the Dragonfly Algorithm. The conceptual representation of the dragonfly algorithm is shown in Fig. 6. The DA follows five mathematical stages, which are as follows:

Separation: The separation phase aims to prevent collisions while they exist in proximity. x_i is the present position of a specific element and x_j as other components other than x_i, the proximity between them is given as:

$$S_i = -\sum_{j=1}^{N} (x_i - x_j) \quad (15)$$

Alignment: Alignment is the propensity of a search agent to modify its velocity about other search agents in the same neighbourhood. V_j is the velocity of its neighbourhood and A_i is the proper alignment of a standard exploration agent, and it can be expressed as follows:

$$A_i = \frac{1}{N}\sum_{j=1}^{N} V_j \quad (16)$$

Cohesion: Cohesion is a dragonfly characteristic of flying toward the centre of search agents. Cohesion is mathematically represented in (17)

$$C_i = \frac{1}{N}\sum_{j=1}^{N} x_j - x_i \quad (17)$$

Attraction: When a dragonfly is searching for food, the attraction of a food source is a reaction from a search agent. x_i is the dragonfly position, and f is the site of the food.

$$\boldsymbol{F}_i = \boldsymbol{f} - x_i \quad (18)$$

Distraction: This response happens when search agents uncover a potentially harmful object in their immediate vicinity. Given x_i as the dragonfly's position and e is the enemy's location. The following equation determines under distraction phase followed as:

$$E_i = e + x_i \quad (19)$$

The position and velocity of the dragonfly should be updated if it has at least a single neighbour. A formula, such as the PSO method, can be employed to alter the velocity. To update the position, we have used the following equation.

$$x_{t+1} = x_t + dx_{t+1} \quad (20)$$

t represents the present iteration x_{t+1} indicates the following updated position x_t represents the current position and dx_{t+1} represents as step vector and it is formulated as

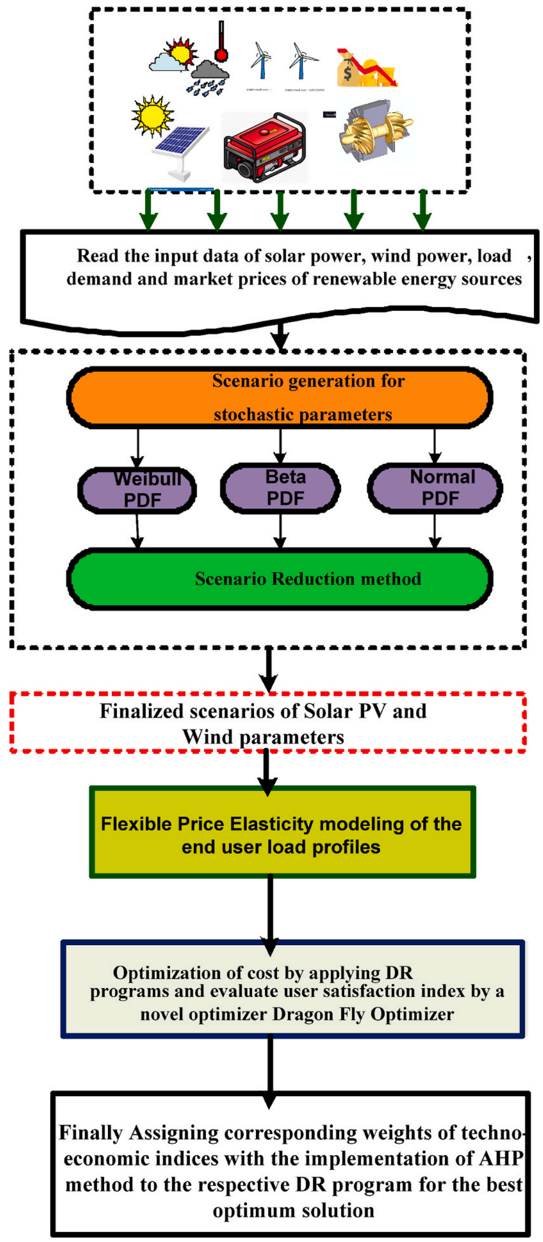

Fig. 7. Proposed methodology.

$$dx_{t+1} = s.S_i + a.A_i + c.C_i + f.F_i + e.E_i + 1.\ dx_t \quad (21)$$

dx_t indicates the recent step vectors; s, a, c, f, e represents the corresponding weights of separation, alignment, cohesion, food factor and enemy factors respectively.

If the dragonfly does not have a neighbour in some circumstances, it must perform certain random orientation. As a consequence, Levy's flight, which is effectively a random walk approach, must be used to update the position. The formula is as follows:

$$x_{t+1} = x_t + levy.x_t \quad (22)$$

The proposed framework's detailed methodology is presented in Fig. 7. Initially, the uncertain parameters, namely irradiation emits from the solar rays, and wind speed, are quantified through scenario generation and reduction processes. The resulting scenarios are then utilized in an optimization solver to determine the optimal scheduling configuration for the day ahead, while adhering to equality and inequality constraints. To evaluate the techno-economic performance indices, DR programs are integrated using the AHP method, assigning appropriate weights. Subsequently, AHP is employed to establish weights for each criterion, and the optimal alternative is derived by considering the chosen DRP, and the corresponding user satisfaction index has been evaluated. Many existing research studies overlook the inclusion of real-time price elasticity coefficients when characterizing the end user load demand profile. In this proposed research work, we address this gap by incorporating real-time price elasticity coefficients to accurately characterize the end user load profile. Additionally, we evaluate user satisfaction indexes while considering reliability and consistency factors. The challenges associated with microgrid energy management frequently include intricate and nonlinear optimization issues. The efficiency and effectiveness of the Dragonfly Algorithm in exploring the solution space can contribute significantly to the identification of global or near-global optimum solutions. This capability is of utmost importance in the context of microgrids, as it enables the maximization of both economic and operational efficiency. The operations of microgrids are susceptible to a range of variables, including the volatility of renewable energy output and the variability of power pricing. The management of microgrid energy frequently encompasses a range of objectives that may be in conflict with one another, including the minimization of costs, the reduction of emissions, and the development of dependability. The Dragonfly Algorithm is having the capability to effectively address multi-objective optimization issues by generating a collection of Pareto-optimal solutions [50]. This allows decision-makers to make informed choices by selecting the most appropriate trade-off among the many objectives. Microgrids exhibit a range of dimensions and intricacy, encompassing modest home installations as well as more extensive industrial and commercial configurations. In the context of microgrid energy management, the expeditiousness of the algorithm in generating solutions might confer a significant benefit, particularly in scenarios necessitating real-time decision-making. The Dragonfly Algorithm's ability to explore the solution space efficiently might result in decreased computing expenses, a crucial factor for real-time or resource-limited applications in microgrids [50].

