Impact of demand side management approaches for the enhancement of voltage stability loadability and customer satisfaction index

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Abstract –This research work presents the tri-level optimization framework for the optimal scheduling of grid-connected and autonomous microgrids to diminish power losses and maximize loadability. Since the network's voltage profile depends on the loading level, the flexible load shaping-based demand-side management strategy is incorporated to investigate its impact on microgrid loadability. With the consideration of uncertain parameters related to renewable power generation, load demand, and power loss, voltage limit constraints, the resultant problem is formulated as a stochastic mixed-integer non-linear problem to enhance microgrid loadability and optimize daily operating costs. The interdependency of demand side management program and microgrid loadability is investigated. The seasonal load profiles covering the weekend and weekday loads in winter, summer, and spring/fall seasons are examined in this research work. The enhanced versions of the distribution networks IEEE-33 and IEEE-69 based microgrid test systems are chosen to evaluate the proposed framework in both off-grid and autonomous modes of operation. Simultaneously, the overall customer satisfaction index is evaluated and improved according to the seasonal load profiles winter weekday, winter-weekend, summer-weekday, summer-weekend, spring-weekday, and spring-weekend by 8.68%, 7.97%, 16.7%, 19.62%, 17.14%, 20.50% respectively. The recently reported Whale Optimization Algorithm is adopted to solve the proposed optimization problem, and the obtained simulation results are validated by comparing them with popular metaheuristic algorithms. The computational burden on the utility is reduced for optimal scheduling of grid-integrated microgrid to extract maximum power by maintaining network voltage profile.

***Keywords*:** Energy Management, Loadability, Whale optimization algorithm, Microgrid Operation and Planning

Nomenclature

Indices			
i	Distributed generator unit index	P_{mn}, Q_{mn}	Active and reactive power between bus m and bus n
j	Battery storage device index	$\vec{X}(t)$	Location of the search Agent
t	Scheduling time index	$\vec{A}, \vec{C}$	Coefficient vectors
ND	Total number of distributed generators	b	Logarithmic spiral shape
NB	Total number of battery storage devices	l	Random number
NL	Load demand index	**Abbreviations**	
Nb	Number of buses	BS	Battery Storage
Parameters		DG	Distributed Generation
$F(x)$	Cost objective function	FC	Fuel Cell

P_{DGi}^{t}	Output power of DG units	FFA	Firefly Algorithm
P_{u}^{t}	Utility power output	GWO	Grey Wolf Optimization
P_{d}^{t}	Load Demand	MG	Microgrid
B_{DGi}^{t}	DG units bidding cost	MLI	Maximum Loadability Index
MP_{ut}^{t}	Utility Market price	MT	Microturbine
$S_{DGi}^{on}, S_{DGi}^{off}$	DG unit startup/shutdown costs	PSO	Particle Swarm Optimization
P_{loss}^{t}	Power losses	PV	Photovoltaic
$P_{DGi,mn}^{t}$, $P_{DGi,mx}^{t}$	Minimum and Maximum power limits of DG unit	QPSO	Quantum Particle Swarm Optimization
$P_{BSj,mn}^{t}$, $P_{BSj,mx}^{t}$	Minimum and Maximum power limits of BS device	QTLBO	Quantum Teaching Learning Based Optimization
$P_{ut,mn}^{t}$, $\mathcal{P}_{ut,mx}^{t}$	Minimum and maximum values of utility power exchange	SSA	Sparrow Search Algorithm
V/δ	Voltage magnitude/Phase	TLBO	Teaching Learning Based Optimization
Y/θ	Line admittance magnitude/ Phase	VDI	Voltage Deviation Index
r_{mn}, x_{mn}	Resistance and Reactance between bus m and bus n	WT	Wind Turbine

1. Introduction

The evolution from fossil fuel-based conventional centralized power generation to prosumer-based distributed generation (DG) enables efficient, reliable, and more economical operation of power systems. Integrating such prosumer-based DG sources with information and communication infrastructure plays a crucial role in the smart grid paradigm [1]. However, this transition brings various operational challenges, such as energy management, control strategies for seamless integration of DG sources, and managing intermittent renewable energy resources. The concept of microgrids (MG) has emerged as one of the building blocks for smart grid architecture to cope with the above challenges and maximize the resiliency and reliability of the power grid in the face of contingencies [2]. The principal characteristic differentiating MG from DG sources is controllability, having control strategies defined for grid-connected and isolated operation modes. The voltage and frequency control for balancing loads and generation within the MG system is typically managed by centralized, decentralized, and distributed architectures [3]. The typical centralized MG architecture with power and communication flow among DG sources and loads is shown in Figure 1.

The optimization strategies of the MG network operation have been highly influenced over a decade to yield energy security and economic benefits. In this regard, optimal power flow (OPF) has been considered a powerful economic and technical tool to support the operator during microgrids' planning, operation, and control. The detailed taxonomy of OPF with single and multi-objective and corresponding methodologies are listed in [4]. As per the comprehensive literature survey conducted by the authors in [5], the power losses at the distribution level account for 70% of total power network losses. In light of this, alleviating power dissipation in the microgrid network at the smart distribution network level is paramount. Although several literature indices related to power loss and voltage profile enhancement are considered, the loadability index is least considered at the distribution level [6]. The recently reported state-of-the-art covers the detailed research analysis on enhancing loadability in balanced [7] and unbalanced [8] distribution networks as well as microgrid networks in on grid and isolated modes of operation [9].

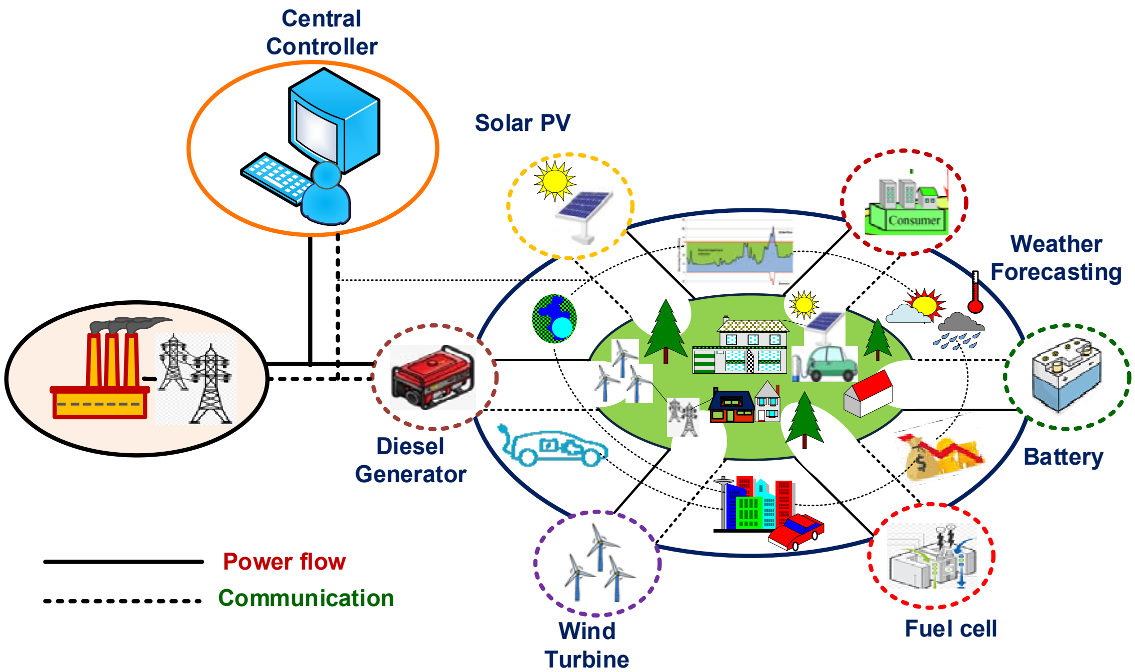

Figure 1. Typical centralized microgrid architecture

The most straightforward approach to enhance the loadability of a distribution system is to determine the voltage gradient at the weakest bus and placing the DG source at the appropriate node, such as in [7], where an analytical approach based on saddle-node is implemented to find the weakest bus. In [8], the future load scenario is evaluated and considered in the optimization problem to enhance the loadability of an unbalanced radial distribution network. The critical loading point of the system is evaluated, and the look-ahead approach is designed to develop a new voltage stability index. However, the proposed stability index only detects the most stressed feeder, thus only leading to a marginal improvement in the lodabilty by rescheduling the control variables. Similarly, a two-level microgrid control hierarchy is proposed in [9], where local controllers control the DG sources installed in the MG network to optimize energy and power in a synchronous mode of operation. But this approach leads to an active power loss over a fifteen-minute schedule during a one-day optimization period. The authors in [10] have modified the DC continuation power flow approach to determine the loadability limit of a distribution network. The impedance matrix of the above approach is modified by adding mathematical models of DC-DC converters to investigate their impact on loading capability. Their simulation results report that the approach only helps identify the weakest node in a network to formulate a stability index for a DC distribution system with only two DRs like PV and fuel cells. In [11], the authors proposed an analytical approach for mitigating voltage unbalances and enhancing the loadability of the distribution network. Here, only battery energy storage is used to leverage benefits like robust capacity support and voltage regulation and the loadability point is treated as a voltage stability loading margin. The computational burden for their approach is enormous, and their system validation is only done for a local distribution network utilizing only one optimization technique without providing any fair comparison with other metaheuristic techniques.

From the viewpoint of intermittent power output from renewable energy sources (RES), the day-ahead optimized load management of reconfigurable MG networks is linked with operational risk. A TOU DR scheme is implemented in [12] to enhance loadability on transmission lines under contingencies and dynamic stability for a local distribution network (Columbia). The obtained outcomes show that their DR strategy works only when the penetration level is =>30 % and enhances the distribution system's frequency and rotor angle fluctuations. The results are based only on PowerFactory DIgSILENT software, and the strategy is applied directly without any changes to the DR program or variables. Similarly, a risk-based hourly configuration is determined in [13] in the presence of a reward/penalty scheme. But their method is only suitable for 10 and 32-bus small systems for short-term scheduling and has limitations in applicability to large network systems with multiple DR units. In [14], the demand response concept is integrated with the volt/var optimization problem to investigate the influence of load level due to the application of DR against voltage profile to mitigate voltage instability. The devices influencing the volt/var optimization, such as circuit breakers, tap-changing transformers, inverters, and solar PV, were considered. Reactive power loads affecting these devices were rescheduled to minimize loss and unbalance with cost optimization. The maximum load that can be supplied within the isolated MG network without violating frequency and voltage limits is one of the major concerns for its optimal operation to maintain the MG network's reliability, which has not been investigated in the above work. Also, the loadability maximization problem of an islanded MG in the presence of multiple storage systems and RES is not explored.

Although a few works, such as [15], reported a multi-objective approach to optimize emission and operational costs using a multi-objective Ant Lion optimizer, the effect of variable renewable generation sources on the loadability limit of microgrids is not investigated. The independent and correlated variables in the non-linear optimization problem are identified by employing the global sensitivity analysis method in [16] for determining the loadability limit of islanded microgrids for only a 33-bus system. Similarly, in [17], the droop control, distributed line capacity limits, and tie-line limits were considered to achieve the optimum loadability of islanded MG. In [18], the effect of DSM on loading margin and network losses with higher penetration of electric vehicles and pumps are presented. The shifting and reconnection of constant impedance loads on network performance are investigated before and after applying for DSM programs with prioritization of impedance and induction motor loads. The authors in [19] formulated a supervisory control system for AC-DC hybrid MG to enhance the overall loadability of the system. The active and reactive power mismatches in the three-phase loading are balanced with the help of a power routing mechanism. Although their simulated results prove that the loadability index is maximized, voltage fluctuations and MG energy losses are reported.

