Research Article

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Intelligent techno-economical optimization with demand side management in microgrid using improved sandpiper optimization algorithm

Abstract: The energy management system is established in the microgrid system for optimally integrating the Distributed Energy Resources (DERs) and generating the power distribution grids. At last, diverse mechanisms have been highly concentrated on cost reduction and at the same time, both the technical indices and economic factors are considered. Thus, this research work suggests a new heuristic algorithm termed Modified Sandpiper optimization algorithm (M-SOA) for optimal integration of DER-like Photo Voltaic (PV), wind turbines, and Energy Storage Systems (ESS) into microgrids. Here, the techno-economical optimization with ISOA is designed for determining the optimal capacity of PV, Wind Turbine, and ESS via the multi-objective function concerning measures like network power losses, voltage fluctuations, Electricity Supply Costs, initial cost, operation cost, fuel cost, and demand side management. Finally, the optimal energy management is done on distributed energy resources, and this developed model experiments on the IEEE-33 bus network. Throughout the result analysis, the developed M-SOA obtains 3.84 %, 0.98 %, 5.72 %, and 4.63 % better performance with less latency than the AGTO, BOA, WOA, and SOA. Finally, the result evaluation is done for minimizing the Electricity Supply Costs, initial cost, operation cost, and fuel cost and maximize energy efficiency.

Keywords: demand side management; microgrid; techno-economical optimization; modified sandpiper optimization algorithm; distributed energy resources

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Notation table

ST_D	Solar cell temperature
Noct	General operating cell temperature
SUN	The intensity rate has been taken based on the solar radiation
ST_{amb}	Ambient temperature
σ_s^2 and μ_s	Statistical data
η_{pv}	The energy efficiency of the solar cell
ρ, Ar and Le	Air density, area secured by the turbine blades, and turbine blade length
α_{Dch}	Self-discharging rate
η_{Ess}	Discharging or charging efficiency of ESS
$pw_{Ess}^{Chr/Dch}$	The discharging or charging power
Δtt_{Ess}	The period for discharging or charging
η_{Conv}	The efficiency of the DC/AC converter
Ecap	Capacity of ESS
μ_d and σ_d	Lognormal distribution
DST^{Max}	Maximum distance
Bcap	Battery capacity
F_D	Energy consumption is computed per mile
T_{Arvl}	Arrival time
T_{Deprt}	Departure time
T_{Durtn}	Time duration
q_{EV}^{Chr}	Charging rate
OC_{WT}	Optimal capacity of wind turbine
OC_{PV}	Optimal capacity of PV
OC_{ESS}	Optimal capacity of ESS
BL_{PV}	Bus location of PV
BL_{WT}	Bus location of wind turbine
BL_{ESS}	Bus location of ESS
ΔT_n^{Chr}	Charging duration of EV
ΔT_{Ess}^{Chr}	Charging duration of ESS

1 Introduction

In developed countries, nearly 40 % of the total energy is consumed by commercial and residual usage (Martínez Ceseña et al. 2020). This will further increase the energy demand in the buildings in the future generation due to the electrical usage of household heating, urbanization, population growth, and raising penetration of Electric Vehicles (EVs) (Cai and Kong 2017). To resolve these issues, most of the

works have been focused on developing Microgrid aided future electrical power systems for enhancing performance. A microgrid is considered a Low Voltage (LV) power network comprising shared energy sources like fuel cells, micro-wind turbines, energy storage devices, and PV (Mohamed et al. 2022). In addition, the energy efficiency in the microgrid has enhanced with the appropriate Direct Current (DC) distribution without being dependent on the utilization of traditional AC-aided distribution (Bourhim et al. 2021). Microgrid development is steadily observed to be a general mechanism to help entities by reducing grid reliance and energy costs as well as enhancing sustainability and also for obtaining higher resilience (Erdogan, Kucuksari, and Cali 2022). On the other hand, there are more limitations occurred in the development of microgrids like the requirement of capital investment. Microgrid operation is considered to be challenging because of requiring certain implementation of robust control schemes containing the ability to combine diverse disparate technologies. The main perspective of designing the microgrid is focused on techno-economic optimization (Gao, Jia, and Marnay 2019). Such implementation involves the comparison of operational and capital investments over the economic gain on the technological investment like Thermal Energy Storage (TES), wind turbines, Energy Storage Systems (ESS), solar PV, and Fuel-Fired Generators (GEN). For generating the established economic decision, this evaluation has to consider the complete demand data, parameters related to project financing, regulations, investment cost, utility tariff information, and local weather scenarios (Tsai et al. 2020).

With the analysis of the recently developed research works, it has shown that the expanded computations were done through these present works, yet the interpretation of the optimization constraints and objective functions without considering the economic and technical parameters reduces the accuracy rate and efficiency of the optimized outcomes (Murty and Kumar 2020a). Moreover, these conventional models do not establish a particular mechanism for controlling the unmanageable discharging and charging of ESS and EVs for attaining the optimal operation condition of the power system, which has also resolved the problem of economic power dispatch (Shaheen and El-Sehiemy 2021). It is unable to find the conventional research works on the power system to develop a comprehensive model that contains the ability to determine the optimal configuration belongs to the microgrid and at the same time, it has to assure as the energy management mechanism for coordinating the grid-implemented DERs along with the support of centralized power plant (Queen, Moses Babu, and Thota 2021).

Various optimization algorithms are presented for handling optimization issues and also solving the objectives of a single optimization problem (Venkatasubramanian, Jately, and Azzopardi 2021). These heuristic approaches are utilized for resolving the heuristic issues having more technical constraints that have various difficulties because of raising the non-linearity problem. For better utilization of RESs over the economic condition, it is highly significant to make the optimal sizing of microgrid components (Shekari, Golshannavaz, and Aminifar 2017). Based on the variant of the optimization approach, supremacy in the microgrid performance and the complete usage of RESs can be provided (Jahid et al. 2020). Therefore, many optimization algorithms are focused on utilizing the microgrid performance in recent research works (Kolhe 2009). Various developed works have considered the techno-economic evaluation independent of considering the effects of Demand Response (DR) (Alhasawi and Milanovic 2012). In addition, the effective advantages of the DR program are not mentioned in their evaluation which is highly essential for performing the efficient microgrid operation. The dispatching of optimal energy having fused energy sources is observed to be a challenging task based on the aspect of load as well as generation uncertainties that are required to be included in the evaluation for enhancing the system scheduling (Lopez-Lorente et al. 2021). Furthermore, the comparative testing of techno-economic advantages belonging to diverse combined power systems is not established based on the seasonal load variation and also with the DR program (Taheri 2022). Hence, novel research towards the techno-economical optimization for microgrid performance is focused on in this research work, particularly on PV, Wind turbines, and ESS.

The main contributions of the developed Demand Side management system in Microgrid are given as follows.

– Design an efficient microgrid system with the support of techno-economic optimization for demand side management and also for conserving the optimal capacity of PV, Wind turbines, and ESS.
– Implement a hybrid optimization algorithm named M-SOA integrated with the techno-economic optimization considering the multi-objective function concerning network power losses, voltage fluctuations, electricity supply costs, initial cost, operation cost, and fuel cost by tuning the parameters like PV capacity, wind turbine capacity, ESS capacity, PV bus location, wind turbine bus location, and ESS bus location.
– Examine the developed demand side management system in microgrid with the comparison over the conventional heuristic algorithms with the convergence analysis along with the analysis over the power loss, supply, and voltage fluctuations.

The rest of the sections of the developed model are described as follows. In Section 2, the conventional works on techno-economic optimization in microgrids are discussed. In Section 3, the system components are modeled and in Section 4, the demand side management for techno-economic optimization in a microgrid is discussed along with multi-objective function. In Section 5, the developed M-SOA for techno-economic optimization in a microgrid is described. In Section 6, the results obtained are given and in Section 7, the conclusion about the implemented model is given.