5. Integration of AHP method on the evaluation of users satisfaction

User satisfaction in the context of load demand and renewable energy power supply can be defined as the degree to which the user's energy needs are met by a reliable and sustainable supply of energy. It can be measured by comparing the actual supply of energy to the user's demand for energy and assessing the level of reliability and consistency of the supply. Various DRPs are implemented based on the user load profile characteristics in which the user demand profile is modified according to the corresponding program while satisfying the customer satisfaction index. In addition, the weight of each satisfaction indicator differs among the different types of implementing demand response programs. To determine the weight of each satisfaction indicator of the end-user load profile w. r.t to the corresponding DR program, the Analytic Hierarchy Process (AHP) method is utilized. The AHP method was selected because it has been widely used for decision making across various fields, including economics, social sciences, and management. This method employs a systematic approach to solving complex problems, incorporating mathematical and psychological principles. Due to its precision, simplicity, and broad applicability, the AHP has become popular multiple criteria decision-making (MCDM) techniques used by researchers globally. So far already above-mentioned research works is not considering reliability factor and consistency factors while evaluating the user satisfaction index. But in this research the incorporation of reliability and consistency factors for achieving accurate real time results.

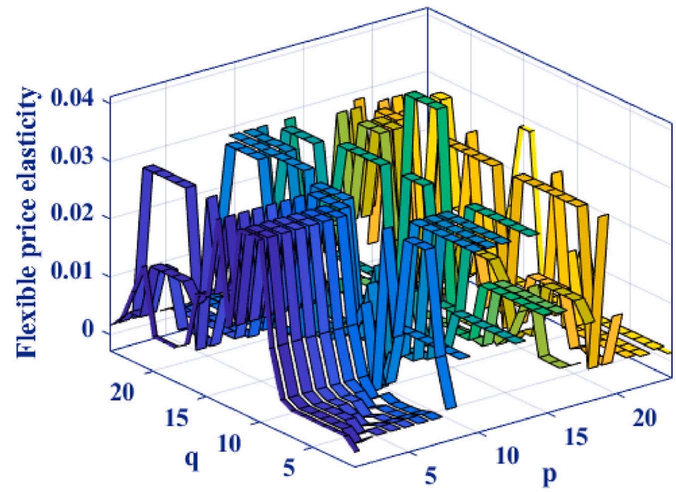

Fig. 8. 3 d-represention FPE of RTP.

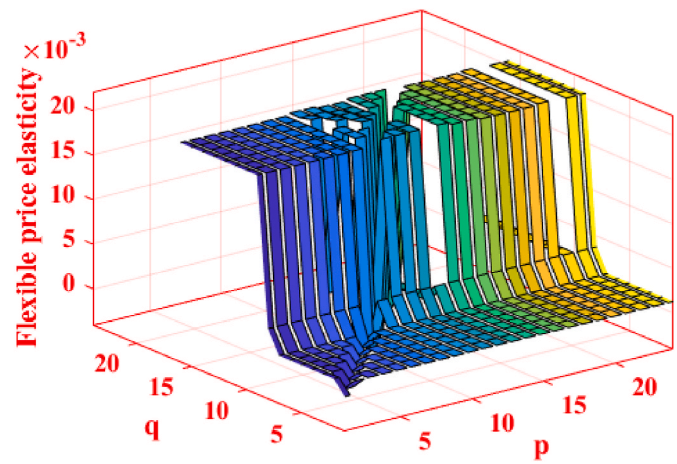

Fig. 9. FPE model of TOU.

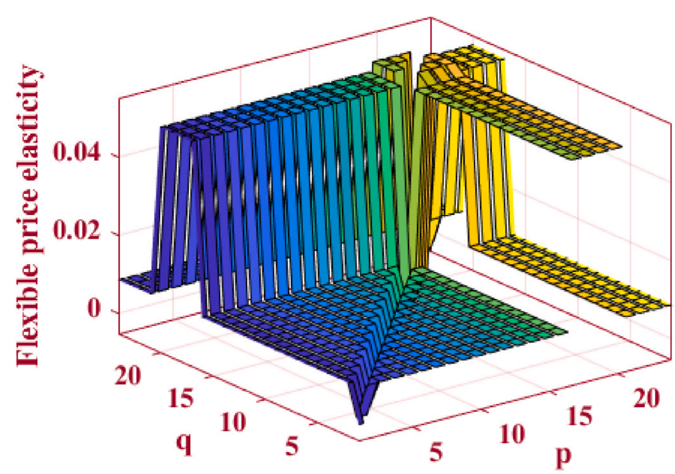

Fig. 10. FPE model of CPP.

Table 2
Algorithm tuning parameters.

Algorithm	Control parameters
DFA	Separation weight, Alignment weight, Cohesion weight, Food attraction weight is 2
QPSO	Contraction and expansion coefficient α = 0.75
TLBO	No Algorithm Specific Parameters
QTLBO	No Algorithm Specific Parameters
PSO	Cognitive constant = 2, Social constant = 2, Maximum inertia = 0.7, Minimum inertia = 0.5
FFA	Randomization Parameter = 0.2, Attractiveness Parameter = 0.2, Absorption Coefficient = 1
GWO	Distance Control Parameter (a): 0<a<2

Table 5
Optimal costs for day-ahead scheduling of MG.