Further, an operation management scheme was developed to solve the day-ahead scheduling of a distributed islanded microgrid test system [20]. The proposed problem is formulated as multi-period mixed integer non-linear programming. This study only considers an isolated MG system and is not evaluated for large-scale active network systems. In [21], the authors utilized FACTS devices, i.e., enhanced dynamic voltage restorer (EDVR), to compensate for the voltage levels and stabilize the grid-connected microgrid. The control strategy consists of two sub-control units with an enhanced synchronous reference frame control unit and fuzzy control unit for the performance of EDVR. The controller's response is dynamic and fast at every iteration process, but the unavoidable time delay in the control process makes the microgrid unstable because of numerous heterogeneous inefficiencies.

To handle the time delays issue for improving the stability condition of the microgrid [22] proposes a general cyber-physical model of a synchronously controlled, distributed microgrid based on inverters, considering numerous time delays. The method in this study only assumes the partially distributed MG control. The model predictive control strategy technique is adopted for hybrid poly-generation power system plants by incorporating two variables method for the optimal microgrid operation and maintaining the system stability [23]. The study shows an overall capacity loss of around 3%, and battery ageing is not considered exclusively. The control strategies discussed in the above-discussed works were adopted to control the decision variables with different methodologies for obtaining microgrid stability with the dynamic response of the controllers. But the distributed generator units associated with any microgrid should be provided adequate power during the scheduled time for the optimal operation of the microgrid.

In this case, if the associated DGs, RES, and BES should not dispatch the required power to the respective loads and extract power from the utility, the system burden would increase with the power outages that may cause system instability.

A 2-stage novel stochastic optimization approach is implemented to handle a rural microgrid's energy management problem as a case study in [24]. The stochastic approach is compared with the deterministic approach. It proves that the proposed methodology outperforms in terms of the quality of the solution. Still, the convergence speed is slow compared to other stochastic algorithms, and fewer case scenarios were considered to evaluate the algorithm. In [25], green energy is generated by employing electrolyzes with high participation levels of RES sources of a medium voltage distributed network microgrid, and the problem is formulated as a bi-level mathematical model. The incentive-based demand response program is implemented to enhance consumer consumption flexibility, but congestion concerns on the utility side were not considered while calculating the overall system performance. A physical-model-free voltage control method utilizes a deep supervised learning methodology facilitated by surrogate models to investigate the connection between the power injections and voltage variations of individual nodes [26]. The surrogate model, which was discussed in a controlled way, utilizes a limited quantity of collected historical information. Furthermore, the deep learning method is employed to develop an ideal control method based on continuous interactions with the surrogate model. Still, it does not support the topology change in the active distribution network.

The interdependency of loadability and the voltage enhancement of distributed microgrid networks is described in [27]. It has been observed that there is a convergence issue between undervoltage load-shedding and maximum loadability limit when load growth is considered. Several operational scenarios where the maximum loadability can be reached before triggering any load-shedding scheme are discussed, such as the loadability assessment by replacing synchronous generators with wind power plants [28]. Similarly, the overall power loss indices were proposed to characterize the distribution network losses considering wind power integration in [29]. Wind power farms' sizing and siting and effect on voltage stability margin are analyzed. However, with 34% wind power penetration, the loadability margin reaches a voltage instability point. Authors in [30] provided a solution for optimal placement of DG sources in reducing network losses and improving voltage profile. Likewise, other works in the literature have focused either on optimal microgrid scheduling, including stochastic-based energy management approaches [31], load dynamics [32], [33], but their optimal scheduling of DG sources in a microgrid network considering the loadability margin is not fully covered.

Further, utility-oriented DSM programs [34] and customer-oriented price-driven [35], and incentive-driven [36] DR programs can enhance the operational costs to a certain extent of on-grid MGs, the changes in load profile due to DSM influence voltage profile and network loadability is yet to be investigated. For instance, the maximization of loadability in droop-controlled islanded MGs is studied, and the influence of random input variables on islanded MG loadability is investigated in [39]. In the case of research works studied on grid-connected networks, the impact of BS on the loadability of MG is investigated in [38]. The effect of annual load growth on distribution system loading capacity with penetration of multiple DG units is studied in [41]. In a similar work [46], the optimal placement of capacitors and DG units is considered to improve the voltage profile. The two essential functions of microgrid energy management are demand-side management and efficient power scheduling. Although prior research has studied numerous indices related to power loss and voltage profile enhancement, the influence of demand-side management strategies on the loadability index and customer satisfaction index is least considered at the microgrid network level.

To summarize, the majority of the studies in the literature on MG loadability are confined to either on-grid or islanded systems. As outlined in the above-discussed research works, none have considered both operating modes simultaneously to maximize the system loadability with provisions of network power flow and voltage stability constraints. A brief comprehensive comparison of existing research works with the proposed work associated with different optimization techniques and the corresponding technical indices considering different objectives for grid-connected and islanded microgrid systems applicable to large networks is iterated in Table 1.

Table 1. A comprehensive comparison of existing research outcomes with proposed work

Ref	Test System	Grid-Connected	Islanded	Optimization approach	Objective Outcome
[37]	IEEE 33-bus	-	✔	Droop control	Enhancing the system's maximum loadability and minimizing the system generation cost
[38]	IEEE 69-bus	✔	-	PSO	Power loss minimization, system loadability and voltage enhancement.
[39]	IEEE 38-bus	-	✔	Density-based GSA Method	Evaluation of uncertainties on performance in Islanded MGs.
[40]	UFSC 16 node test feeder	✔	-	Sequential Monte Carlo approach	Assessment of voltage signal quality and loadability enhancement
[41]	IEEE 33-bus	✔	-	PSO	Optimum siting/ sizing of DGs to cater to several feeders' loads.
[42]	IEEE 33, IEEE 69-buses	✔	-	Butterfly Optimization	Minimize the losses and Maximizing the loadability margin factor
[43]	IEEE 33, IEEE 69-buses	✔	-	DIgSILENT Power Factory	To detect maximum loadability at connected buses and improve the voltage profile
[44]	IEEE 6, IEEE 33-buses	✔	-	Differential approach	Enhancement of maximum loadability index
[45]	IEEE 33, IEEE 69-buses	-	✔	Multi-objective harmony search approach	Estimate the voltage stability margin and loadability index for islanded MG
[46]	IEEE 33, IEEE 85-buses	✔	-	WIPSO-GSA	Loss minimization and loadability enhancement of radial distributed
[47]	IEEE 12, IEEE 34, IEEE 108-buses	✔	-	PSO	Optimal placement/sizing of capacitors based on Shannon's entropy and min. of power losses.
[48]	IEEE 14-bus	✔	-	PSO	Minimization of power losses and voltage deviation at corresponding buses are evaluated on the 14-bus Kumamoto system in japan.
[49]	12kV,33kV feeders	✔	-	CYME software	Optimal sizing of BESS and mitigate the voltage losses
[50]	-	-	-	Decomposition method	Wind speed forecasting using Neural Networks, and the Grey Wolf Optimization approach

[51]	IEEE-33 bus	✓	-	Stochastic programming	Minimizing the overall operating costs of the microgrid with the integration of demand response programs
[52]	IEEE-69 bus	✓	-	Benders Decomposition approach	To ensure fair trade-off for local energy markets without raising the energy cost.
[53]	IEEE-33 bus (7-Node)	✓	✓	Mixed integer second-order cone programming	a multi-stage resilient enhancement technique and multi-level decentralized storage for the electricity-gas incorporated energy infrastructure for optimal scheduling and fault restoration schedule framework.
[54]	IEEE-24 bus	-	✓	Binary Particle swarm Optimization	Optimal location of wind and storage unit of 24-bus distributed network feeder.
[55]	IEEE 12, IEEE 34, IEEE 141-buses	✓	-	Sine-cosine optimization approach	Optimal sizing and placement of DERs to reduce the annual costs of DERs and power losses for improving the system's reliability.
[56]	IEEE-33 bus	✓	-	Machine learning technique	To improve the resiliency of multi-microgrids in extreme operating conditions
[57]	IEEE-33 and 118 buses	✓	-	Reinforcement learning strategy	Optimal placement of DG units, RESs, and Energy storage units to reduce the power losses and improve the voltage profile.
[58]	IEEE test systems	✓	-	Neural Networks	To enhance the scalability and computational efficiency of the distributed test systems.
Proposed Work	IEEE 33-bus, IEEE 69-bus	✓	✓	WOA Optimization	Voltage enhancement and maximizing the loadability of grid-connected and islanded systems using DSM strategy incorporating customer satisfaction index.

Moreover, enhancing the loadability of MGs in light of applying utility-induced DSM strategies is an area left unexplored in the literature. The relationship between loadability and voltage is not studied extensively for grid-connected and islanded systems in the literature. The customer satisfaction index is also not considered when evaluating the test systems to enhance microgrid reliability. Thus, a new optimal scheduling problem of an MG is formulated for effective day-ahead planning and operation in both on-grid and islanded modes, respectively. The proposed problem considers the stochastic parameters involved with Solar PV, Wind power, and utility market prices and has been solved using the recently reported Whale Optimization Algorithm. A new tri-level optimization framework is proposed and verified on enhanced versions of IEEE-33 & 69 bus networks. The customer satisfaction index is also evaluated on different real-time seasonal load profiles for enhancing the microgrid reliability and operation. The superiority of the obtained simulation results proves the proposed approach's efficacy and significance in distinguishing from available metaheuristic methods of system operation. The brief contribution of this research paper is listed below.

1. A new optimum scheduling problem of an MG in on-grid and islanded systems is formulated by considering various network-flow constraints.
2. In the first stage of the proposed three-tiered framework, uncertainty parameters in the MG network are addressed. Second, by strategically placing DG units and a capacitor simultaneously, we may

reduce network flow losses and boost the quality of the voltage distribution. Third, we look into the interdependence of the DSM program's implementation and its effect on loadability while incorporating the customer satisfaction index.

3. The framework is implemented using upgraded IEEE-33 and 69 distributed networks, and the influence of the variable load-shaping DSM method on power losses, loadability, operational cost, and customer satisfaction index is evaluated. The Whale Optimization Algorithm (WOA) increases MG operating expenditures and determines the best day-ahead plan for on-grid and islanded system operation. The suggested approach is compared to state-of-the-art algorithms to demonstrate its efficacy in solution quality, convergence rate, and computational time.

The organization of the research paper is as follows. Section 2 covers the details regarding problem formulation, and a brief description of the mathematical modelling of the microgrid is discussed in Section 3. In Section 4, the tri-level implemented framework is elaborated with details on the proposed algorithm to solve the proposed problem. Finally, the simulation results with technical discussions on outcomes are provided in Section 5.

2. Problem Formulation

The proposed MG scheduling problem consists of continuous and discrete variables as decision variables during optimization. Hence, it is articulated as an MINLP to minimize MG's daily operating and utility power exchange expenses. The network flow constraints and voltage stability index are considered for evaluation.