2 Literature survey

2.1 Related works

In 2020, Rezaeimozafar et al. (2020) proposed a novel two-layered heuristic framework for reducing operational expenses along with power losses and voltage fluctuations that occurred in the microgrids. When observing the outer layer, the capacity and size of the DERs included with the EV, RES, and ESS were acquired simultaneously. Similarly, the inner layer used for performing the scheduled operation belongs to ESSs and EVs with the support of the Integrated Coordination Model (ICM). This acted as the fuzzy interface that was incorporated for solving the multi-objectivity considered with cost function implemented according to the electricity response, the charge state of ESS and EVs, and hourly demand response. Demand response was developed within the ICM for evaluating the impact of electricity costs for optimal energy management. For resolving the heuristic issue as well as load-flow equations, a fusion of optimization algorithms was used for deployment correspondingly. One-day experiment outcomes were used for revealing the effectiveness of the developed model based on the analysis of voltage fluctuations, electricity supply cost, and power loss that has enhanced the energy efficiency and stability of the power system.

In 2020, Murty and Kumar (2020b) investigated the benefits of techno-economic advantages, optimal capacity, and energy dispatching in a remote area over Tamilnadu. Microgrids containing fused energy sources with the Diesel Generator (DG), Battery ESS (BESS), and wind turbine. Diverse case studies were developed using fused energy sources and a comparison among the advantages of techno-economic was made for every case study. Eight diverse configurations were designed for fused energy sources using renewable fractions. The heuristic evaluation was done with the support of the Hybrid Optimization Model for Electric Renewable (HOMER) software. The effect of demand responses was also confirmed based on the techno-economic

merits and energy dispatching. The experimental analysis was made for testing the optimal capacity belonging to fuel cost, payback period consisting of seasonal load variation, Cost Of Energy (COE), State Of Charge (SOC), operational expenses, initial expenses, and emission penalty of greenhouse gas. The simulation report has revealed the reduced emissions of CO_2 using the hybrid optimization algorithm when compared to the traditional isolated distribution system using DG.

In 2021, Ishraque et al. (2021) analyzed the implementation and optimization of the developed off-grid fused microgrid systems for diverse load dispatch mechanisms with the evaluation of diverse cost evaluations, system responses, and component sizes of the developed system. This research work was comprised of optimization of sizing in the fused microgrid systems comprised of diesel generator, wind turbine, solar PV, storage unit, and load profile with the help of five dispatch techniques such as integrated dispatch mechanism, load following, HOMER predictive dispatch, cycle charging, and generator order. The involved microgrids were considered for tuning to get the reduced CO_2 emission, Levelized Cost Of Energy (LCOE), and Net Present Cost (NPC). Here, the two microgrids were tested based on the five dispatch approaches according to HOMER software and consequently, the efficiency of the system performance along with the availability study of the microgrids was considered. The analysis reports have assured the instruction of estimating the diverse probable costs and component size for processing optimal operation done in the developed microgrids using the diverse constraints related to loading dispatch. The experiments were made to confirm the optimal dispatch mechanism which was the load-following mechanism for providing consistent power system responses consisting of lower net power cost, CO_2 emission rate, and operational cost. In addition, the fused dispatch mechanism was declared as the poor dispatch approach for the developed off-grid fused microgrid implementation comprising of higher operational cost, CO_2 emission rate, and LCOE.

In 2020, Bandyopadhyay et al. (2020)) presented a brief heuristic model for tuning the grid converter, battery, and PV belonging to the microgrid system with the consideration of diverse objectives such as capital costs, payback period, power autonomy, and energy autonomy. The developed technique was incorporated with the development of a holistic techno-economic microgrid framework according to the parameters such as electricity tariffs, capital investment, converter ratings, battery size, azimuth angle, and system power of PVs. The implemented approach was applicable for determining the optimum capacity of the BSS and PV system to estimate the impact of meteorological scenarios over the

relative capacity of the battery and PV. According to the heuristic outcomes, thumb rules were obtained for performing the optimal system sizing, which has supported facilitating the microgrid design engineers at the time of starting the implementation phase.

In 2021, Mathiesen et al. (2021) introduced an advanced and faster approach for tuning the DER expenditure and also for doing the dispatch schedule to take over the intra-hour variability. A new collection of conditions functioned using the intra-hour data for supporting the mixed-integer-linear-program microgrid expenditure optimization. Variability was described using the single fluctuations of worst-case intra-hour, which has enabled the rapid optimizations when correlated with other approaches considered for the evaluation. This developed model has confirmed the optimality at 2 % and also minimized the runtime by involving all time steps explicitly.

In 2020, Nagapurkar and Smith (2019) developed a new approach for evaluating the environmental as well as the techno-economic performance of the small microgrid. When assuring an uninterrupted power supply, the microgrid was comprised of seven different components like H_2 tanks, electrolyzers, fuel cells, biodiesel generators, lead acid batteries, wind turbines, and solar PVs. Initially, the brief mathematical frameworks were used for hourly energy production for every component that was evaluated after implementation. Then, the configurations containing the minimum LCOE were computed based on the electricity dispatch mechanism with the support of a Genetic Algorithm (GA). The result obtained from the individual microgrid was validated based on the exhaustive search algorithm that was useful for scanning the complete implementation for determining the minimum LCOE configurations. The microgrid size was constantly increasing for meeting the power requirements and also, novel minimum LCOE configurations were computed with the support of GA for evaluating the economies of scale impact over the robustness.

In 2020, Ganjeh et al. (2020) proposed a new multi-level optimization based on the techno-economic technique along with the recent time-varying price model to enhance the involvement in the coalition system and also for reducing the energy cost of home microgrid and finally, evaluate the reliability and voltage stability of the grid. The developed model has considered the apartments of certain units that included thermal as well as electrical energy generators and energy storage devices and also can share the energy among the upstream network. The developed approach has utilized an algorithm for smart discharging or charging of both EVs and energy storage for enhancing energy efficiency. The efficacy of the developed algorithm was evaluated based on come thermal and electrical loads configurations and also IEEE bus networks were enclosed for ensuring the efficacy of the coalition system among the microgrids on a huge scale.

In 2021, Yu et al. (2021) analyzed the effects of the developed demand response program considering the outcomes of microgrid planning that were included with the investigation on the utility grid's emission generation, NPC, COE, best configuration, and sizing were done. The optimization outcomes have demonstrated that the implemented demand response program was comprised of a positive impact on the environmental, economic, and technical perspectives of microgrids. The COE and NPC were minimized along with the component size which has led to reducing the initial cost.

In 2023, Rizvi, Pratap, and Singh (2023) presented the development of demand-side management for minimizing the dispatch of optimal power and cost of operation. Here, the microgrid was fused with the natural gas network to resolve the renewable energy. Especially, the electric network has been incorporated with a new hybridization of two optimization approaches grasshopper and flower pollination algorithms to ignore the congestion in a gas network. At last, the designed scheme was experimented with using a seven-node with the 33-bus IEEE test system.

In 2023, Dey, Dutta, and Marquez (2023a) developed an intelligence-technique-based DSM for the reduction of the overall cost of using the MG structure. Additionally, there are seven diverse cases are reviewed which cover various electricity market pricing strategies, DSM programs, and grid participation. Thus, the simulation results of the designed method have been obtained using the DSM scheme regarding cost savings.

In 2023, Dey, Basak, and Bhattacharyya (2023b) introduced a bi-level optimization approach to reduce the operating costs of a low-voltage microgrid system. Based on the initial optimization of DSM was utilized to the reorganize level load model (Rodezno et al. 2023). Here, the distributed generator scheduling ideas and the restructured load demand models were for reducing the microgrid system's generating costs.