Case	Base	RTP	TOU	CPP
Cost ($/day)	164.25	157.54	152.08	143.85

inspired optimization approaches like PSO, QPSO, TLBO, QTLBO, FFA, GWO. The three-dimensional plot of the FPE parameters of price driven DRPs is derived and represented in Figs. 8–10, respectively. The tuning or control parameters of the implemented optimization techniques for solving the proposed problem are tabulated in Table 2 respectively.

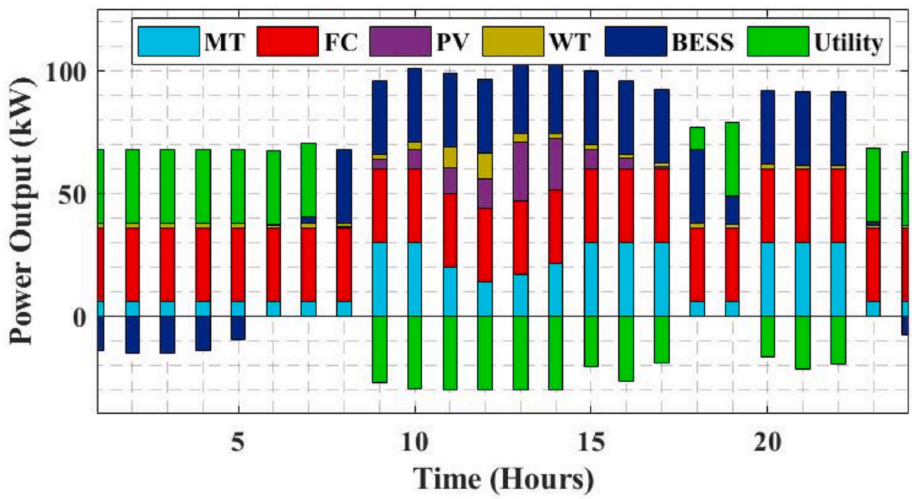

Fig. 11. MG optimal dispatch scheduling for RTP.

Table 3
Optimal scheduling costs ($/kWh).

Optimization approach	BC ($/kWh)	WC ($/kWh)	MC ($/kWh)	SD	CT (s)
DFA	**164.25**	**164.25**	**164.25**	**0**	**27.270**
FFA	167.16	169.36	168.26	0.0242	48.323
GWO	169.92	172.36	171.14	0.029768	51.778
QPSO	170.17	173.62	171.895	0.059513	60.746
QTLBO	173.16	176.33	175.64	0.009522	68.017
TLBO	175.23	177.54	176.385	0.026681	73.926
PSO	176.97	179.98	178.5	0.043808	78.769

$$\mathrm{USI} = \begin{cases} \dfrac{P_{Avg}}{E_{avP}} & P_{Avg} \le E_{aveP} \\ 1 & P_{Avg} > E_{aveP} \end{cases} \tag{23}$$

6. Numerical analysis and discussion

In this section, the intended EMS problem is evaluated effectively, and the statistical study findings are successfully presented. The efficacy of DFA is evaluated with state-of-art heuristics meta-heuristics and quantum-

The evaluated results for deploying PB-DRPs and the related program price elasticities with 3 d representation are depicted in Figs. 9–11, respectively. The FPE coefficients assessed for each PB-DRP are used to modify baseload demand. Renewable energy is harvested to the most significant degree possible, and excess electricity is traded in from the utility, particularly through peak periods. The charging and discharging cycles of the battery have been enhanced by implementing PB-DRPs, particularly in CPP, as compared to RTP and TOU programs during Peak hours. The battery performance is also enhanced with the implementation of price-driven DR programs, and the best performance is achieved during the CPP DR program, respectively. Because of this, the DR programs have gained more significance on energy management problems in both connected and autonomous modes, respectively.

More customers are willing to participate in DR programs by adjusting their respective loads and shifting with respect to time such that the system performance and stability have been enhanced for the optimal operation of MG. The overall optimal operating cost of microgrids with and without DR program implementation is tabulated in Table 3 and Table 4, respectively. The corresponding technical aspects of implementing DR programs are represented in Table 5. Initially, no demand response program participation is implemented, and the operating cost is evaluated on the hourly average load. Later the DRP

Table 4
Techno-Eonomic indices of Implementing Price driven DR Programs ($/kWh).

	Peak	Peak reduction (%)	Load factor	Peak to valley distance	Energy consumption (Kwh)	% Reduction in energy consumption
Base case	90	–	0.7779	0	1695	0
RTP	81.29	9.67	0.833	8.79	1680.76	0.84
TOU	79.30	11.88	0.8485	10.7	1655.46	2.33
CPP	71.96	20.04	0.8651	18.04	1611.72	4.91

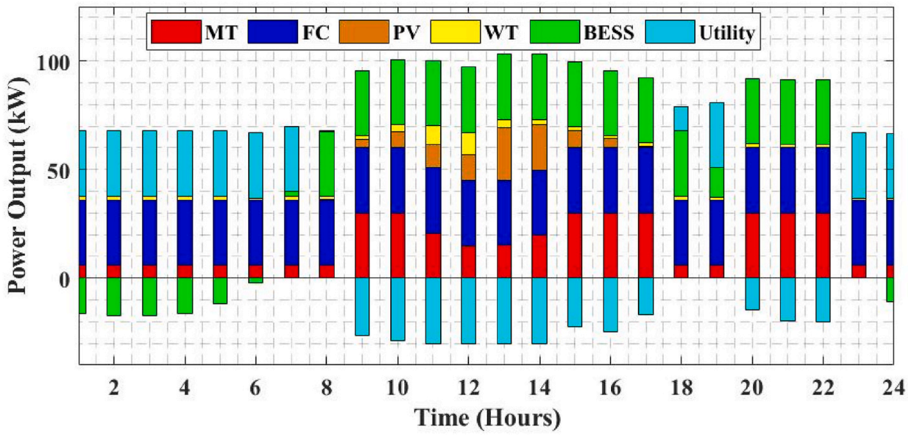

Fig. 12. MG optimal dispatch for TOU.