2.1 Objective function

$F(x)$ is the objective function for the proposed MG daily operating cost-minimization problem is represented in (1), which consists of DG procurement costs DG_c, battery storage costs BS_c and utility power exchange prices. The final objective cost function value, which is determined by decision variables, are arranged in a x vector as represented by (2). Since the overall operation cost of the DG sources and battery storage devices involves startup/shutdown costs and bidding costs, the expanded version of DG operating costs DG_c and battery storage operating costs BS_c are given in (3) and (4).

$$\mathrm{F}(x) = \sum_{t=1}^{T} Operating\ Cost = \sum_{t=1}^{T}\left\{\sum_{i=1}^{ND}[\mathrm{DG}_c] + \sum_{j=1}^{NB}[\mathrm{BS}_c] + P_u^t MP_u^t\right\} \tag{1}$$

$$x = \left[P_{DG1}^t, P_{DG2}^t, .. P_{ND}^T, P_{BS1,}^t P_{BS2,}^t .. P_{NB}^T,\ p_u^1,\ p_u^2,\ p_u^3, \dots,\ P_u^T\right] \tag{2}$$

$$DG_c = \left[u_i^t P_{DGi}^t B_{DGi}^t + S_{DGi}^{on} max\{0, u_i^t - u_i^{t-1}\} + S_{DGi}^{off} max\{0, u_i^{t-1} - u_i^t\}\right] \tag{3}$$

$$BS_c = \left[u_j^t P_{BSj}^t B_{BSj}^t + S_{BSj}^{on} max\{0, u_j^t - u_j^{t-1}\} + S_{BSj}^{off} max\{0, u_j^{t-1} - u_j^t\}\right] \tag{4}$$

2.2 Operational constraints

The performance of MG networks depends on effective planning and operation to mitigate total power loss and improve system voltage and loadability. The objective function $F(x)$ is subjected to the power balance equation shown in (5) where P_{loss}^t is the power loss in the microgrid. The feasible operation of DG units and battery storage units is assured when the evaluated power is obtained within the minimum and maximum boundary values, as shown in (6). The proposed problem considered active and reactive network flow constraints are represented in (7) and (8). In (7), the active power flow calculation of the distributed network subjected to network constraints is represented in (7), and the reactive power flow calculation of the distributed network subjected to network flow constraints is represented in (8), respectively. With the application of the BFS power flow algorithm [59], the power losses at each bus of the proposed test system are obtained. As mentioned earlier, the network's voltage profile enhancement depends on the loading factor. The maximum loadability index [60] between two consecutive buses can be evaluated from (9). The typical power-voltage characteristics for determining the maximum loading point with and without the DG unit's consideration are shown in Figure 2.

$$\sum_{i=1}^{ND} P_{DGi}^{t} + P_{u}^{t} = \sum_{l=1}^{NL} P_{d}^{t} + P_{loss}^{t} \tag{5}$$

$$\begin{cases} P_{DGi,mn}^{t} \leq P_{DGi}^{t} \leq P_{DGi,mx}^{t} \\ P_{BSj,mn}^{t} \leq P_{BSj}^{t} \leq P_{BSj,mx}^{t} \\ P_{u,mn}^{t} \leq P_{u}^{t} \leq P_{u,mx}^{t} \end{cases} \tag{6}$$

$$\mathrm{E}(P_{m}^{t}) = \sum_{n=1}^{Nb} E(V_{m}^{t}) E(V_{n}^{t}) Y_{mn} \cos(\theta_{mn} + E(\delta_{m}^{t}) - E(\delta_{n}^{t})) \tag{7}$$

$$\mathrm{E}(Q_{m}^{t}) = \sum_{n=1}^{Nb} E(V_{m}^{t}) E(V_{n}^{t}) Y_{mn} \sin(\theta_{mn} + E(\delta_{m}^{t}) - E(\delta_{n}^{t})) \tag{8}$$

$$MLI = \frac{V_{m}^{2}\left[-(r_{mn}.P_{mn} + x_{mn}.Q_{mn}) + \sqrt{(r_{mn}^{2} + x_{mn}^{2})(P_{mn}^{2} + Q_{mn}^{2})}\right]}{2.(x_{mn}.P_{mn} - r_{mn}.Q_{mn})^{2}} \tag{9}$$

$$VDI = \sum_{v=1}^{Nb} \left| \frac{v_{ref} - v_{v}}{v_{ref}} \right| \tag{10}$$

$$S_{m} = P_{m} + j(Q_{m} - Q_{c,m}) \tag{11}$$

$$F_{loss} = Min \sum_{t}^{T} g_{m,n} [V_{m}^{2} + V_{n}^{2} - 2V_{m}V_{n} cos\,(\theta_{m} - \theta_{n})\,]^{2} \tag{12}$$

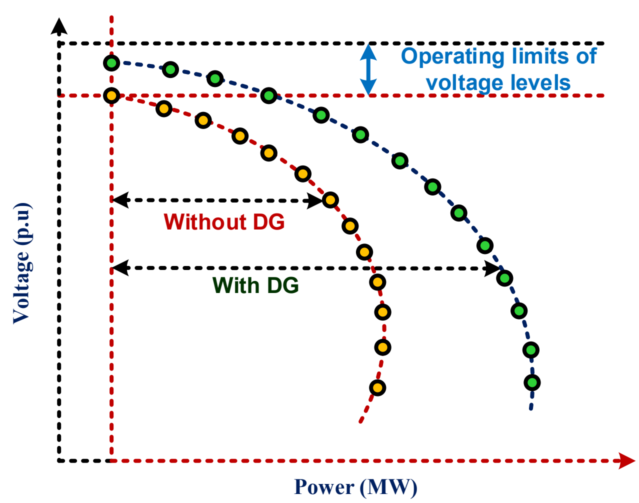

Figure 2. Power-Voltage characteristic curve

The voltage profile at each node must be sustained within the prescribed operational limits to ensure stable and reliable operation of the microgrid network. The highest value of the voltage deviation index [6] in (10) implies enriched voltage levels of the corresponding bus. The parameters v_v and v_{ref} depicts the actual node voltage and the reference voltage. To enhance the system's voltage profile, installing capacitors at the optimal locations is done to evaluate the total power loss. With this viewpoint, the BFS-based load flow algorithm is chosen to determine the power loss matrix and to inject the reactive power $Q_{c,m}$ into the bus, as shown in (11). The current in the respective branch, say m to n is evaluated in the backward sweep based on injected current and again, in the forward-sweep, the current from the branch m to n is evaluated based on a voltage of the bus m [61]. Finally, the overall active power loss taken in the optimal placing of capacitors is evaluated as per (12).

2.2.1 Customer satisfaction for Power Export/Import of Microgrid:

The Distributed energy resources are integrated with the microgrid to provide an adequate amount of energy to critical and non-critical loads at optimal scheduling configuration to satisfy load demand during the day ahead scheduling. Therefore, customer satisfaction for a microgrid is to extract the maximum amount of energy from the distributed energy resources instead of power import from the utility to minimize the microgrid's overall operating cost and provides better optimal scheduling of interconnected DG units in the microgrid. From the power scheduling perspective, the Customer Satisfaction Index (CSI) is satisfied when the DG sources extract the maximum energy instead of importing power from the utility [62]. Suppose more power is imported from the utility to the microgrid; in that case, the overall operating cost is increased due to the dynamic nature of the market bid prices, and the increased market price results in the user dissatisfaction index of the microgrid. If the customer satisfaction is more than one indicates, surplus power can be extracted through the DG units and supplied to BS unit such that the MG can export power to the utility to optimize the overall operating cost of the MG and enhance customer satisfaction needs. The CSI is expressed as follows.

$$CSI = \begin{cases} \frac{P_{Total}}{E_{Total}} & P_{Total} \leq E_{Total} \\ 1 & P_{Total} > E_{Total} \end{cases} \tag{13}$$

P_{Total}, E_{Total} represents the actual and expected output power extracted from the distributed energy resources to meet the load demand for the day-ahead scheduling problem of grid-connected microgrid.

2.3 Demand Side Management

The demand-side management is categorized into utility-oriented and customer-oriented strategies, and it has been given greater attention in microgrid research owing to several techno-economic benefits [63]. The flexible load-shaping based DSM approach [64] is implemented in the proposed research work to modify the existing load demand profiles with 10% load participation. Implementing such a strategy can fully leverage the time independence of flexible loads, especially in the residential feeder. In general, the central DSM controller at the utility will receive the load forecast data, produce the desired load profile, and modify the customer load accordingly. The consumers keen to contribute to the DSM program will receive these signals via two-way communication architecture in the smart microgrid paradigm. The objective is to minimize the gap between the targeted load and desired load profile. The targeted load is formulated by taking forecasted, connected, and disconnected loads at a given scheduling period. The detailed mathematical analysis for the DSM strategy can be found in the research works [34] and [65].

3. Numerical Modelling

The considered problem is assessed on the enhanced version of the IEEE 33-bus and IEEE 69-bus distribution feeder-based microgrid network, as shown in Figure 3 and Figure 4, respectively. The prime difference between the standard and enhanced versions lies in incorporating multiple DG units subjected to minimizing the network losses through optimal placement strategy. The enhanced IEEE 33-bus system consists of several DG units, such as one PV unit, two WT units, two FC units, two MT units, and one battery storage unit, to sustain the power demand equilibrium in-between utility and customers. Similarly, the enhanced IEEE-69 bus test network consists of two units of WT, PV, FC, and MT, each with one BS unit supporting renewable sources and maintaining the energy balance. The Backward-Forward Sweep (BFS) based optimal DG placement strategy [59] is implemented to evaluate the power loss matrix and optimally allocate the DG sources in both test systems. Moreover, the power scheduling configuration for each DG source is obtained from the MGCC. With an assumption of receiving switch-over command from the MGCC during appropriate times, a unified conversion over on-grid and islanded system operation modes is done with the help of an intelligent switch placed near the point-of-coupling. The stable operation of the network is subjected to deviations in estimating power from RES. The numerical modelling of individual DG units is represented in the following section.

3.1 Solar Photovoltaic (PV)

The PV output power is dependent on the rated efficiency η_{pv}, area A_{pv}, and solar irradiance I_r. Out of these parameters, the output power of the solar PV is solely dependent on solar irradiance. Solar power prediction is truly challenging to network operators in practical conditions due to its intermittent nature. The nominal output power generated by the PV Solar panel is represented in (14).

$$P_o = \eta_{pv} \times A_{pv} \times I_r \tag{14}$$

3.2 Wind Turbine (WT)

The WT output power relies on wind velocity (m/s) and its direction. As a result of wind speed's uncertain nature, the relationship between power output and wind speed is considered non-linear. The WT's output power is zero when the range is below cut-in (v_{ci}) and above cut-out (v_{co}) speed. The rated wind output power P_{rated} is mathematically represented in (15).

$$P_{o(wT)} = \{0 \quad 0 \le v \le v_{ci} \ or \ v \ge v_{co} \ \frac{v^2 - v_{ci}^2}{v_r^2 - v_{ci}^2} \times P_{rated} \qquad v_{ci} \le v \le v_{co}$$

$$= \{v_{rated} \ P_{rated} \qquad\qquad v_{rated} \le v \le v_{co} \tag{15}$$

3.3 Microturbine (MT), Fuel cell (FC) and Battery Storage (BS) modelling

MT and FC advantages are analogous to diesel generator in perspective of backup generation, reliable and efficient power supply units installed at consumer premises. The cost function of MT and FC are typically considered as quadratic cost functions given in (16) and (17), where ɑ, ɓ, c are cost coefficients and P_{MT}, P_{FC} are MT, and FC power outputs, respectively. Due to the dynamic response nature of the MT and FC, the microgrid system attains good stability and is able to supply the required demand to the consumer end. The relative bid price coefficients B_{DG} are represented in terms of production cost P_c, depreciation cost D_c, investment costs A_c are expressed in (18).

$$F_{MT} = ɑP_{MT}^2 + ɓP_{MT} + c \tag{16}$$

$$F_{FC} = ɑP_{FC}^2 + ɓP_{FC} + c \tag{17}$$

$$\{B_{DG} = C_{fuel} \frac{P_{DG}}{\eta_{DG}} + A_c \ A_c = D_c \frac{P_{DG,n}}{P_c} \tag{18}$$

The following expressions (19) and (20) characterizes the charge level and the rate limit set for the BS charge and discharge.

$$Q_{BS,t} = Q_{BS,t-1} + \eta_c P_c \delta t - \frac{1}{\eta_d} P_d \delta t \tag{19}$$

$$\begin{cases} Q_{ES,mn} \le Q_{ES,t} \le Q_{ES,mx} \\ P_{ch,t} \le P_{ch,mx}; P_{dch,t} \le \ P_{dch,mx} \end{cases} \tag{20}$$

where $Q_{BS,t}$ and $Q_{BS,t-1}$ represents the net energy stored during the period t and $t-1$. $P_c(P_d)$ and $\eta_c(\eta_d)$ are rate of charge/discharge allowed and BS efficiency during charging/discharging, for a set period of time δt. $Q_{ES,mn}(Q_{ES,mx})$ and $P_{c,mx}$ $(P_{d,mx})$ represents the min./max. limitations and upper bound on the charge/discharge rate of the BS. The hourly utility market price and feasible generation-limits of DG-units with its hourly bid prices are taken from the reference [34] and also provided in the supplementary martial attached.