2.2 Problem statement

Some techno-economical optimization approaches on microgrids are listed in Table 1. GA-PSO (Rezaeimozafar et al. 2020) minimizes the electricity supply cost, voltage fluctuations, and power loss and significantly enhances the energy efficiency and stability of the power system. It does not handle the uncertainties in hourly updated information. The hybrid Optimization Model (Murty and Kumar 2020b) tries

to reduce emissions, operation reserve, and reduced energy demand and guarantees grid resilience. The real-time implementation of this model is costly. HOMER pro (Ishraque et al. 2021) ensures the performance regarding the LCOE, NPC, and CO_2 gas emissions and ensures an uninterrupted supply of electrical power. It suffers from processing the real-life Barishal and Chattogram distribution network via the considered distribution line in the Simulink study. PSO (Bandyopadhyay et al. 2020) performs better by deriving trade-offs among various objectives such as simple payback period, power autonomy, self-sufficiency, and lifetime capital cost and examines the effect of feed-in tariffs and the electricity pricing tariffs on optima sizing of battery and PV systems. It suffers from higher payback periods. Mixed-integer-linear-program (Mathiesen et al. 2021) incorporates the intra-hour variability into the microgrid and reduces the runtime and maintained the optimality. It does not explore purchases on utility on power demand charges. In the Genetic Algorithm (Nagapurkar and Smith 2019), the economies of scale impacts are examined on sustainability and verify the power requirements and achieve a lower carbon footprint. It does not explore the social cost of carbon on a utility-scale microgrid. Multi-level optimization (Ganjeh et al. 2020) increases the performance owing to grid reliability and voltage quality and the network efficiency is enhanced regarding reliability indices, voltage quality, thermal dumped energy, and total cost. It faces complications regarding the generality of the designed model. K-means clustering (Yu et al. 2021) maximizes the flexibility of the system via techno-economic analysis of an off-grid microgrid and efficiently alters the load profiles for economic reasons. The results are affected by the uncertainties of renewable energy sources. Thus, there is a need on designing a new techno-economical optimization approach using a microgrid.

3 Modeling of system components: solar cell, wind turbine, and energy storage systems

3.1 Solar cell

Based on the considerations in (Rahbari et al. 2017), the resultant power obtained from the solar cells gets affected by factors like solar cell temperature ST_D which is given in Eq. (1).

$$ST_C = ST_{amb} + \frac{Noct - 20°}{0.8} \times SUN \qquad (1)$$

Here, the term SUN denotes the intensity rate taken based on the solar radiation, ST_{amb} represents the ambient temperature that is considered to be °C and the general operating cell temperature depicted by Noct. For generating the pattern from solar radiation, the beta possibility distribution function is given as shown in Eq. (2).

$$f(SUN, \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) + \Gamma(\beta)} \times SUN^{\alpha-1} \times (1 - SUN)^{\beta-1} \qquad (2)$$

$$\beta = (1 - \mu_s) \times \left(\frac{\mu_s(1 + \mu_s)}{\sigma_s^2} \right) - 1 \qquad (3)$$

$$\alpha = \left(\frac{\mu_s \times \beta}{1 - \mu_s} \right) \qquad (4)$$

Here, the terms β and α are correspondingly the parameters related to beta distribution, which are computed in Eqs. (3) and (4), respectively. The standard deviation and mean of the solar radiation acquired through the statistical data are indicated by σ_s^2 and μ_s, respectively. Finally, the resultant output power belonging to the solar cell is computed in Eq. (5).

$$Pw_{pv} = Pw_{Npv} \times [\eta_{pv} \times (ST_C - 25)] \qquad (5)$$

Here, the term η_{pv} indicates the energy efficiency of the solar cell.

3.2 Wind turbine

The output power obtained through the wind turbine is computed based on three parameters such as air mass direction, wind speed, and turbine location as mentioned in (Rahbari et al. 2017). At the same time, the wind speed contains a huge impact on the turbine output and thus, the Weibull possibility distribution function is employed for generating the arbitrary wind speed variation (Abedini, Moradi, and Hosseinian 2016) that is depicted in Eq. (6).

$$ff(v, l, \lambda) = \left(\frac{l}{\lambda} \right)\left(\frac{v}{\lambda} \right)^{l-1} \times e^{-\left(\frac{v}{\lambda} \right)^l} \qquad (6)$$

Here, the term l indicates the shape parameter and λ represents the scale parameter. The kinetic energy for the airflow is considered with the wind speed v and mass M that is shown in Eq. (7).

$$KIE_{Air} = \frac{1}{2} Mv^2 \qquad (7)$$

$$M = \rho ArLe \rightarrow \frac{dM}{dt} = \rho Ar \frac{dLe}{dt} = \rho Arv \qquad (8)$$

Next, the generated power through the wind turbines is determined in Eq. (9).

Table 1: Features and challenges of traditional techno-economical optimization approach using microgrid.

Author (citation)	Methodology	Features	Challenges
Rezaeimozafar et al. (2020)	GA-PSO	– It minimizes the electricity supply cost, voltage fluctuations, and power loss. – It significantly enhances the energy efficiency and stability of the power system.	– It does not handle the uncertainties in hourly updated information.
Murty and Kumar (2020b)	Hybrid optimization model	– It tries to reduce emissions, operation reserve, and reduced energy demand. – It guarantees grid resilience.	– The real-time implementation of this model is costly.
Ishraque et al. (2021)	HOMER pro	– It ensures the performance regarding the LCOE, NPC, and CO_2 gas emissions. – It ensures an uninterrupted supply of electrical power.	– It suffers from processing the real-life Barishal and Chattogram distribution network via the considered distribution line in the simulink study.
Bandyopadhyay et al. (2020)	PSO	– It performs better by deriving trade-offs among various objectives such as a simple payback period, power autonomy, self-sufficiency, and lifetime capital cost. – It examines the effect of feed-in tariffs and electricity pricing tariffs on the optimal sizing of battery and PV systems.	– It suffers from higher payback periods.
Mathiesen et al. (2021)	Mixed-integer-linear-program	– It incorporates the intra-hour variability into the microgrid. – It reduces the runtime and maintained the optimality.	– It does not explore purchases on utility on power demand charges.
Nagapurkar and Smith (2019)	Genetic algorithm	– The economies of scale impacts are examined on sustainability. – It verifies the power requirements and achieves a lower carbon footprint.	– It does not explore the social cost of carbon on a utility-scale microgrid.
Ganjeh et al. (2020)	Multi-level optimization	– It increases the performance owing to grid reliability and voltage quality. – The network efficiency is enhanced regarding reliability indices, voltage quality, thermal dumped energy, and total cost.	– It faces complications regarding the generality of the designed model.
Yu et al. (2021)	K-means clustering	– It maximizes the flexibility of the system via techno-economic analysis of an off-grid microgrid. – It efficiently alters the load profiles for economic reasons.	– The results are affected by the uncertainties of renewable energy sources.

$$Pw_{\text{Wind}} = \frac{d\text{KIE}_{\text{Air}}}{dt} = \frac{1}{2}\frac{dM}{dt} \quad v^2 = \frac{1}{2}\rho A r v^3 \qquad (9)$$

This kinetic energy is utilized for acquiring the transmission power through the wind turbine blades. Here, the terms ρ, Ar and Le are correspondingly denoted for air density, area secured by the turbine blades, and turbine blade length.

3.3 Energy storage systems

The optimal scheduling performed for ESS causes increasing frequency stability and power balance (Atia and Yamada 2016). ICM is involved in deriving the optimal discharging and charging patterns belonging to the storage system. The specifications considered for the ESS are given in Table 2 (Delfino et al. 2019; Jarraya et al. 2019).

Table 2: Specifications considered for the ESS.