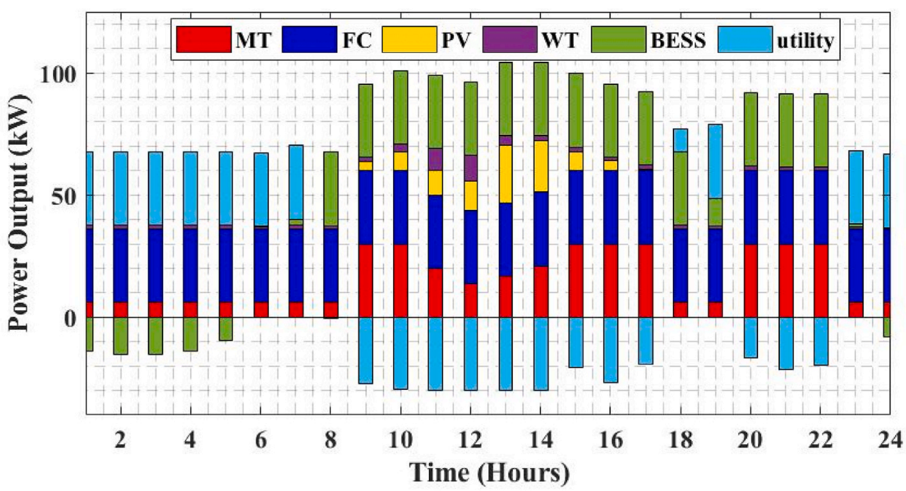

Fig. 13. MG optimal dispatch for CPP.

Table 6
Pair wise Comparison matrix with final weights.

	COST	LF	PR	EC	Final weights
RTP	0.913101	1.095169	0.885226	0.950867	0.960731
TOU	0.945884	1.057212	0.90744	0.973578	0.970579
CPP	0.986654	1.000625	0.98665	0.996254	**0.999864**
Base load	0.875799	1.141814	0.799556	0.950867	0.941002

participation is employed on the base load profile to investigate the accurate time characterization of customer load responses. Figs. 11–13 represents the day ahead scheduling of DG units of a grid connected with the incorporation of DR programs respectively. With this the best scheduling is obtained in case of CPP program out of three cases including base case. The power import from the utility is less and extracts the most quantity of energy from the RESs to meet the consumer loads without any interruptions when compared to RTP and TOU DR programs.

The Analytical hierarchical process approach is utilized to estimate the weight of each techno economic indices with respect to the DR programs for obtaining customer satisfaction. The AHP method is widely applied in complex engineering problems such as mathematics, social, and management sciences respectively [34]. In Table 6 the pairwise comparison matrix is tabulated with the final weights of each technical indices concerning each DR Program.

The final weight is achieved to CPP DR program among the technical indices from the obtained results. Based on the obtained final weights, the consistency index is 0.0518, and the consistency ratio is 0.0426, which is always less than 1; it represents the final weights that are assessed with respect to each technical indices are significant and accurate concerning to the technical indices that are related to MG. The initial real-time base load profile is considered and modified with the implementation of DRPs for obtaining the optimal operation of MG is evaluated in this research work. The user satisfaction index of the end users based on the implementation of the different DR programs like RTP, TOU, CPP respectively. The overall User satisfaction index of the end user in this proposed energy management problem is evaluated and in comparison, with and without application of DR programs is tabulated in Table & respectively. The overall consistency index of the proposed demand response programs with and without implementation of DR programs are 0.753305, 0.771029, 0.829589 and 0.910243 respectively.

The simulation findings reveal that DFA surpasses all other metaheuristic and quantum-inspired algorithms regarding optimum costs, computing time, and convergence, as depicted in Fig. 14 and Table 3, respectively. It is worth mentioning that the critical peak pricing DR Program has the lowest operating costs when compared to other DR programs like TOU and CPP. The state of health of battery is represented in Fig. 15 and illustrates how the health condition of a battery is enhanced with and without the implementation of DR programs.

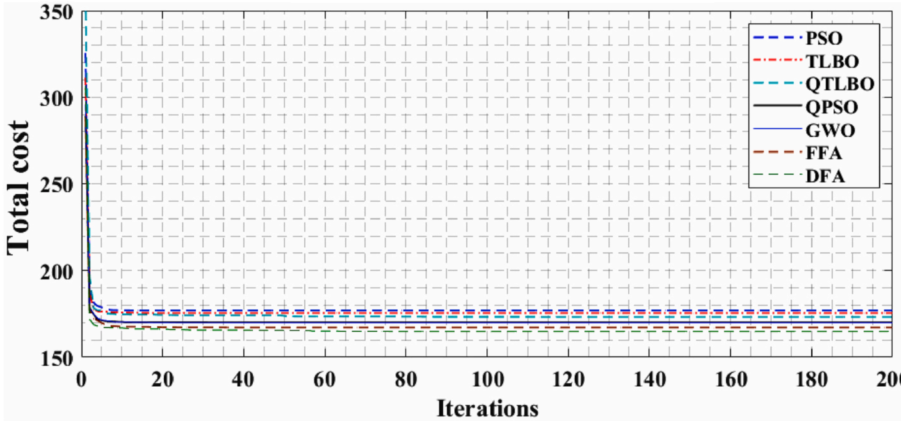

Fig. 14. Convergence characteristics.