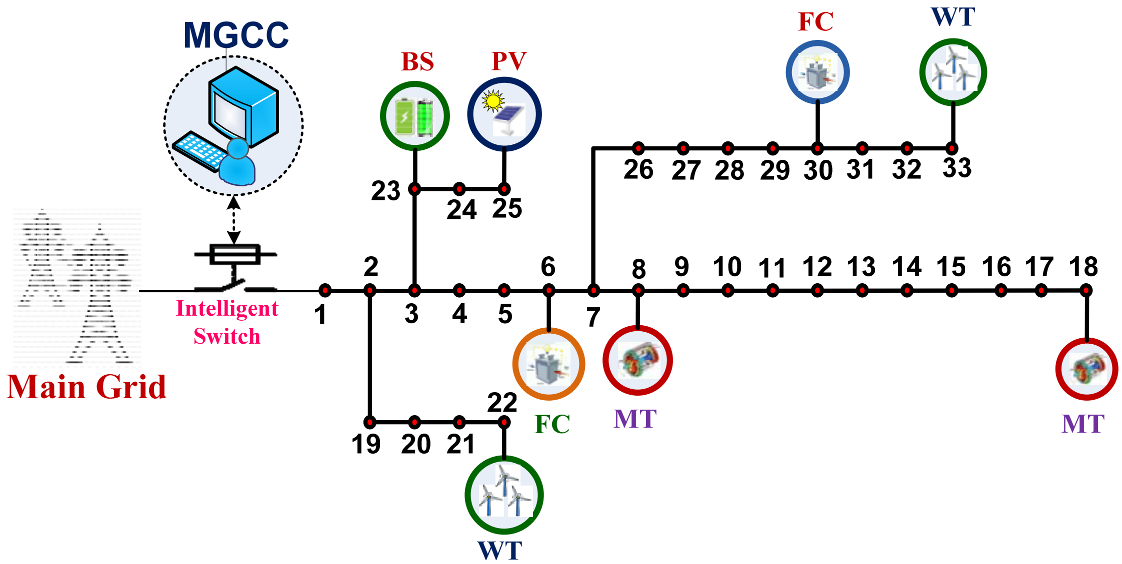

Figure 3. Enhanced IEEE 33-bus distribution network

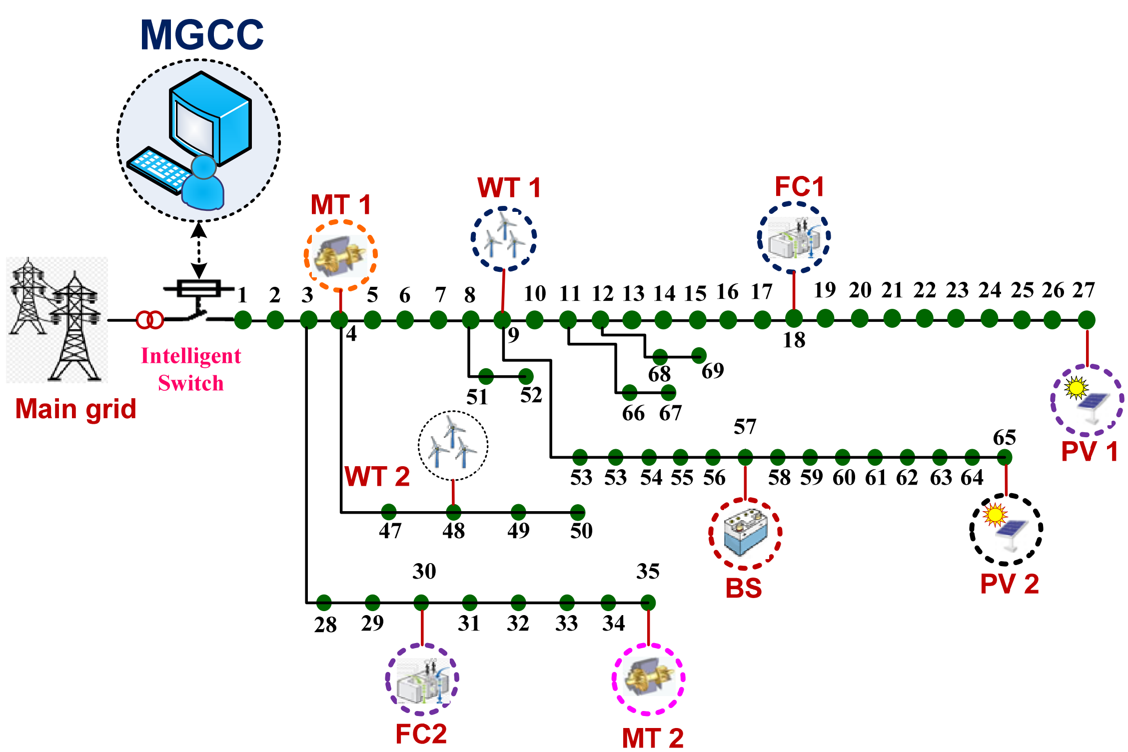

Figure 4. Enhanced IEEE 69-bus distribution network

3.4 Scenario generation and reduction process

The intermittent energy sources exhibit stochastic behavior due to their uncertain nature. The stochastic input variables such as solar irradiance, wind velocity, and market prices are addressed in this research work. Since solar irradiance and wind velocity are random parameters, they cannot be modelled using a normal distribution function. Hence, Beta PDF and Weibull PDF are commonly used in literature. The related mathematical modelling of uncertain parameters is taken from the work [15]. With the consideration of 9 levels of probability density evaluation, as represented in Figure 5 for each uncertain parameter, a total of $(9)^3 = 729$ scenarios will be generated to address the random input variables. To reduce the computational burden, the scenarios for solar irradiance, wind velocity and utility market prices are reduced to 9 scenarios and their respective output power are evaluated each as illustrated in Figure 6, Figure 7 and Figure 8.

Figure 5. Discretization of probability densities

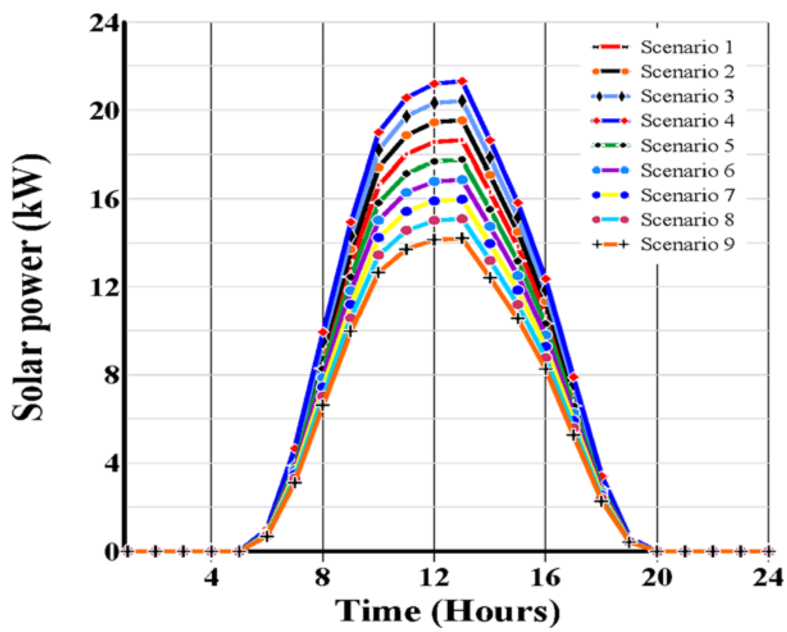

Figure 6. Scenarios for Solar power generation

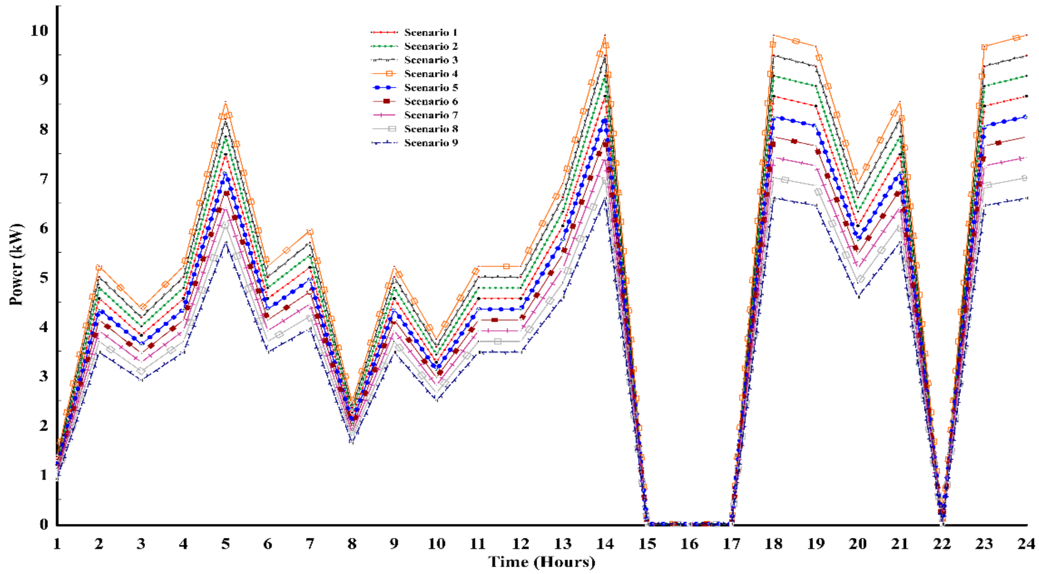

Figure 7. Scenarios for Wind power generation

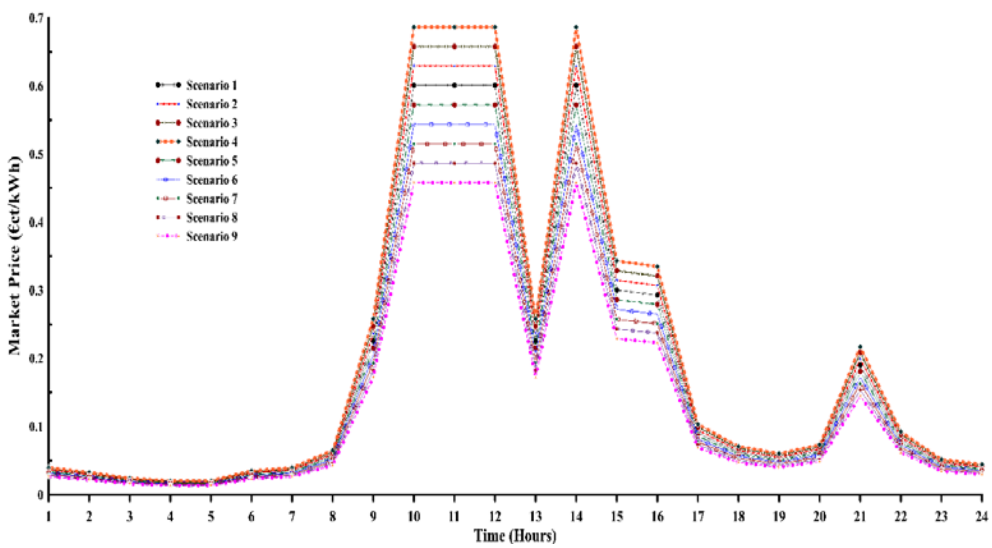

Figure 8. Scenarios for utility market prices

4. Methodology

4.1 Tri-level stochastic optimization framework

The tri-level stochastic optimization framework is presented in Figure 9, which is utilized to work out the considered MG optimum scheduling problem in on-grid and islanded systems operation subjected to maximizing the loadability and minimizing the operating costs and voltage deviation. The challenges in solving the proposed problem are i) Intermittency of RES, ii) Voltage deviations, iii) Loadability Enhancement in on-grid and islanded systems operation iv) Optimal scheduling configuration based on the DSM application. Since the problem involves diversified objectives, the proposed tri-level stochastic optimization framework is envisioned to meet the above-mentioned challenges. The detailed description at each level is as follows.

a) Level-1: Stochastic Optimization

Since random input variables such as solar irradiance, wind speed, and utility market prices were considered, the stochastic scenario generation and reduction method is implemented to handle the uncertainties. Level 1 in the framework determines the final reduced scenarios based on the probability distribution function for the optimization process.