Terms	SOC
SOC1 upper limit (%)	90
SOC lower limit (%)	20
Self-discharge rate (%Energy/month)	5
Efficiency (%)	95

Then, the SOC for the hourly ESS is acquired in Eq. (10).

$$\text{SoC}_{\text{Ess}}(tt) =$$

$$
\begin{cases}
(\text{SoC}_{\text{Ess}}(tt-1) \times (1-\alpha_{\text{Dch}})) + \left(\dfrac{(Pw_{\text{Ess}}^{\text{Chr}} \eta_{\text{Ess}} \Delta tt_{\text{Ess}}^{\text{Chr}})}{Ecap}\right), \text{Chr} \\[4ex]
(\text{SoC}_{\text{Ess}}(tt-1) \times (1-\alpha_{\text{Dch}})) + \left(\dfrac{\left(\dfrac{Pw_{\text{Ess}}^{\text{Dch}} \Delta tt_{\text{Ess}}^{\text{Dch}}}{\eta_{\text{Ess}}}\right)}{Ecap}\right), Dch
\end{cases}
$$

(10)

$$pw_{\text{Ess}}^{\frac{\text{Chr}}{\text{Dch}}}(tt) = \frac{\begin{array}{c}Pw_G + Pw_{pv}(tt) + Pw_{\text{Wind}}(tt) \\ + Pw_{\text{Park}}(tt) - Pw_D(tt) - Pw_{\text{Lss}}(tt)\end{array}}{\eta_{\text{Conv}}}$$

(11)

Here, the term α_{Dch} denotes the self-discharging rate, η_{Ess} indicates the discharging or charging efficiency of ESS, $pw_{\text{Ess}}^{\frac{\text{Chr}}{\text{Dch}}}$ depicts the discharging or charging power, Δtt_{Ess} is used for representing the period for discharging or charging, η_{Conv} shows the efficiency of the DC/AC converter, and Ecap represents the capacity of ESS.

3.4 System model

The DSM act as a significant role in handling renewable power generation and load. The core concept of this DSM is to reduce the emission rate, electricity cost, and peak demand. The critical key issues in the existing approaches are not well examined in the microgrids (Mbungu et al. 2023) to reduce the electricity cost. Owing to the stochastic behavior of wind and solar energies, it affects the accuracy rate of the system. Therefore, in this research work the latest hybrid ISOA algorithm is integrated into the microgrid system for reducing fuel cost electricity supply costs, initial costs, energy efficiency, and operation cost.

The diagrammatic representation of the presented techno-economic optimization in a microgrid with a demand-side management model is shown in Figure 1. Here, the Wind Turbine, ESS, optimal capacity of PV is determined by the novel techno-economical optimization with ISOA model using multi-objective function concerning metrics like network power losses, voltage fluctuations, electricity supply costs, initial cost, operation cost, fuel cost, and demand side management. At last, the experiments on the IEEE-33 bus network are conducted for achieving optimal energy management which is done on distributed energy resources.

4 Demand side management for techno-economic optimization in microgrid with multi-objective function

4.1 Demand side management

Demand-side involvement is a significant part of the scheduling of optimal energy with superior security and minimum cost (Zakariazadeh, Jadid, and Siano 2014). Demand response is considered as the standard approach for the demand side involvement that motivates the users for adjusting their elastic loads based on the request of the users or with the price signals. Generally, elastic loads are categorized into curtailable and shiftable loads. The advantages of demand response for the users have included continuity and fewer expenses for electricity. In addition, it contains the profits for microgrid operators in terms of avoiding the expensive generators, optimal operations with the intention of cost savings, and minimal purchasing of costly power through the load curve flattening and the main grid. Generally, the demand responses are categorized into two significant classes belonging to Incentive-Based and Time-Based Rate (TBR) programs. Here, the IB programs are modified based on user demand with the consideration of penalty and incentive options, and at the same time, the TBR program is modified based on the consideration of variations in the electricity costs at various times.

According to Amini and Moghaddam (2013), a single EV probabilistic demand is designed for acquiring the hourly demand of parking lots based on diverse kinds of EVs and diverse driving modes. The specifications of EVs are represented in Tables 3 and Table 4 that is obtained from (Mozafara, Hadi Amini, and Hasan Moradi 2018). As battery life is reduced by the full battery discharge, the Depth of Discharge (DOD) is considered to be 80 %.

The Log-Normal distribution function is employed for computing the routine mileage of the estimated EVs (Domínguez-García, Heydt, and Suryanarayanan 2011; Roe et al. 2030) that are shown in Eq. (12).

$$\text{DST} = e^{(\mu_d + \sigma_d \times Y)}$$

(12)

Here, the arbitrary variable is indicated by Y that is having a mean value of 0 and a variance of 1. The parameters of the lognormal distribution are given by μ_d
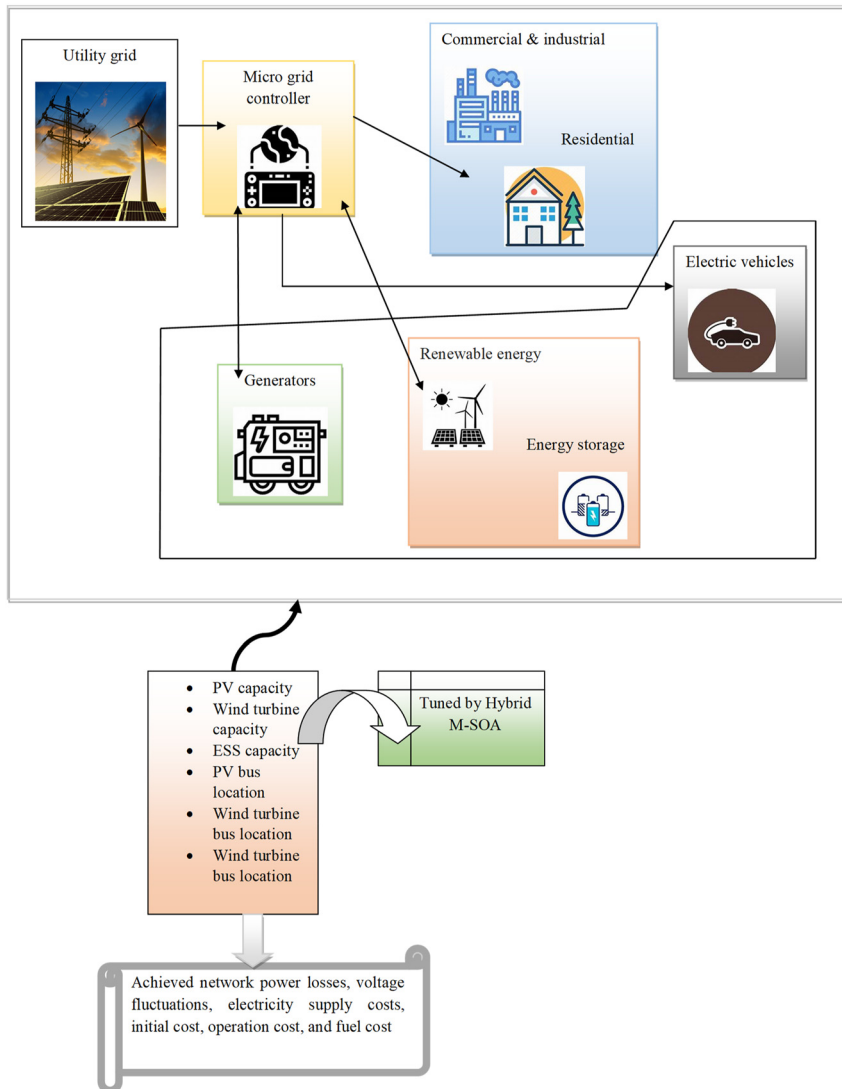
Figure 1: Structural view of the developed techno-economic optimization in a microgrid with demand side management model.

Table 3: Specifications related to EV.

EV Type		A	B	C	D	Mean value
Battery cap (kWh)		35	16	18	12	18.54
Energy consumption (kWh/mile)	Road	0.14	0.13	0.16	0.16	0.1397
	City	0.182	0.168	0.21	0.21	0.1945
	Freeway	0.21	0.194	0.242	0.242	0.2245
	High traffic	0.213	0.196	0.245	0.245	0.2274
Market share (%)		38	9	25.5	27.5	

Table 4: Charging rates of EV.