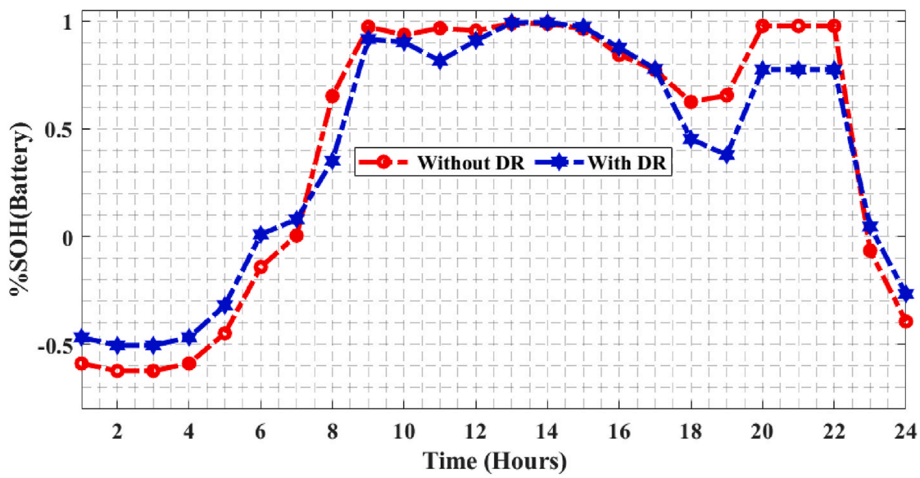

Fig. 15. SOH of a battery with and with out implementation of DR Programs.

7. Conclusion

This research proposes and solves a unique stochastic optimum scheduling issue of a distributed MG under grid-connected mode. DG energy sources like dispatchable, non-dispatchable energy sources and BES are integrated with the enhanced version of the IEEE-34 node test system. A scenario-based strategy is used to resolve the uncertainties associated with solar irradiation and wind speed by developing seven unique scenarios. The effect of price driven DRPs on total operational expenses, energy consumption, and peak controlling is studied. The DFA is used to address the difficulties in the stated problem. The price oriented DRPs are employed to the base load profile, and the simulation results were evaluated and verified in MATLAB atmosphere. The numerical findings are contrasted with recently reported heuristic, meta-heuristic, and quantum-inspired approaches. Significantly, the suggested approach is outstanding in terms of convergence rate, improving the quality of the solution, and computing time is represented in Fig. 14. The Dragon Fly Algorithm optimizes power export to the utility, determines the optimum power dispatch configuration for DG units, and compares results with and without demand response program participation is tabulated in Table 5 respectively. The implemented research work compares the Dragon Fly Algorithm with other heuristic approaches, resulting in a 12.42 % reduction in overall operating costs and the efficacy of the proposed algorithm is shown in Fig. 14. Further, the techno-economic possibilities of adopting different demand response programs are briefly reviewed with respect to Table 6. The AHP method is utilized is to find out each technical index for each DR program are evaluated effectively with the decision-making analysis. The implementation of AHP enables the evaluation of the User Satisfaction Index, which shows that the CPP demand response program achieves the highest level of user satisfaction is 0.92881 respectively. The user satisfaction index describes how distributed energy sources are effectively provided adequate amount of energy to meet the load demand without compromising the customer dissatisfaction respectively. Tabulated results in Table 7 represent the best weight and rank assigned to the CPP program with the help of decision-making analysis whose demand is fully satisfied in all technical aspects. On a practical note, the "Demand Response Auction Mechanism" deployed in various nations offers a tangible illustration of a demand response blueprint which is highlighted in this study. During peak consumption or grid fluctuations, grid overseers might solicit temporary consumption cutbacks from participating entities, such as industries or businesses, offering monetary rewards. Participating consumers, in gratitude for their cooperation, are either compensated or benefit from reduced energy tariffs. This fosters a robust power network and empowers individuals to have greater autonomy over their energy expenses. Prospective expansions of this research will encompass multi-microgrid systems, using advanced

Table 7
User Satisfaction index with different DR Programs.

S. No	Without DR	RTP	TOU	CPP
Base load	0.7686	0.78675	0.84619	**0.92881**

benchmarks like IEEE-69 and IEEE-123, and will incorporate advancements in machine learning while contrasting results with heuristic, meta-heuristic, and other cutting-edge algorithms.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr. Arvind R. Singh reports article publishing charges was provided by University of Pretoria.

Data availability

No data was used for the research described in the article.

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Appendix

DG	Distributed Generation
AC	Annual Cost
DC	Depreciation cost
IC	Investment Cost
PSO	Particle Swarm Optimization
TLBO	Teaching Learning Based Optimization
GWO	Grey Wolf Optimization
RTP	Real time Pricing
TOU	Time of Use
CPP	Critical Peak Pricing
DN	Distribution Network
DER	Distributed Energy Resources
RES	Renewable Energy Sources
MP	Market Price
IBDR	Incentive Based demand response
LF	Load Factor
PR	Peak Reduction
EC	Energy Consumption
ACO	Ant Colony optimization
AFSO	Artificial Fish Swarm Optimization
PD	Probability distribution
PDF	Probability distribution function
MG	Microgrid
EMS	Energy Management System
MT	Micro Turbine
FC	Fuel Cell
FPE	Flexible Price Elasticity
BES	Battery Energy Storage
DFA	Dragon Fly Algorithm
FFA	Firefly Algorithm
PBDR	Price Based demand response

Indices.