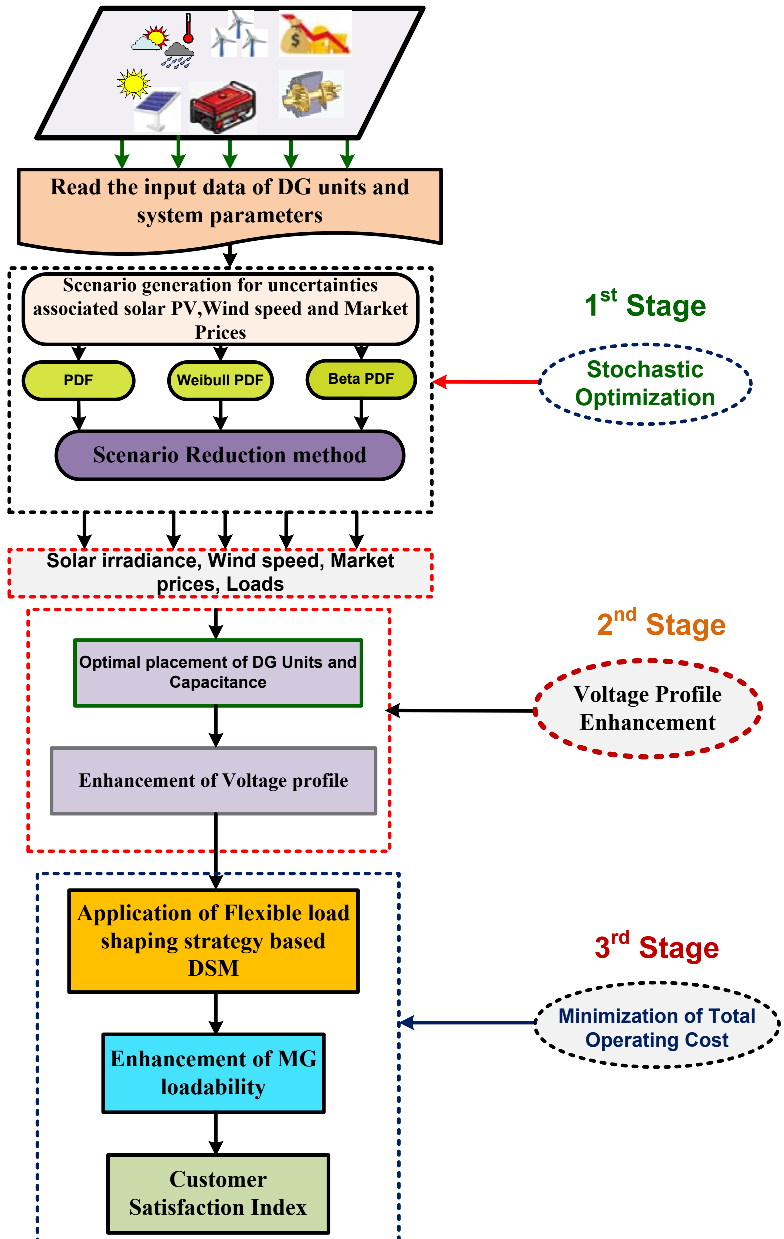

Figure 9. Proposed three-level stochastic optimization framework

b) Level-2: Voltage profile enhancement

In Level 2, the enhanced IEEE 33-bus and IEEE 69-bus distribution networks are considered to evaluate voltage profile and mitigation of power losses by incorporating DG sources and capacitors in optimal locations. Both grid-connected and islanded modes of operation are considered for evaluating voltage profiles. The overall power losses were evaluated based on Backward-Forward Sweep (BFS) based load flow algorithm [67].

c) Level-3: Loadability enhancement, optimal scheduling of DG Units and customer satisfaction index

The maximum loadability is evaluated based on the loading factor at different DG bus locations. Later, the DSM strategy is applied in Level 3 of the proposed framework to determine the day-ahead hourly optimum scheduling of on-grid and islanded MG networks. The impact of DSM on microgrid loadability enhancement and MG operational costs considering real-time seasonal load profile is investigated. Further, the Customer satisfaction index is evaluated based on the optimum scheduling of DG units for enhancing the microgrid reliability and operation. With the evaluation of CSI, The WOA is chosen to obtain optimal scheduling configuration. The details regarding the proposed Whale Optimization Algorithm are as follows.

4.2 Whale Optimization Algorithm (WOA)

The complex engineering optimization problems which involve continuous and discrete variables as optimization parameters needs powerful metaheuristic algorithms to solve without getting stuck at the local optimum point [68]. According to the theories behind the inspiration of metaheuristic algorithms, they are categorized into several distinct groups of algorithms: nature-inspired, swarm intelligence, evolutionary, and human-based algorithms. In view of this one of the applications WOA is bio-printing-3D for artificial tissues and organs in the field of plastic surgery to avoid errors during bio-printing process [69]. The recently reported WOA [70] comes under nature-inspired technique is that the whales are remarkable creatures consisting of spindle cells in their brain, enabling whales to think, judge, learn, and communicate. The unique preying behavior used by humpback whales is called the 'bubble-net feeding' strategy, and it is the inspiration behind the mathematical modelling of this algorithm. The mathematical modelling of WOA consists of three stages. When the location of prey is identified, the humpback whale encircles the prey, and this concept is utilized to update the search agents in the solution space.

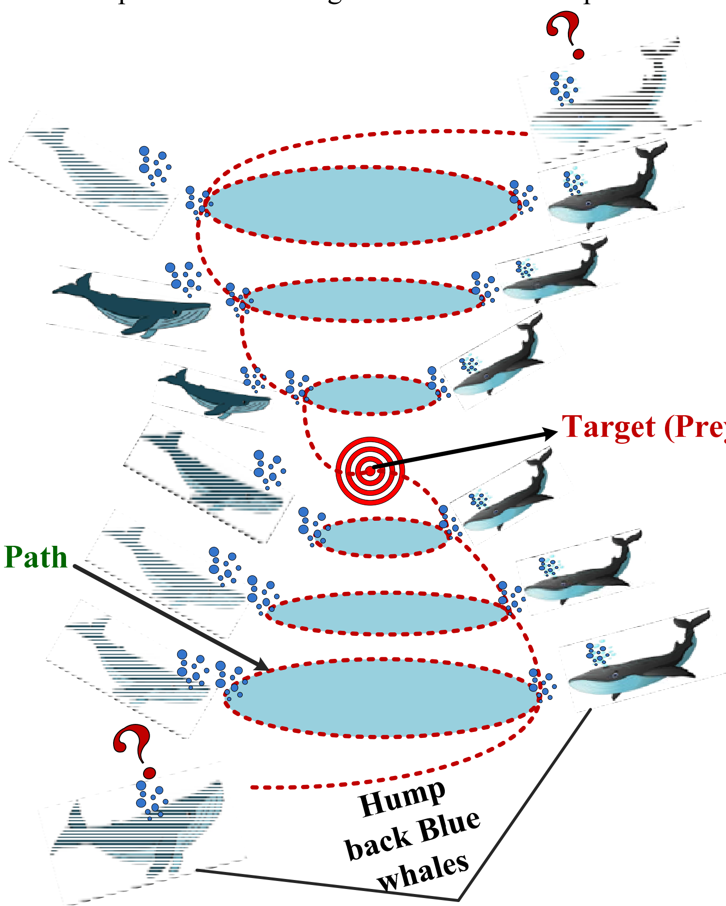

Figure 10. Helix-shaped encircling behaviour of whales

$$\vec{D} = \left|\vec{C}.\overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{21}$$
$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \tag{22}$$
$$\vec{X}(t+1) = \overrightarrow{D'}.e^{bl}.cos\,(2\pi l) + \overrightarrow{X^*}(t) \tag{23}$$
$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A}.\vec{D} & if\ p < 0.5 \\ \overrightarrow{D'}.e^{bl}.cos\,(2\pi l) + \overrightarrow{X^*}(t) & if\ p \geq 0.5 \end{cases} \tag{24}$$
$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{rand}} - \vec{X}\right| \tag{25}$$
$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \tag{26}$$

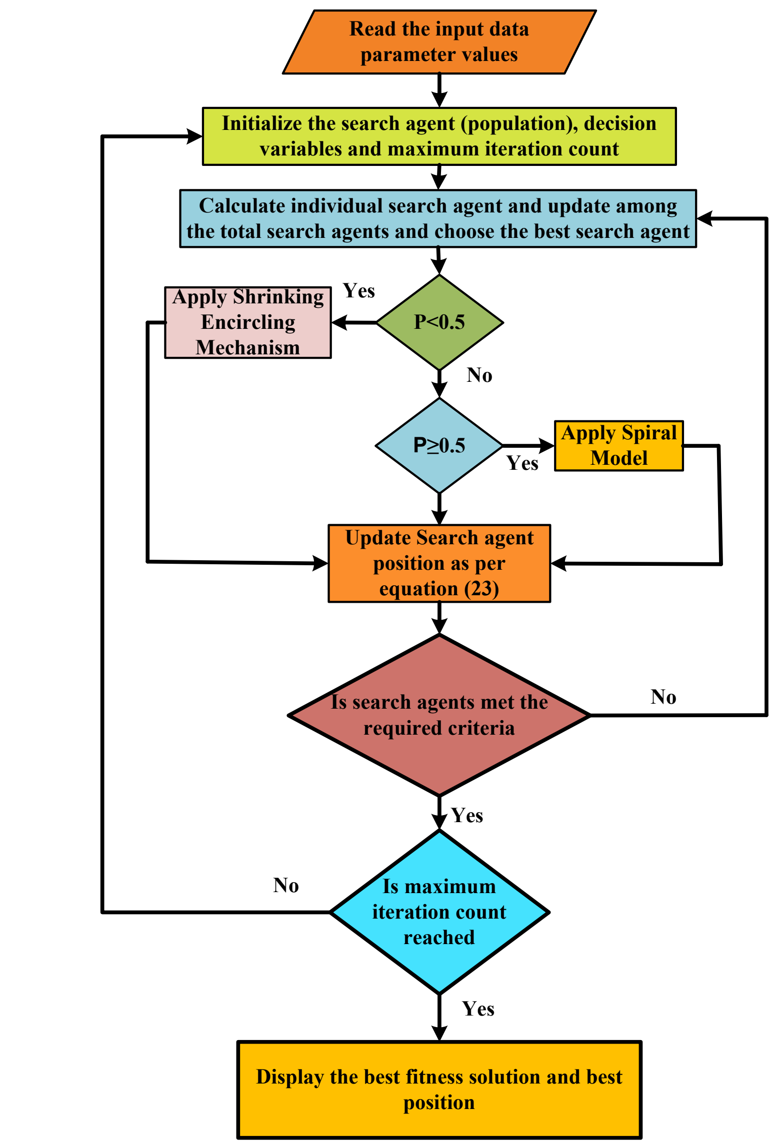

Figure 11. Flowchart of WOA

At first, the current best solution $\vec{X}(t)$ is assumed to be at the optimum point, and its position gets updated after the best agent $\overrightarrow{X^*}(t)$ is defined in the iterative process according to (21) and (22). The parameters $\vec{A}$ and $\vec{C}$ are the coefficient vectors. In the exploitation phase, the bubble net strategy of humpback whales is mathematically modelled with the help of a spiral equation as represented in (23). This equation models their helix-shaped movement shown in Figure 10, where $\overrightarrow{D'}$ denotes the distance between the current position and the best position in the solution space. The logarithmic spiral's form is determined by the constant values indicated by the parameter b, whereas l is a random integer. Humpback whales' encircling habit is specified by a random parameter p that ranges evenly from 0 to 1. During this phase of exploitation, humpback whales use two distinct methods to pursue their prey. The former tactic relies on a contracting encircling mechanism, whereas the later employs a spiral model mechanism. However, the odds of using any of these tactics are even, thus a uniformly random value is used to describe the arbitrary parameter p. A contracting encircling mechanism is selected if $p < 0.5$, whereas a spiral model is selected if $p > 0.5$ (21). In the exploration phase, the random searching behaviour is modelled with the determination of coefficient vector $\vec{A}$ as either greater than 1 or less than -1 to enhance the global search capability. The position of whales is mathematically updated as per (25) and (26). The overall procedure for applying WOA to solve the proposed problem is shown in Figure 11.