Charging/discharging power (kW)	0.1	0.3	1.0
Charging mode	Slow charging	Slow charging	Slow charging

and σ_d, respectively, which are determined based on the standard deviation and mean of the distance traveled with the EVs according to statistics (Amini and Moghaddam (2013); Jarraya et al. 2019). These formulations are made as follows.

$$DST_S = 0.39 \times DST \tag{13}$$

$$DST_D = 0.31 \times DST \tag{14}$$

$$DST_G = 0.22 \times DST \tag{15}$$

$$DST_U = 0.08 \times DST \tag{16}$$

Then, the maximum distance DST^{Max} is computed for finding the traveling capacity of the EVs containing a fully charged battery which is shown in Eq. (17).

$$DST^{Max} = \frac{Bcap}{F_D} \tag{17}$$

Here, the term Bcap denotes the battery capacity of the EV in terms of kWh, and the energy consumption is computed per mile that is indicated by F_D. For computing the estimated energy demand belonging to EVs, four diverse driving modes are considered in Eq. (18).

$$E_{EV} = \left(E_{EV,S} + E_{EV,D} + E_{EV,G} + E_{EV,U}\right) \tag{18}$$

$$E_{EV,S} = \left(DST_S \times E_{EV,S}^{Avg}\right) \cdot DST_S \leq DST^{Max} \tag{19}$$

$$E_{EV,D} = \left(DST_D \times E_{EV,D}^{Avg}\right) \cdot DST_D \leq DST^{Max} \tag{20}$$

$$E_{EV,G} = \left(DST_G \times E_{EV,G}^{Avg}\right) \cdot DST_G \leq DST^{Max} \tag{21}$$

$$E_{EV,U} = \left(DST_U \times E_{EV,U}^{Avg}\right) \cdot DST_U \leq DST^{Max} \tag{22}$$

Furthermore, the computation of respective SOC at the time of relieving the parking lot is done by utilizing the arrival time T_{Arvl}, the duration of EVs availability over the parking lot, and the departure time T_{Deprt}. Then, the time duration T_{Durtn} is acquired as in Eq. (23).

$$\begin{cases} T_{Arvl} = \mu_{Arvl} + (\sigma_{Arvl} \times Y_1) \\ T_{Deprt} = \mu_{Deprt} + (\sigma_{Deprt} \times Y_2) \\ T_{Durtn} = T_{Deprt} - T_{Arvl} \end{cases} \tag{23}$$

Here, the term μ denotes the mean value and σ indicates the standard deviation considered for arrival and departure time according to historical data. The generally distributed arbitrary variables are given by Y_1 and Y_2.

$$SOC_{EV} = \min\left\{\left[Soc_{EV}^{Ini} + \frac{E_{EV}}{Bcap}\right], \left[SOC_{EV}^{Ini} + \left(\frac{T_{Deprt}}{Bcap} \times q_{EV}^{Chr/Dch}\right)\right]\right\} \tag{24}$$

Then, the required SOC is computed with the determined parameters and also with the charging rate q_{EV}^{Chr} that is given in Eq. (24).

4.2 Derived multi-objective function

The developed M-SOA is used for optimizing the microgrid constraints like optimal capacity as well as bus location of PV, Wind Turbine, and ESS for meeting the demand side management in the Microgrid system based on the concept of techno-economic optimization. The main objective of the techno-economic optimization is to reduce the power loss, voltage fluctuations, and electricity supply costs that are shown in Eq. (25).

$$FF = \underset{\{OC_{PV},OC_{WT},OC_{ESS},\ BL_{PV},BL_{WT},BL_{ESS}\}}{\arg\min} \left(pLs + vFl + EsC + PN\right) \tag{25}$$

Here, the terms OC_{PV} denote the optimal capacity of PV that is in the range of [0.002, 0.009], OC_{WT} indicates the optimal capacity of wind turbine that is in the range of [0.2, 0.8], OC_{ESS} represents the optimal capacity of ESS that is in the range of [0.2, 0.8], BL_{PV} describes the bus location of PV that is in the range of [2, 33], BL_{WT} depicts the bus location of wind turbine that is in the range of [2, 33] and BL_{ESS} describes the bus location of ESS that is in the range of [2, 33]. Here, the penalty value is included for avoiding the worst solution from the model and this penalty value is indicated by *PN*. This penalty will be added to the solution if the solution does not satisfy objective constraints like demand-supply balance, bus voltage limitations, and pricing constraints. The penalty value is considered to be 0.1.

Power loss *pLs* is considered the first objective to be reduced as shown in Eq. (26).

$$pLs = \sum_{T=1}^{24} \sum_{j=1}^{Nb} \sum_{k>1}^{Nb} Z_{jk} \left[\begin{array}{l} V_j^2(tt) + V_k^2(tt) + 2V_j(tt)V_k(tt) \\ \cos\left(\delta_j(tt) - \delta_k(tt)\right) \end{array}\right] \tag{26}$$

Then, the voltage fluctuation *vFl* is considered as the second objective to be reduced as shown in Eq. (27).

$$vFl = \sum_{T=1}^{24} \sum_{j=1}^{Nb} \left|1 - V_j(tt)\right| \tag{27}$$

At last, the electricity supply costs have to be reduced as the third objective as given in Eq. (28).

$$EsC = \sum_{T=1}^{24} \left(Pw_{Sub}(tt) \times \pi^{tou}(tt)\right) + ff_{Chr} - ff_{Dch} \tag{28}$$

$$Pw_{Sub}(tt) = \sum_{j=1}^{Nb} \begin{array}{l} Pw_{e,j}(tt) + Pw_{Loss}(tt) + Pw_{Pkg}(tt) \\ -Pw_{Pv}(tt) - Pw_{Wnd}(tt) + Pw_{Ess}(tt) \end{array} \tag{29}$$

$$ff_{Chr} = \sum_{j=1}^{Nb} \left(\begin{array}{l} \left(\sum_{n=1}^{n_{st}} Pw_{Pkg}(tt) \times \Delta T_n^{Chr}\right) \\ + \left(Pw_{Ess}(tt)\Delta T_{Ess}^{Chr}\right) \times \pi^{tou}(tt) \end{array}\right) \tag{30}$$

$$ff_{Dch} = \sum_{T=1}^{24} \left(\begin{array}{l} \left(\sum_{n=1}^{n_{st}} Pw_{Pkg}(tt) \times \Delta T_n^{Dch}\right) \\ + \left(Pw_{Ess}(tt)\Delta T_{Ess}^{Dch}\right) \times \pi^{tou}(tt) \end{array}\right) \tag{31}$$

$$Pw_{\text{Pkg}}(tt) = \sum_{m}^{M_{EV}} Pw_{EV,m,o}^{\frac{\text{Chr}}{\text{Dch}}} \qquad (32)$$

Here, the charging durations of EV are given as ΔT_n^{Chr}, and also for ESS is depicted by $\Delta T_{\text{Ess}}^{\text{Chr}}$.

5 Development of modified sandpiper optimization algorithm for techno-economic optimization in microgrid with demand side management

5.1 Proposed M-SOA

The developed M-SOA integrated with the techno-economic optimization considering the multi-objective function concerning network power losses, voltage fluctuations, electricity supply costs, initial cost, operation cost, and fuel cost by tuning the parameters like PV capacity, wind turbine capacity, ESS capacity, PV bus location, wind turbine bus location and ESS bus location of the microgrid. SOA is chosen in the developed model since it can solve the multi-objective problem and is also able to balance the exploration and exploitation phase efficiently. However, this algorithm shows a slight deviation in the convergence performance due to the random update of the parameters. Therefore, a new improvement is made in the SOA and the improved optimization algorithm is named M-SOA for solving the conventional problems. In the implemented M-SOA, the additional variable D_B in the collision avoidance phase of the conventional SOA is updated with the fitness-based concept as shown in Eq. (33).

$$D_B = 0.5*\left(\frac{\sqrt{(\text{Fit}_{\min} + \text{Fit}_{\max})}}{2} \right) \qquad (33)$$

Here, the term $\text{Fit}_{\min}$ denotes the minimum fitness value and $\text{Fit}_{\max}$ indicates the maximum fitness value.

SOA (Kaur, Jain, and Goel 2020): This heuristic algorithm is derived from the attacking behavior of the seabirds which are observed to be highly sharp birds, which utilizes the bread crumbs for hunting the fishes and are also very efficient in generating the rain-like sound with the support of their feet for catching the underground earthworms. These sandpipers have excellent behaviors of migrating as well as attacking characteristics. These behaviors are described as follows.