$\mathscr{A}$	Decision variable vector
DSG	Distributed Generator
ψ	DG Unit Status
mx	Maximum
BS	Battery Storage
ith	ith DG Unit
jth	jth Battery storge Unit
MP	Market price
$\mathscr{P}_{ue}^{t}$	Power export/import to/from the utility during time interval t.
P_{BS}^{t}	Active power output of Battery storage unit during time interval t.
P_{DSG}^{t}	Active power output of distributed generator unit
$P_{c,t}$	Battery charging during time interval t.
$P_{d,t}$	Battery discharging during time interval t
$E_{BS,t}$	Amount of Energy stored in the battery during time interval t
$\mathscr{P}_{pv}$	Output Power of solar
I_{rad}	Solar irradiance
$T_{\mathscr{c}}$	Module Temperature
$\mathscr{V}_{r}, \mathscr{V}_{ci}, \mathscr{V}_{co}$	Rated, cut-in, cut-out speeds of wind turbine
P_{r}	Rated Wind power
$\mathscr{S}_{DSG_{\mathscr{i}}}^{on}, \mathscr{S}_{DSG_{\mathscr{i}}}^{off}$	Start-up/Shutdown status of DG units
$\mathscr{A}_{\mathscr{c}}$	Annual Cost
$\mathscr{D}_{\mathscr{c}}$	Depreciation Cost

References

[1] Alireza SoltaniNejad Farsangi, Shahrzad Hadayeghparast, Mehdi Mehdinejad, Heidarali Shayanfar, A novel stochastic energy management of a MG with various types of distributed energy resources in presence of demand response programs, Energy 160 (2018) 257–274, https://doi.org/10.1016/j.energy.2018.06.136. ISSN 0360-5442.

[2] Seyed Saeed Fazlhashemi, Mostafa Sedighizadeh, Mohammad E. Khodayar, "Day-ahead energy management and feeder reconfiguration for MGs with CCHP and energy storage systems", J. Energy Storage 29 (2020), 101301, https://doi.org/10.1016/j.est.2020.101301. ISSN 2352-152X.

[3] Jesus Aguila-Leon, Carlos Vargas-Salgado, Cristian Chiñas-Palacios, Dácil Díaz-Bello, " energy management model for a standalone hybrid MG through a particle swarm optimization and artificial neural networks approach", Energy Convers. Manag. 267 (2022), 115920, https://doi.org/10.1016/j.enconman.2022.115920. ISSN01968904.

[4] Santosh Chalise, Jason Sternhagen, Timothy M. Hansen, Reinaldo Tonkoski, Energy management of remote MGs considering battery lifetime, Electr. J. 29 (6) (2016) 1–10, https://doi.org/10.1016/j.tej.2016.07.003. ISSN 1040-6190.

[5] Shuoqi Wang, Dongxu Guo, Xuebing Han, Languang Lu, Kai Sun, Weihan Li, Dirk Uwe Sauer, Minggao Ouyang, "Impact of battery degradation models on energy management of a grid-connected DC MG, Energy 207 (2020), 118228, https://doi.org/10.1016/j.energy.2020.118228. ISSN 0360-5442.

[6] Soham Mandal, Kamal K. Mandal, Optimal energy management of MGs under environmental constraints using chaos enhanced differential evolution, Renewable Energy Focus 34 (2020) 129–141, https://doi.org/10.1016/j.ref.2020.05.002. ISSN 1755-0084.

[7] Ramin Torkan, Ilinca Adrian, Milad Ghorbanzadeh, A genetic algorithm optimization approach for smart energy management of MGs, Renew. Energy 197 (2022) 852–863. ISSN 0960-1481.

[8] M. Rawa, Y. Al-Turki, K. Sedraoui, S. Dadfar, M. Khaki, Optimal operation and stochastic scheduling of renewable energy of a microgrid with optimal sizing of battery energy storage considering cost reduction, J. Energy Storage 59 (2023), 106475.

[9] Hai-Tra Nguyen, Usman Safder, Jorge Loy-Benitez, ChangKyoo Yoo, Optimal demand side management scheduling-based bidirectional regulation of energy distribution network for multi-residential demand response with self-produced renewable energy, Appl. Energy 322 (2022), 119425, https://doi.org/10.1016/j.apenergy.2022.119425. ISSN 0306-2619.

[10] Yingying Zheng, Bryan M. Jenkins, Kurt Kornbluth, Alissa Kendall, Chresten Træholt, Optimization of a biomass-integrated renewable energy MG with demand side management under uncertainty, Appl. Energy 230 (2018) 836–844, https://doi.org/10.1016/j.apenergy.2018.09.015. ISSN 0306-2619.

[11] Dimitrios Thomas, Gaspard D'Hoop, Olivier Deblecker, Konstantinos N. Genikomsakis, Christos S. Ioakimidis, "An integrated tool for optimal energy scheduling and power quality improvement of a MG under multiple demand response schemes", Appl. Energy 260 (2020), 114314, https://doi.org/10.1016/j.apenergy.2019.114314. ISSN 0306-2619.

[12] Lavinia Amorosi, Luca Cedola, Paolo Dell'Olmo, Francesca Lucchetta, " Multi-objective mathematical programming for optimally sizing and managing battery energy storage for solar photovoltaic system integration of a multi-apartment building", Eng. Optim. (2020) 1–20.

[13] Nima Nikmehr, Sajad Najafi-Ravadanegh, Khodaei Amin, Probabilistic optimal scheduling of networked MGs considering time-based demand response programs under uncertainty, Appl. Energy 198 (2017) 267–279, https://doi.org/10.1016/j.apenergy.2017.04.071. ISSN 0306-2619.

[14] H. Haddadian, R. Noroozian, Multi-MG-based operation of active distribution networks considering demand response programs, IEEE Trans. Sustain. Energy 10 (4) (Oct. 2019) 1804–1812, https://doi.org/10.1109/TSTE.2018.2873206.

[15] M. Mohammadjafari, R. Ebrahimi, V. Parvin Darabad, Optimal energy management of a MG incorporating a novel efficient demand response and battery storage system, J. Electr. Eng. Technol. 15 (2020) 571–590, https://doi.org/10.1007/s42835-020-00345-5.

[16] T. Adefarati, R.C. Bansal, M. Bettayeb, R. Naidoo, Optimal energy management of a PV-WTG-BSS-DG MG system, Energy 217 (2021), 119358, https://doi.org/10.1016/j.energy.2020.119358. ISSN 0360-5442.