5. Simulation results and discussion

5.1 Performance of WOA

The enhanced IEEE 33-bus and IEEE 69-bus distribution network-based MG test system is chosen to evaluate the proposed optimal scheduling problem in both grid-connected and islanding modes. The WOA is determined to solve the proposed problem in the MATLAB R2022b M-file programming having a system configuration of 64-bits, core i9, 3.20 GHz processor, 16 GB RAM with dedicated GPU of 8 GB. The MG test system consists of DG sources, including dispatchable and non-dispatchable energy sources. To validate the efficacy of the proposed approach, a baseload shown in Figure 12 is considered, and the optimal operating cost subjected to operational constraints is obtained by solving with WOA. The simulation results are compared with eight state-of-the-art algorithms, namely RCGA, PSO, TLBO, QTLBO, QPSO, FFA, GWO, and SSA. The initial population of one-hundred fifty and iteration count of two hundred is selected, and each algorithm is run for 30 successful trial runs for a reasonable comparison. The details regarding algorithm-specific parameters are shown in Table 2. In the later part of this section, the detailed analysis of applying DSM strategy to weekend and weekday seasonal load profiles shown in Figure 12 is discussed.

With the consideration of above-mentioned state-of-the-art algorithms, a brief comparative study is conducted to validate the efficiency of proposed algorithm. Table 3 and Table 4 shows the obtained optimal operation costs of on-grid and islanded system of IEEE 33-bus distribution network by solving the proposed optimization problem with WOA. Similarly, the simulation results for on-grid and islanded system of IEEE 69-bus distribution network are shown in Table 5 and Table 6.

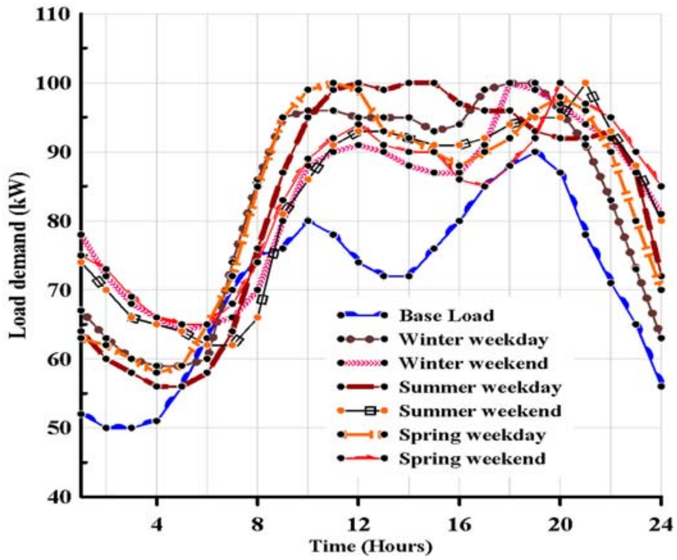

Figure 12. Seasonal load profiles

The obtained simulation results in both test networks prove the superiority of WOA in comparison to solution efficacy and computational time required. From the obtained results in both test systems, it is observed that the bid prices considered for the power exchange with the utility in on-grid mode incurs less operating cost. The islanded mode of operation where the DG units alone incurs high operating cost based on their bid prices. The proof of convergence for IEEE 33-bus distribution network is shown in Figure 13, where WOA is observed to converge to the optimum solution in less than 40 iterations.

Table 2. Specific control parameters for algorithms

Algorithm	Control parameters
SSA	Number of Producers & Scroungers = 0.8 & 0.2
BWO	Procreation, Mutation & Cannibalism rates = 0.8, 0.6 & 0.2
QPSO	Contraction coefficient & expansion coefficient $\alpha = 0.75$
TLBO	No Explicit Parameters
QTLBO	No Explicit Parameters
PSO	Cognitive, Social constant value = 2, Maxi. & Min inertia = 0.7 & 0.5
FFA	Randomization & Attractiveness Parameter value = 0.2, Absorption Coefficient value =1
GWO	Distance Control Parameter value (a): $0 < a < 2$
WOA	Coefficient vector constant (a): $0 < a < 2$ Logarithmic spiral constant (p): $-0.5 < p < 0.5$ Arbitrary parameter constant (k): [-1, 1]

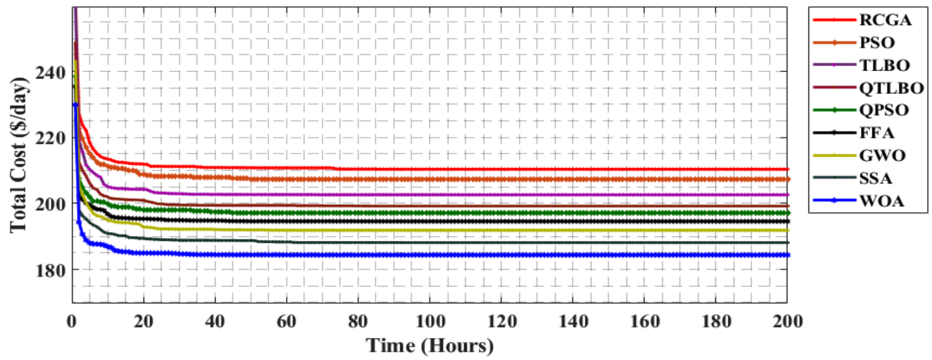

Figure 13. Convergence characteristics of WOA

Table 3. Simulation results of grid-connected enhanced IEEE 33-bus distribution network

Algorithm	Best Cost ($/day)	Mean Cost ($/day)	Worst Cost ($/day)	Standard Deviation	Computational time (s)
RCGA	210.41	212.5925	214.775	0.154326	56.866
PSO	207.44	209.2525	211.065	0.128163	45.242
TLBO	202.64	204.1525	205.665	0.10695	41.034
QTLBO	199.23	200.7125	202.195	0.104829	35.502
QPSO	197.19	198.45	199.71	0.089095	30.568
FFA	194.66	195.685	196.71	0.072478	28.273
GWO	191.96	192.485	193.01	0.037123	21.063
SSA	188.15	188.482	188.814	0.023476	16.688
WOA	**184.47**	**184.486**	**184.502**	**0.001131**	**12.337**

Table 4. Simulation results of islanded enhanced IEEE 33-bus distribution network

Algorithm	Best Cost ($/day)	Mean Cost ($/day)	Worst Cost ($/day)	Standard Deviation	Computational time (s)
PSO	400.38	402.915	405.45	0.2070	46.06146
RCGA	394.51	396.08	397.65	0.1282	36.64602
TLBO	390.59	391.865	393.14	0.1041	33.23754
QPSO	384.16	385.2	386.24	0.0849	28.75662
QTLBO	376.68	377.58	378.48	0.0735	24.76008
FFA	373.5	373.805	374.11	0.0249	22.90113
GWO	368.59	369.105	369.62	0.0420	17.06103
SSA	360.26	360.94	361.62	0.0555	13.51728
WOA	**348.68**	**348.82**	**348.96**	**0.0114**	**9.99297**

Table 5. Simulation results of grid-connected enhanced IEEE 69-bus distribution network

Algorithm	Best Cost ($/day)	Mean Cost ($/day)	Worst Cost ($/day)	Standard Deviation	Computational time (s)
RCGA	157.02	160.32	163.62	0.07260	0.269444
PSO	155.23	157.39	159.55	0.03110	0.176363
FFA	154.95	156.29	157.63	0.01197	0.109411
TLBO	150.17	151.89	153.61	0.01972	0.140437
QPSO	149.92	151.27	152.62	0.01215	0.110227
QTLBO	147.16	148.42	149.67	0.01050	0.102470
SSA	146.41	147.28	148.14	0.00499	0.070627
GWO	145.92	146.40	146.88	0.00154	0.039192
WOA	**144.63**	**144.71**	**144.79**	**0.00043**	**0.006532**

Table 6. Simulation results of grid-connected enhanced IEEE 69-bus distribution network

Algorithm	Best Cost ($/day)	Mean Cost ($/day)	Worst Cost ($/day)	Standard Deviation	Computational time (s)
PSO	206.53	208.26	209.98	0.01984	0.140846
RCGA	203.24	205.55	207.86	0.03557	0.188611
TLBO	202.85	204.25	205.65	0.01307	0.11431
QTLBO	202.5	203.68	204.86	0.00928	0.096347
QPSO	201.06	202.36	203.66	0.01127	0.106145
GWO	199.15	200.95	202.74	0.02148	0.146561
FFA	197.88	198.89	199.89	0.00673	0.082058
SSA	193.97	194.30	194.62	0.0007	0.026536
WOA	**192.44**	**192.75**	**193.06**	**0.00064**	**0.025311**

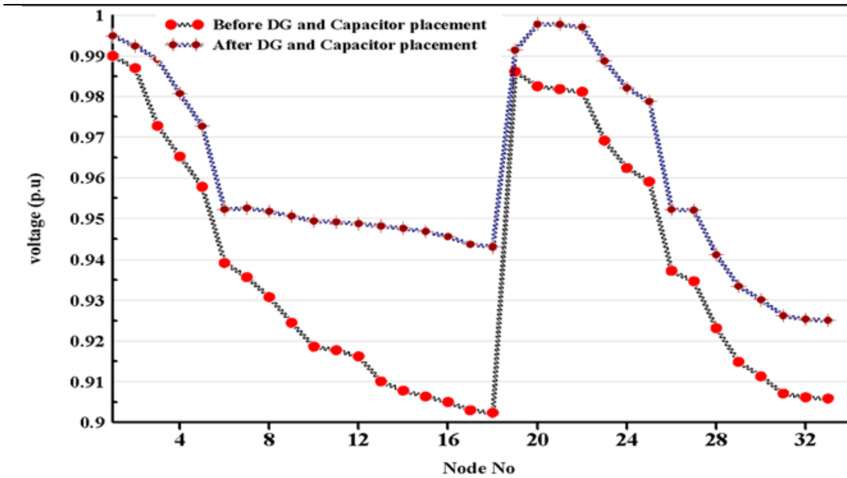

Figure 14. Voltage profile (p.u.) evaluated at each bus

5.2 Evaluation of loadability and voltage deviation

The improved IEEE 33-bus radial distribution network's voltage profiles are assessed at each bus after the optimum location of DG-units, as shown in Figure 14. With the simultaneous incorporation of DG units and capacitors at optimal locations [45] in the network, the voltage profile is enhanced in contrast with the case without any DG sources and capacitors are considered. For instance, the improvement of voltage at bus 19 is increased by 2.836 % with the incorporation of DG units.

Despite the fact that the voltage stability is subjected to change with loading factor, the initial load demand profile is modified by applying flexible load shaping DSM strategy. An increase of voltage of 4.272% is again observed at bus 19 in the enhanced IEEE 33-bus distribution test system as shown in Figure 14. The loadability factor presented in (9) is evaluated with WOA at the buses where DG units are located. To show the effectiveness of both enhanced test systems, the comparison of parameters being assessed with and without consideration of DG units, and DSM strategy is provided in Table 7 and Table 8. The obtained simulation results show that the interdependency of loadability factor and incorporation of flexible load shaping DSM strategy. The overall voltage deviations and power losses are evaluated by solving the proposed algorithm and a comparative analysis with existing state-of-the-art algorithms is presented. Table 9 shows the simulated results without consideration of DG units, and Table 10 shows the simulated results with consideration of DG units. And it is evident that a significant extent of overall voltage deviation and power losses are mitigated as shown in Table 10. From the obtained simulation results, it is observed that the voltage profile and loadability factor are enhanced and the overall voltage stability gets improved to accommodate peak loads effectively.