Exploration phase (Migration behavior): This algorithm tests the set of sandpipers that propagates from one place to another place at the time of migration. A sandpiper has to meet the upcoming three constraints.

Avoid the collision: A supplementary variable D_B is utilized for determining the new sandpiper's location for avoiding collision among their nearby sandpipers. This is formulated in Eq. (34).

$$\overrightarrow{D}_{SP} = D_B \times \overrightarrow{Q}_{SP}(a) \qquad (34)$$

Here, the term $\overrightarrow{Q}_{SP}$ denotes the present position of the sandpiper, $\overrightarrow{D}_{SP}$ indicates the location of the sandpiper that collided with the remaining sandpiper, a defines the present iteration, and D_B represents the propagation of the sandpiper among the searching dimension that is adaptively computed in Eq. (33).

Convergence towards the optimal neighbor's direction: Followed by avoidance of collision, the search agent propagates in the path of reaching the best neighbor as shown in Eq. (35).

$$\overrightarrow{N}_{SP} = D_C \times \left(\overrightarrow{Q}_{Bst}(a) - \overrightarrow{Q}_{SP}(a) \right) \qquad (35)$$

Here, the term $\overrightarrow{N}_{SP}$ denotes the positions of the sandpiper $\overrightarrow{Q}_{SP}$ moving to the direction of the optimal fittest search agent (sandpiper) $\overrightarrow{Q}_{Bst}$ and D_C indicates the arbitrary parameter that is a suitable exploration that is determined as in Eq. (36).

$$D_C = 0.5 \times S_{nd} \qquad (36)$$

Here, the term S_{nd} indicates the arbitrary number that stays between [0, 1].

Position Upgrade based on the position of the best search agent: At last, the sandpiper gets updated with their position concerning the optimal sandpiper, and the distance between the sandpiper and the optimal sandpiper is given in Eq. (37).

$$\overrightarrow{E}_{SP} = \overrightarrow{D}_{SP} + \overrightarrow{N}_{SP} \qquad (37)$$

Here, the term $\overrightarrow{E}_{SP}$ is used for representing the gap between the optimal fittest sandpiper and the normal sandpiper.

Exploitation phase (Attacking characteristic): At the time of migration, the sandpipers modify their angle and speed of the attack continuously. It enhances the altitude by utilizing their wings. Here, the sandpipers produce the spiral characteristic for attacking the prey, which is observed to perform in the 3D plane as shown below.

$$y' = Rd \times \sin(j) \tag{38}$$

$$z' = Rd \times \cos(j) \tag{39}$$

$$a' = Rd \times j \tag{40}$$

$$s = v \times e^{lw} \tag{41}$$

Here, the term Rd denotes the radius of every spiral turn, j indicates the variable that lies in-between $[0 \le l \le 2\pi]$, and the constant parameters are correspondingly indicated by v and w for describing the spiral shape and e denotes the logarithm base. Then, the improved position of the sandpiper is determined as in Eq. (42) based on the computations made in Eqs. (38)–(40).

$$\vec{Q}_{SP}(a) = \left(\vec{E}_{SP} \times (y' + z' + a') \right) \times \vec{Q}_{Bst}(a) \tag{42}$$

Here, the term $\vec{Q}_{SP}(a)$ helps to upgrade the search agent's position and secures the optimal solution. The pseudocode of the developed M-SOA is depicted in Algorithm 1.

Algorithm 1: Developed M-SOA

Population initialization $\vec{Q}_{SP}$
Get the parameters D_C
Determine the best search agent $\vec{Q}_{Bst}$
  Compute the fitness of all search agents
  While ($a<Mx_{it}$) do
    For every sandpiper do
    Compute the additional variable D_B with the adaptive concept as in Eq. (33)
      Update the sandpiper's position based on Eq. (42)
    End for
    Update the value of parameters
    Determine the fitness value after the position update
    $a \leftarrow a+1$
  End while
Return $\vec{Q}_{Bst}$
End

The flowchart of the developed M-SOA is depicted in Figure 2.

5.2 Constraints to meet

Three constraints are considered as the objective constraints and the optimal solution should satisfy these objective constraints or else a penalty will be added to it for removing the particular solution for solving the objective problem. The objective constraints are described as follows.
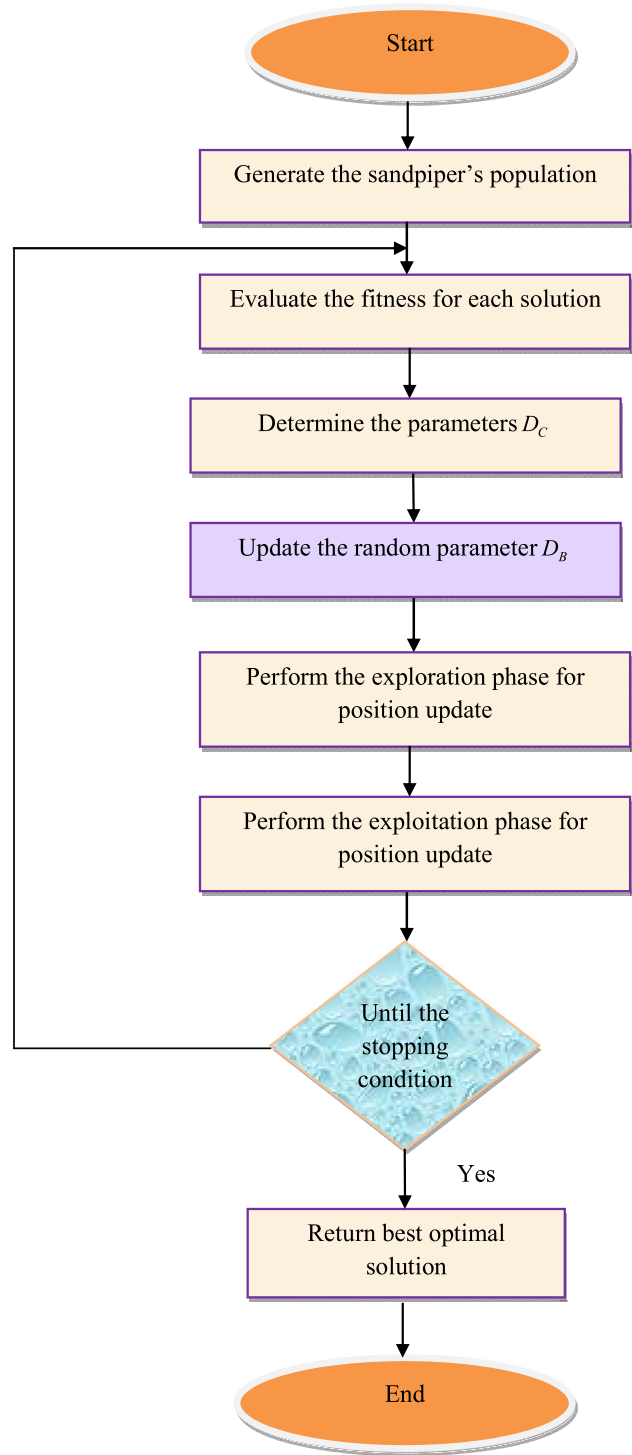
(a) Demand supply balance is depicted as follows.