[17] Mohammadreza Daneshvar, Behnam Mohammadi-Ivatloo, Kazem Zare, Two-stage optimal robust scheduling of hybrid energy system considering the demand response programs, J. Clean. Prod. 248 (2020), 119267, https://doi.org/10.1016/j.jclepro.2019.119267. ISSN 0959-6526.

[18] Alireza Soltani Nejad Farsangi, Shahrzad Hadayeghparast, Mehdi Mehdinejad, Heidarali Shayanfar, "A novel stochastic energy management of a MG with various types of distributed energy resources in presence of demand response programs", Energy 160 (2018) 257–274, https://doi.org/10.1016/j.energy.2018.06.136. ISSN 0360-5442.

[19] Ramin Nourollahi, Pouya Salyani, Kazem Zare, Behnam Mohammadi-Ivatloo, "Resiliency-oriented optimal scheduling of MGs in the presence of demand response programs using a hybrid stochastic-robust optimization approach", Int. J. Electr. Power Energy Syst. 128 (2021), 106723, https://doi.org/10.1016/j.ijepes.2020.106723. ISSN 0142-0615.

[20] Ghasemi Ahmad, Mehdi Enayatzare, Optimal energy management of a renewable-based isolated MG with pumped-storage unit and demand response, Renew. Energy 123 (2018) 460–474, https://doi.org/10.1016/j.renene.2018.02.072. ISSN 0960-1481.

[21] E. Shahryari, H. Shayeghi, B. Mohammadi-ivatloo, M. Moradzadeh, A copula-based method to consider uncertainties for multi-objective energy management of MG in presence of demand response, Energy 175 (2019) 879–890, https://doi.org/10.1016/j.energy.2019.03.129. ISSN 0360-5442.

[22] Javad Najafi, Peiravi Ali, Amjad Anvari-Moghaddam, JosepM. Guerrero, An efficient interactive framework for improving resilience of power-water distribution systems with multiple privately-owned MGs, Int. J. Electr. Power Energy Syst. 116 (2020), 105550, https://doi.org/10.1016/j.ijepes.2019.105550. ISSN 0142-0615.

[23] Pouria Hajiamoosha, Abdollah Rastgou, Salah Bahramara, S. Muhammad Bagher Sadati, Stochastic energy management in a renewable energy-based MG considering demand response program, Int. J. Electr. Power Energy Syst. 129 (2021), 106791, https://doi.org/10.1016/j.ijepes.2021.106791. ISSN 0142-0615.

[24] Fangyuan Xu, Wanli Wu, Fei Zhao, Ya Zhou, Yongjian Wang, Runji Wu, Tao Zhang, Yongchen Wen, Yiliang Fan, Shengli Jiang, A micro-market module design for university demand-side management using self-crossover genetic algorithms, Appl. Energy 252 (2019), 113456, https://doi.org/10.1016/j.apenergy.2019.113456. ISSN 0306-2619.

[25] Roozbeh Morsali, Gokul Sidarth Thirunavukkarasu, Mehdi Seyedmahmoudian, Alex Stojcevski, Ryszard Kowalczyk, A relaxed constrained decentralized demand side management system of a community-based residential MG with realistic appliance models, Appl. Energy 277 (2020), 115626, https://doi.org/10.1016/j.apenergy.2020.115626. ISSN 0306-2619.

[26] R. Seshu Kumar, L. Phani Raghav, D. Koteswara Raju, Arvind R. Singh, Intelligent demand side management for optimal energy scheduling of grid connected MGs, Appl. Energy 285 (2021), 116435, https://doi.org/10.1016/j.apenergy.2021.116435. ISSN 0306-2619.

[27] Bishoy E. Sedhom, Magdi M. El-Saadawi, M.S. El Moursi, MohamedA. Hassan, Abdelfattah A. Eladl, IoT-based optimal demand side management and control scheme for smart MG, Int. J. Electr. Power Energy Syst. 127 (2021), 106674, https://doi.org/10.1016/j.ijepes.2020.106674. ISSN 0142-0615.

[28] X. Yang, Y. Zhang, H. He, S. Ren, G. Weng, Real-time demand side management for a MG considering uncertainties, IEEE Trans. Smart Grid 10 (3) (May 2019) 3401–3414, https://doi.org/10.1109/TSG.2018.2825388.

[29] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, M. Abapour, S. Asadi, A. Anvari-Moghaddam, Chance-constrained scheduling of hybrid MGs under transactive energy control, Int. J. Energy Res. (2021) 1–8, https://doi.org/10.1002/er.6505.

[30] Yuli Astriani, G.M. Shafiullah, Farhad Shahnia, Incentive determination of a demand response program for MGs, Appl. Energy (2021), 116624, https://doi.org/10.1016/j.apenergy.2021.116624. ISSN 0306-2619.

[31] M.H. Mostafa, S.H.E.A. Aleem, S.G. Ali, A.Y. Abdelaziz, P.F. Ribeiro, Z.M. Ali, Robust energy management and economic analysis of MGs considering different battery characteristics, in: IEEE Access 8, 2020, pp. 54751–54775, https://doi.org/10.1109/ACCESS.2020.2981697.

[32] R. Seshu Kumar, L. Phani Raghav, D. Koteswara Raju, Arvind R. Singh, Impact of multiple demand side management programs on the optimal operation of grid-connected MGs, Appl. Energy 301 (2021), 117466, https://doi.org/10.1016/j.apenergy.2021.117466. ISSN 0306-2619.

[33] S. Mirjalili, Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems, Neural Comput. Appl. 27 (2016) 1053–1073, https://doi.org/10.1007/s00521-015-1920-1.

[34] Weihe Huang, Yichen Li, Weichao Yu, Haitao Yu, Xiangying Shan, Hao Wang, Jing Gong, An evaluation index system of the user satisfaction for the natural gas pipeline network, J. Pipeline Sci. Eng. 1 (Issue 4) (2021) 452–458, https://doi.org/10.1016/j.jpse.2021.11.001. ISSN 2667-1433.