Table 7. Evaluation of Loadability factor with optimal placement of DG sources and implementation of DSM program for enhanced IEEE 33-bus network

Bus no	Without DG units	With DG units	With DSM
6	1.5191	1.792512	2.1151
8	1.9601	2.312875	2.6366
12	2.062	2.432775	2.8950
18	1.1455	1.351647	1.6084
25	1.0793	1.273598	1.5155
28	0.7930	0.935793	1.1697
33	0.4824	0.569225	0.7229

Table 8. Evaluation of Loadability factor with optimal placement of DG sources and implementation of DSM program for enhanced IEEE 69-bus network

Bus no	Without DG units	With DG units	With DSM
1	0.269	0.429	0.622
5	0.412	0.657	0.953
7	0.513	0.818	1.186
9	0.568	0.906	1.314
13	0.696	1.110	1.610
16	0.716	1.142	1.656
57	0.826	1.317	1.910
58	0.939	1.498	2.172
59	1.099	1.753	2.542
60	1.193	2.903	2.759
64	1.293	2.062	2.990
65	1.314	2.096	3.039

Table 9. Evaluation of voltage deviation and power losses without consideration of DG sources

Algorithm	Voltage Deviation (p.u.)	Active Power losses (kW)	Reactive Power losses (kVAR)
RCGA	0.0793	210.47	140.632
PSO	0.0747	210.065	140.112
TLBO	0.0742	209.976	139.965
QTLBO	0.0722	209.62	139.915
QPSO	0.0719	208.889	139.67
FFA	0.0718	208.665	139.12
GWO	0.0711	208.11	138.96
SSA	0.0704	206.932	138.64
WOA	**0.0686**	**206.732**	**137.9**

Table 10. Evaluation of voltage deviation and power losses with consideration of DG sources

Algorithm	Voltage Deviation (p.u.)	Active Power losses (kW)	Reactive Power losses (kVAR)
RCGA	0.0721	203.96	133.84
PSO	0.0706	203.58	133.78
TLBO	0.0689	203.11	133.56
QTLBO	0.0681	202.97	133.08
QPSO	0.0678	202.77	132.95
FFA	0.0671	202.12	132.88
GWO	0.0668	201.91	132.65
SSA	0.0665	201.63	132.11
WOA	**0.0663**	**200.91**	**131.93**

5.3 Simulation results for optimal scheduling of microgrid

The impact of flexible load-shaping strategy improved the overall loadability of the system and thus, the concerned microgrid optimal scheduling is determined. The enhanced IEEE 33-bus system is evaluated with both weekend and weekday loads of distinct seasonal load profiles [43], as shown in Figure 12. The flexible load-shaping DSM approach with 10% load contribution is applied to modify the loads before optimal scheduling configuration is determined. It should be noted that the enhanced test system consists of flexible loads that are utilized as target loads, and the concerned data is sent through the DSM central controller. It is assumed that both renewable sources, i.e., PV and WT, are operated at maximum power point condition. The detailed analysis on hourly scheduling of DG sources in grid-connected MG considering seasonal load profiles is discussed below.

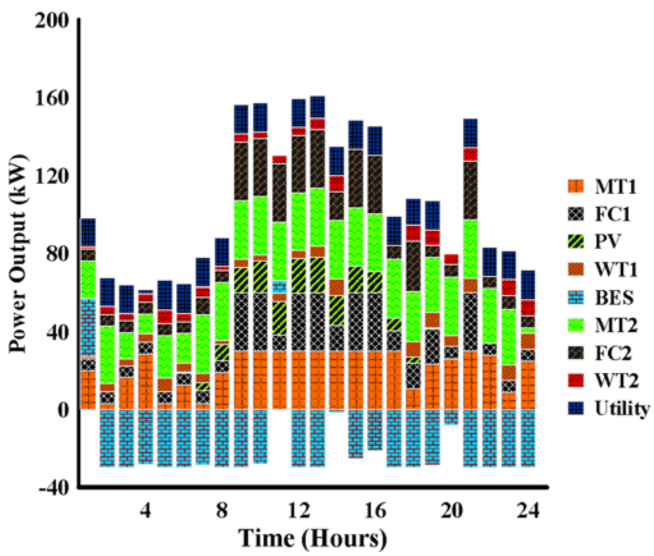

Figure 15. Optimal schedule of microgrid network considering winter weekday load profile

The simulated results obtained for solving the proposed problem on grid-connected enhanced IEEE 33-bus under the winter weekend and weekday load profiles is illustrated in Figure 15 and 16, respectively. In contrast with the winter weekend load profile, the contribution from DG units has increased by a substantial amount. With the application of the DSM strategy, the battery charging profile is enriched by 21.35%. The load factor is improved by 0.34% and 1.01% in weekday and weekend cases, respectively, and the peak demand is reduced to 10%. Concerning bid prices, the optimal configuration is obtained through maximum contribution from MT and FC units. It is observed that the consumption of battery is 14.72% more during weekdays in comparison with weekend loads.

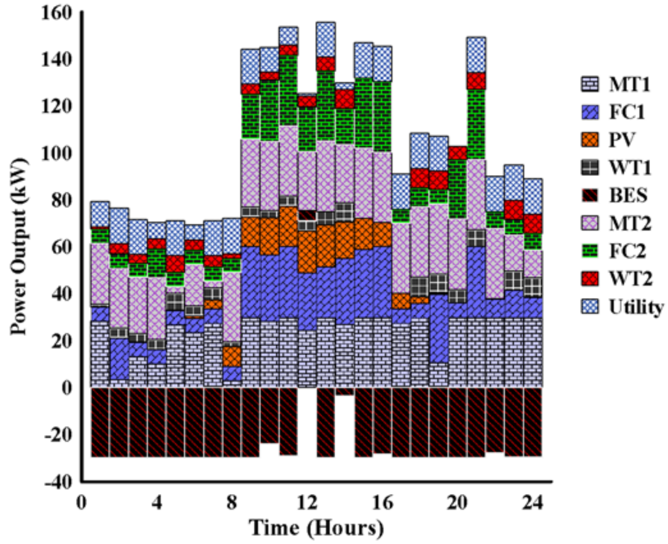

Figure 16. Optimal schedule of microgrid network considering winter weekend load profile

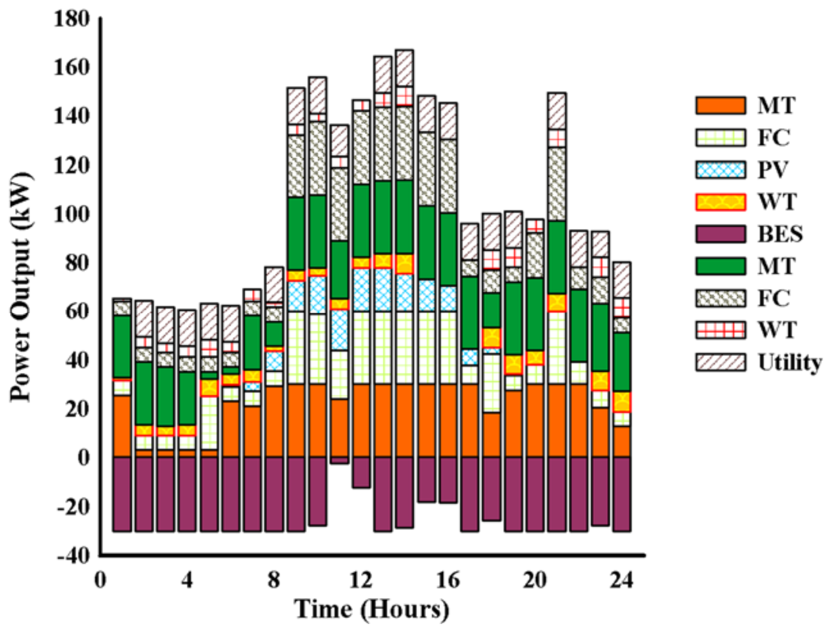

Figure 17. Optimal schedule of microgrid network considering summer weekday load profile

Considering IEEE 33-bus active distribution network case of summer load profiles for weekdays and weekends shown in Figure 17 and Figure 18, the contribution from MT is increased by 6.6% with the employment of the DSM strategy. Similarly, the load profile is boosted by 1.90% and 3.33% for weekday and weekend loads. The peak demand for summer load profile has been reduced by 12.7% with implementing the proposed strategy. From hour 12 to hour 21, the load demand in all seasonal profiles is usually high, especially at the spring load profile.

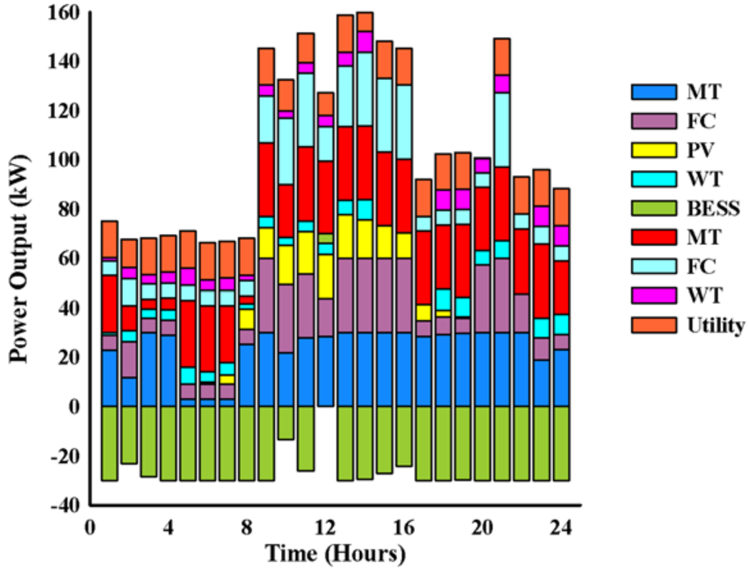

Figure 18. Optimal schedule of microgrid network considering summer weekend load profile

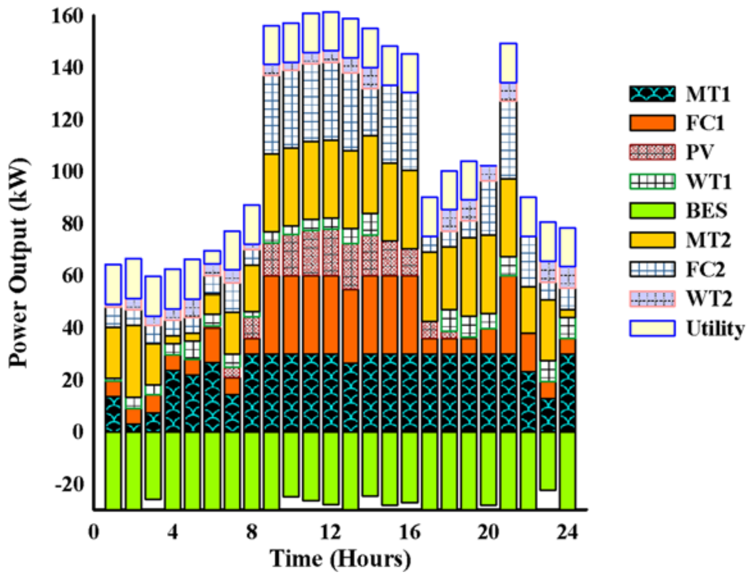

Figure 19. Optimal schedule of microgrid network considering spring weekday load profile

Figure 19 and 20 shows that the contribution from both MT units is high and FC units are low before implementation of DSM strategy, and this scenario changes entirely with the application of DSM. The load factor is improved by 1.58% and 4.53% in weekday and weekend load profiles, respectively. As mentioned earlier, the two WT and solar PV units deliver maximum power to the connected loads over the scheduling horizon. The voltage profiles are enhanced with the proposed WOA optimization technique and compared with different state-of-the-art is represented in Figure 22, respectively.