Figure 2: Flowchart of the developed M-SOA.

$$\begin{aligned} Pw_{h,j}(tt) &- Pw_{e,j}(tt) \\ &= V_j(tt) \sum_{k=1}^{Nb} V_k(tt) Z_{jk} \cos\left(\delta_j(tt) - \delta_k(tt) - \theta_{jk}\right) \end{aligned} \tag{43}$$

$$Qw_{h,j}(tt) - Qw_{e,j}(tt)$$
$$= V_j(tt) \sum_{k=1}^{Nb} V_k(tt) Z_{jk} \sin(\delta_j(tt) - \delta_k(tt) - \theta_{jk}) \qquad (44)$$

Here, the balance between the load demand and power generation overall buses have to be managed. Since DERs combined to be a system, then it can be written as in Eq. (45).

$$Pw_{h,j}(tt) + Pw_{pv,j}(tt) + Pw_{Wnd}(tt) + Pw_{Pkg}(tt)$$
$$+ Pw_{Ess,j}(tt) - Pw_{e,j}(tt)$$
$$= V_j(tt) \sum_{k=1}^{Nb} V_k(tt) Z_{jk} \cos(\delta_j(tt) - \delta_k(tt) - \theta_{jk}) \qquad (45)$$

(b) Bus voltage limitations: Here, the phase and magnitude of the voltage play an important role in assuring stable operation and thus, it is given as in Eqs. (46) and (47).

$$V^{\mathrm{MIN}} \le V_j(tt) \le V^{\mathrm{MAX}} \qquad (46)$$

$$\delta^{\mathrm{MIN}} \le \delta_j(tt) \le \delta^{\mathrm{MAX}} \qquad (47)$$

(c) Pricing constraints: The energy prices are committed to being in the limited range for reducing the expenses of the customers and the permitted range is given in Eq. (48).

$$\pi^{tou}(tt) \le \pi^{tou,\,\mathrm{MAX}}(tt) \qquad (48)$$

Then, the lower bills are assured for customers to motivate them to be actively involved in the demand response program. This is given in Eq. (49).

$$\sum_{T=1}^{24} Pw_{E,j}(tt) \times \pi^{tou}(tt) \le \tau \sum_{T=1}^{24} Pw_{E0,j}(tt) \times \pi(tt) \qquad (49)$$

When the condition ($\tau \le 1$) is satisfied, the distribution network operator gets benefitted.

6 Results and discussions

6.1 Experimental setup

The proposed techno-economic optimization in microgrid with demand side management model was implemented in MATLAB 2020a. The evaluation of the developed system was made to analyze the performance of convergence along with demand, power loss, and supply cost. The developed M-SOA was compared with other algorithms like "Artificial Gorilla Troops Optimizer (AGTO) (Singh et al. 2022), Butterfly Optimization Algorithm (BOA) (Qazani et al. 2020), Whale Optimization Algorithm (WOA) (Zhai et al. 2020), and SOA (Kaur, Jain, and Goel 2020)". Also, objective functions like power loss, voltage fluctuations, and electricity costs were considered for analyzing the benefits of the developed model. This implemented model has been simulated in the IEEE-33 bus

Table 5: Simulation parameters of the developed Demand Side Management in a Microgrid system with techno-economic optimization.

| Parameter description	Ranges
Energy resources	{PV, wind turbine, ESS}
No. of network buses Nb	33
Minimum voltage V^{MIN}	0.002
Maximum voltage V^{MAX}	0.009
Minimum phase angle δ^{MIN}	0.01
Maximum phase angle δ^{MAX}	0.08
The nominal output power of solar cell Npv	5 MW
Solar energy efficiency η_{pv}	2 %
Nominal operating cell temperature Noct	28 °C
The intensity of solar radiation SUN	3 W/m^2
Ambiant temperature ST_{amb}	8 °C
Self-price elasticity of the demand η_{tt}	−0.1
The cross-price elasticity of the demand η_{sg}	0.001
Number of EVs(electric vehicles) at each time interval M_{EV}	7
Minimum charging/Discharging power of ESS F_{MIN}	0.2
Maximum charging/Discharging power of ESS F_{MAX}	0.8
Number of charging stations M_{ST}	3
Minimum charging/Discharging duration of ESS and EV T_{MIN}	0.5
Maximum charging/Discharging duration of ESS and EV T_{MAX}	0.9
The minimum price of ESS $PR_{\mathrm{MIN}}^{\mathrm{ESS}}$	12
Maximum price of ESS $PR_{\mathrm{MAX}}^{\mathrm{ESS}}$	25
The minimum price of electricity PR_{MIN}	144 $/MWh
Maximum price of electricity PR_{MAX}	167 $/MWh
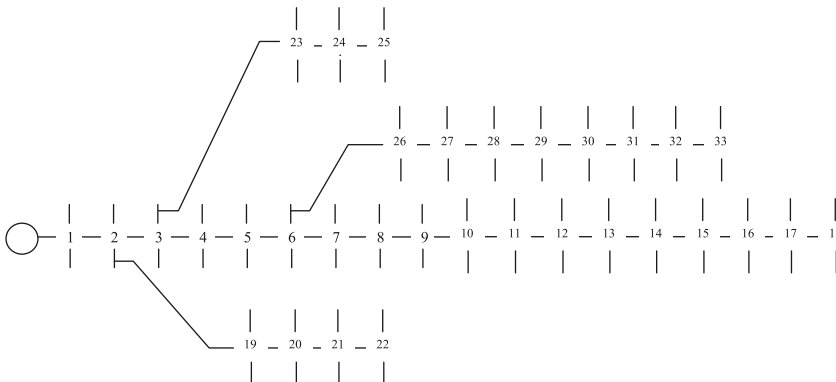
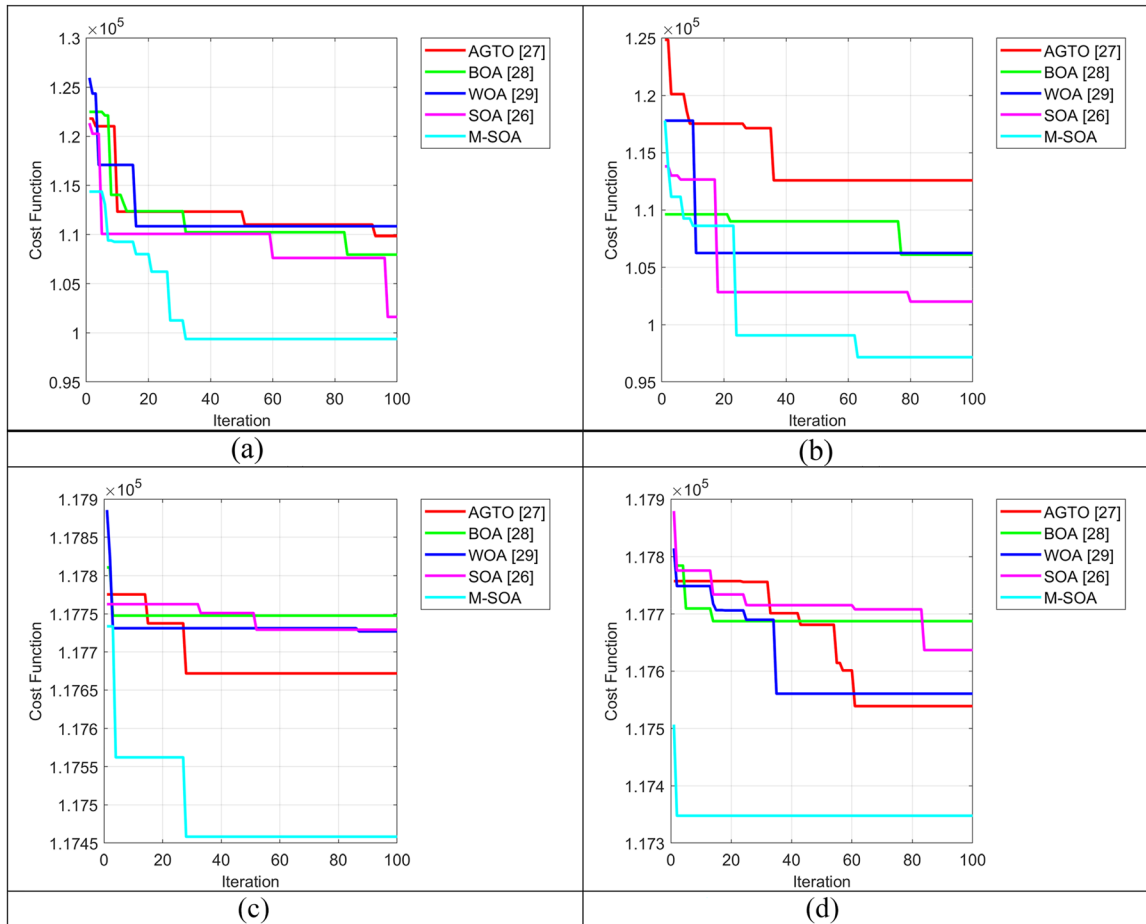**Figure 3:** Architectural representation of the IEEE-33 bus network.