[35] K.S. Ei-Bidairi, H. Duc Nguyen, S.D.G. Jayasinghe, T.S. Mahmoud, Multiobjective intelligent energy management optimization for grid-connected microgrids, in: IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe, EEEIC/I&CPS Europe), Palermo, Italy, 2018, pp. 1–6, https://doi.org/10.1109/EEEIC.2018.8493751, 2018.

[36] O. Abedinia, A. Ghasemi-Marzbali, V. Nurmanova, M. Bagheri, A new reconfigured electricity market bidding strategy in view of players' concerns, IEEE Trans. Ind. Appl. 58 (6) (Nov.-Dec. 2022) 7034–7046, https://doi.org/10.1109/TIA.2022.3200348.

[37] Shoujun Huang, Oveis Abedinia, Investigation in economic analysis of microgrids based on renewable energy uncertainty and demand response in the electricity market, Energy 225 (2021), 120247, https://doi.org/10.1016/j.energy.2021.120247. ISSN 0360-5442.

[38] Chong Wang, Zheng Zhang, Oveis Abedinia, Saeid Gholami Farkoush, Modeling and analysis of a microgrid considering the uncertainty in renewable energy resources, energy storage systems and demand management in electrical retail market, J. Energy Storage 33 (2021), 102111, https://doi.org/10.1016/j.est.2020.102111. ISSN 2352-152X.

[39] Mohammadreza Daneshvar, Behnam Mohammadi-Ivatloo, Kazem Zare, Somayeh Asadi, Transactive energy management for optimal scheduling of interconnected microgrids with hydrogen energy storage, Int. J. Hydrogen Energy 46 (30) (2021) 16267–16278, https://doi.org/10.1016/j.ijhydene.2020.09.064. ISSN 0360-3199.

[40] Mohammadreza Daneshvar, Behnam Mohammadi-Ivatloo, Somayeh Asadi, Amjad Anvari-Moghaddam, Mohammad Rasouli, Mehdi Abapour, B. Gevork, Gharehpetian, "Chance-constrained models for transactive energy management of interconnected microgrid clusters", J. Clean. Prod. 271 (2020), 122177 https://doi.org/10.1016/j.jclepro.2020.122177. ISSN 0959-6526.

[41] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, S. Asadi, A. Anvari-Moghaddam, A novel operational model for interconnected microgrids participation in transactive energy market: a hybrid IGDT/stochastic approach, IEEE Trans. Ind. Inf. 17 (6) (June 2021) 4025–4035, https://doi.org/10.1109/TII.2020.3012446.

[42] Ehsan Akbari, Seyed Farzin Mousavi Shabestari, Sasan Pirouzi, Morteza Jadidoleslam, Network flexibility regulation by renewable energy hubs using flexibility pricing-based energy management, Renew. Energy 206 (2023) 295–308, https://doi.org/10.1016/j.renene.2023.02.050. ISSN 0960-1481.

[43] Ghasem Piltan, Sasan Pirouzi, Alireza Azarhooshang, Ahmad Rezaee Jordehi, Paeizi Ali, Mojtaba Ghadamyari, Storage-integrated virtual power plants for resiliency enhancement of smart distribution systems, Part B, J. Energy Storage 55 (2022), 105563, https://doi.org/10.1016/j.est.2022.105563. ISSN 2352-152X.

[44] Anoosh Dini, Alireza Hassankashi, Sasan Pirouzi, Matti Lehtonen, Behdad Arandian, Ali Asghar Baziar, A flexible-reliable operation optimization model of the networked energy hubs with distributed generations, energy storage systems and demand response, Part A, Energy 239 (2022), 121923, https://doi.org/10.1016/j.energy.2021.121923. ISSN 0360-5442.

[45] Mahmoud Zadehbagheri, Mohammad Javad Kiani, Sasan Pirouzi, Mehrdad Movahedpour, Sirus Mohammadi, The impact of sustainable energy technologies and demand response programs on the hub's planning by the practical consideration of tidal turbines as a novel option, Energy Rep. 9 (2023) 5473–5490. ISSN 2352-4847.

[46] Zhaoyang Qu, Chuanfu Xu, Fang Yang, Ling Fan, Sasan Pirouzi, Market clearing price-based energy management of grid-connected renewable energy hubs including flexible sources according to thermal, hydrogen, and compressed air storage systems, J. Energy Storage 69 (2023), 107981, https://doi.org/10.1016/j.est.2023.107981. ISSN 2352-152X.

[47] XiaoWei Zhang, Xiaoping Yu, Xinping Ye, Sasan Pirouzi, Economic energy managementof networked flexi-renewable energy hubs according to uncertainty modeling by the unscented transformation method, Part B, Energy 278 (2023), 128054, https://doi.org/10.1016/j.energy.2023.128054. ISSN 0360-5442.

[48] Mohammad Reza Jokar, Saeid Shahmoradi, Adil Hussein Mohammed, Loke Kok Foong, Binh Nguyen Le, Sasan Pirouzi, Stationary and mobile storages-based renewable off-grid system planning considering storage degradation cost based on information-gap decision theory optimization, J. Energy Storage 58 (2023), 106389, https://doi.org/10.1016/j.est.2022.106389. ISSN 2352-152X.

[49] Afshin Pirouzi, Jamshid Aghaei, Sasan Pirouzi, Vahid Vahidinasab, Ahmad Rezaee Jordehi, "Exploring potential storage-based flexibility gains of electric vehicles in smart distribution grids", Part C, J. Energy Storage 52 (2022), 105056, https://doi.org/10.1016/j.est.2022.105056. ISSN 2352-152X.

[50] K. Sureshkumar, Vijayakumar Ponnusamy, " Power flow management in micro grid through renewable energy sources using a hybrid modified dragonfly algorithm with bat search algorithm", Energy 181 (2019) 1166–1178, https://doi.org/10.1016/j.energy.2019.06.029. ISSN 0360-5442.