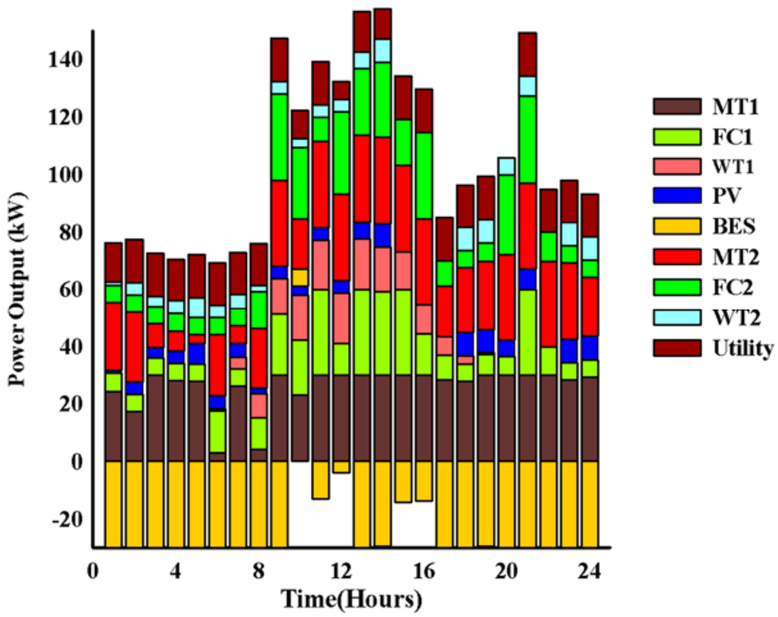

Figure 20. Optimal schedule of microgrid network considering spring weekend load profile

Table 11. Impact of DSM strategy on operating costs ($/day)

Test System	DSM	Winter Weekday	Winter Weekend	Summer Weekday	Summer Weekend	Spring Weekday	Spring Weekend
Grid-connected IEEE 33-bus network	**Without DSM**	273.5	262.7	281.3	260.5	266.1	271
	With DSM	**182.7**	**176**	**174.4**	**170.8**	**197.2**	**169.3**
Islanded IEEE 33-bus network	**Without DSM**	495.98	511.06	487.48	498.83	454.31	499.18
	With DSM	**389.16**	**437.6**	**421.27**	**425.14**	**413.05**	**420.08**
Grid-connected IEEE 69-bus network	**Without DSM**	232.06	237.72	218.82	225.35	226.81	232.94
	With DSM	**177.11**	**180.01**	**184.36**	**189.94**	**187.09**	**196.36**
Islanded IEEE 69-bus network	**Without DSM**	384.56	386.03	370.76	376.71	396.70	387.54
	With DSM	**268.02**	**269.35**	**260.28**	**255.11**	**270.95**	**259.45**

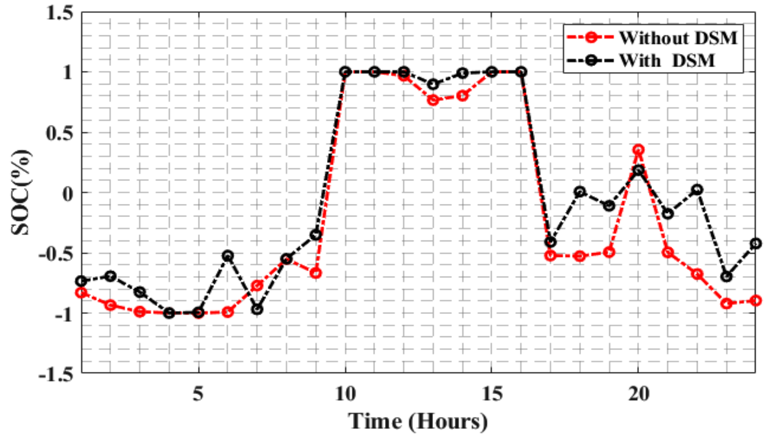

Figure 21. Impact of DSM strategy on battery charging profile

Table 12: Evaluation of Customer satisfaction Index IEEE-69 Bus Grid-Connected Network

	Winter weekday	Winter Weekend	Summer Weekday	Summer Weekend	Spring Weekday	Spring Weekend
CSI (With Out DSM)	0.6034	0.615	0.590	0.598	0.5717	0.601
CSI (With DSM)	0.6608	0.6683	0.7083	0.744	0.69	0.756

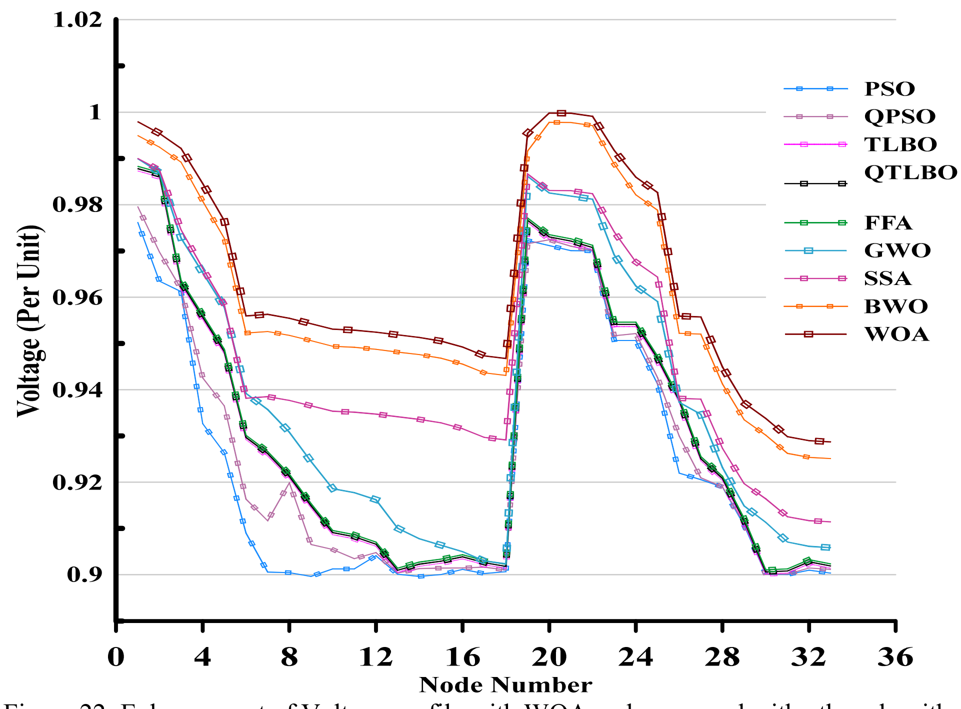

Figure 22: Enhancement of Voltage profile with WOA and compared with other algorithms

6. Discussion

The overall operating cost comparison with the implementation of DSM strategy is shown in Table 11. As discussed earlier, with the load participation of 10%, the flexible load-shaping approach is able to reduce the operating cost of on-grid and islanded system operation to a significant level. For instance, the operating costs for grid-connected IEEE 33-bus system got reduced by 38% for summer weekday profile and in islanded mode, the operating cost on winter weekday got reduced by 21%. Similar comparative study is done on enhanced IEEE 69-bus system and the scalability of the proposed framework is verified effectively. From the observation, it is concluded that the proposed DSM strategy can be applied to obtain cost savings throughout the year and in long run, the DNO can yield potential economic benefits annually. The impact of flexible load shaping DSM strategy on battery state of charge (SOC) for enhanced IEEE-33 bus active distribution network is shown in Figure 21. As the state of charge of the BS unit is improved with the implementation of DSM strategy, their charging and discharging cycle will be improved in long run and provides necessary support to maintain power balance. With the incorporation of demand side management programs on different seasonal load profiles the customer satisfaction index is enhanced for extracting the maximum amount of energy from the distributed energy sources instead of importing power from the utility for reducing the overall operating cost of MG and also provide sufficient amount of power to the respective loads without any interruption to the end users and the evaluated values are tabulated in Table 12, respectively. It should also be noted that it can be computationally challenging to discover the ideal solution to energy management problems because of their complexity and the size of the search space involved. For real-world energy management issues where an optimal solution cannot be found or would be too complex to implement, metaheuristics offer a workable alternative. In this study, we evaluate the proposed algorithm against state-of-the-art algorithms and argue that it provides significant improvements in terms of performance, accuracy, and convergence speed, making it a near-ideal solution for solving difficult issues in energy management.

7. Conclusion

In this study, we explore a new optimum scheduling problem for microgrids coupled with the restrictions of the network's flow, an ideal solution is created and found. In order to measure how well the improved IEEE 33-bus and IEEE 69-bus radial distribution networks function, the maximum loadability index and the voltage deviation index along with customer satisfaction index are considered as evaluation metrics. This research endeavor examines how the loadability of a microgrid is affected by the interplay between a variable load shaping DSM technique and the best placement of DG units. A stochastic scenario-based approach handles the uncertain parameters of solar power and wind power outputs and utility market prices. The three-level framework is designed and implemented to determine optimal power scheduling of microgrids subjected to network flow constraints. The voltage deviation is mitigated by 16.39% with the incorporation of distributed generation units and capacitors at the optimal location and implementation of flexible load shaping based demand-side management strategy. The overall operating cost savings obtained for implementing the proposed DSM strategy for winter-weekday, winter-weekend, summer-weekday, summer-weekend, spring-weekday, and spring-weekend load profiles are 33.19%, 33%, 38%, 34.43%, 25.89% and 37.52%, respectively. The overall system performance in terms of voltage stability is improved, and the power losses are reduced by 4.73 % per day. The loadability of enhanced IEEE 33-bus test system and IEEE 69-bus test system is improved by 33.26% and 37.30%, respectively. The Customer satisfaction index is also evaluated based on the power exchange between utility and the microgrid. With the customer satisfaction index point the maximum power is extracted from the distributed energy resources instead of power importing from the utility to reduce the overall operating costs to satisfy the required load demand at the end users. The overall customer satisfaction index is evaluated and improved according to the seasonal load profiles winter weekday, winter-weekend, summer-weekday, summer-weekend, spring-weekday, and spring-weekend by 8.68%, 7.97%, 16.7%, 19.62%, 17.14%,20.50% respectively. The obtained results using WOA decrease the overall computational burden on the system when compared with other well-established metaheuristic algorithms which has been exclusively discussed with tabular and graphical representation in section 5. The attained results also convey that the annual cost and power losses will be reduced significantly from the perspective of microgrid operators, and the customer satisfaction index is also improved. Further to add, the interdependency of the microgrid is decreased towards utility simultaneously and the overall microgrid stability is enhanced by the associated DGs RESs and storage units with less emissions. An expansion of the proposed approach is now in development as an extension in future work to include thorough modelling with multiple generating and storage systems for a multi-microgrid environment considering uncertainty utilizing machine learning, reinforce learning, distributed learning models and derivative based optimization models or tools such as “General algebraic modeling system (GAMS)”.

Appendix:

RCGA	Real Coded Genetic Algorithm
PSO	Particle Swarm Optimization
SSA	Sparrow Search Optimization
BWO	Black Widow Optimization
QPSO	Quantum Particle Swarm Optimization
TLBO	Teaching Learning Based Optimization
QTLBO	Quantum Teaching Based Optimization
FFA	Firefly Algorithm
GWO	Grey Wolf Optimization
WOA	Whale Optimization Algorithm
CSI	Customer Satisfaction Index
EMS	Energy Management System
MG	Microgrid

Indices:

i	i^{th} DG unit
j	j^{th} energy storage unit
N_b	Bus number
t, T	Time intervals
$E(P_m^t)$	Active power during time interval t
$Q(P_m^t)$	Reactive power during time interval t
mx	Maximum
mn	Minimum
r	Resistance at each bus w.r.t reference node
x	Reactance at each bus w.r.t reference node
MLI	Marginal Loadability Index
VDI	Voltage Deviation Index

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