Figure 4: Cost function evaluation on the developed techno-economic optimization in microgrid with demand side management model for (a) 3 h, (b) 6 h, (c) 9 h, and (d) 12 hours.

network (Delfino et al. 2019), where the electricity supply is conducted through the centralized power plant associated with bus 1. Here, the line diagram is given representing the IEEE-33 bus network as shown in Figure 3.

6.2 Parameter initialization

The parameter generated for the developed Demand Side Management in a Microgrid system with techno-economic optimization is given in Table 5.

6.2 Cost function analysis

The cost function analysis is performed for the developed techno-economic optimization in microgrid with demand side management model by comparing with the
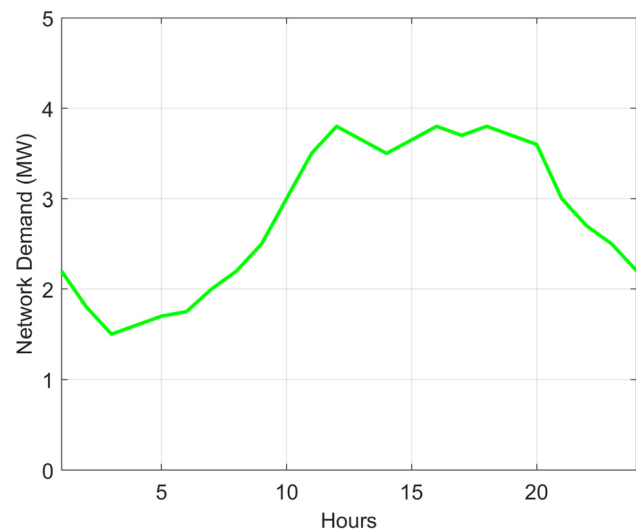

Figure 5: Network demand analysis on developed techno-economic optimization in microgrid model for 24 hours.
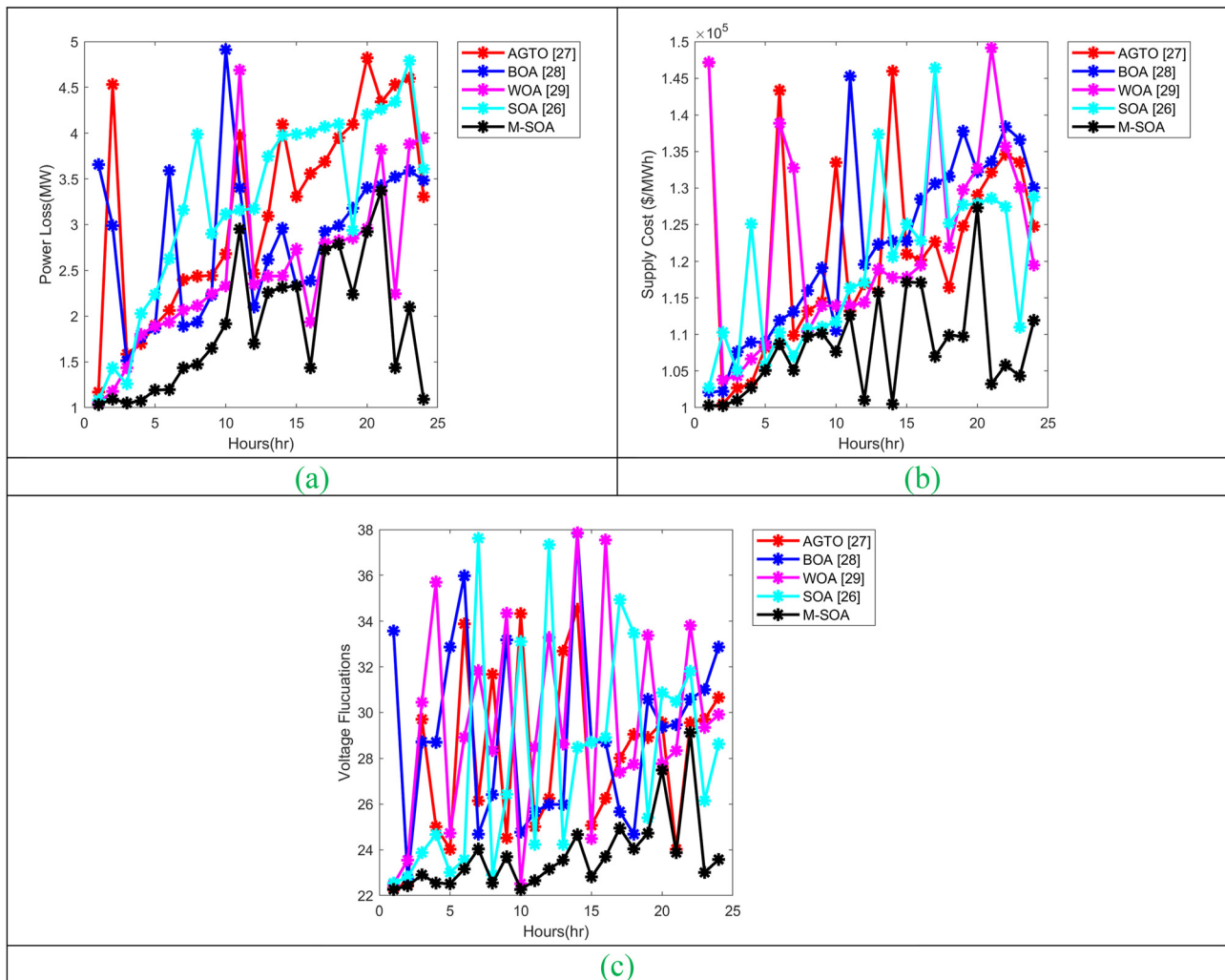
Figure 6: Multi-objective analysis on developed techno-economic optimization in microgrid with demand side management model in terms of (a) power loss, (b) supply costs, and (c) voltage fluctuations.

conventional heuristic algorithms for 24 h, in which 3 h, 6 h, 9 h, and 12 h are given in Figure 4. Here, the developed model has shown minimum convergence rate than the conventional algorithms like AGTO, BOA, WOA, and SOA, respectively that is lower power loss, voltage fluctuation, and minimum pricing constraints are achieved through the developed techno-economic optimization model in microgrids.

6.4 Network demand analysis

The implemented techno-economic optimization in microgrid with demand side management model is compared with the conventional algorithms based on the constraint of

network demand that is shown in Figure 5. On observing the graph, the highest demand occurred between 10 and 15 h, which represents the reduction in the system dependency based on the centralized power plant, which is highly essential for decreasing the costs of the network operation.

6.5 Multi-objective analysis based on power loss, supply cost, and voltage fluctuations

The objective constraints are considered for the analysis of the developed techno-economic optimization in microgrid with demand side management model by comparing with

the conventional algorithms as shown in Figure 6. With the consideration of power loss analysis, the proposed model sudden variations in the power loss between the 10–20 h and finally, get reduced the power loss. Similarly, the reduction in the supply costs and voltage fluctuations takes place.

6.5 Different Scenarios-based power loss, supply cost, and voltage fluctuations analysis

The three constraints like power loss, supply cost, and voltage fluctuations are considered individually in the first three scenarios, and in the fourth scenario, all three objective constraints are combined and involved for the analysis of developed techno-economic optimization in microgrid with

demand side management model as in Figure 7. From this analysis, it is shown that minimum rate of power loss and supply costs that are achieved through the developed M-SOA when compared to the conventional heuristic strategies.

6.7 Statistical analysis of implemented model

The implemented techno-economic optimization in microgrid with demand side management model is taken for the statistical analysis based on statistical measures like best, worst, mean, median, and standard deviation as given in Table 6. The developed model secures minimum mean cost function when compared to the conventional techniques AGTO, BOA, WOA, and SOA, respectively that is customer's
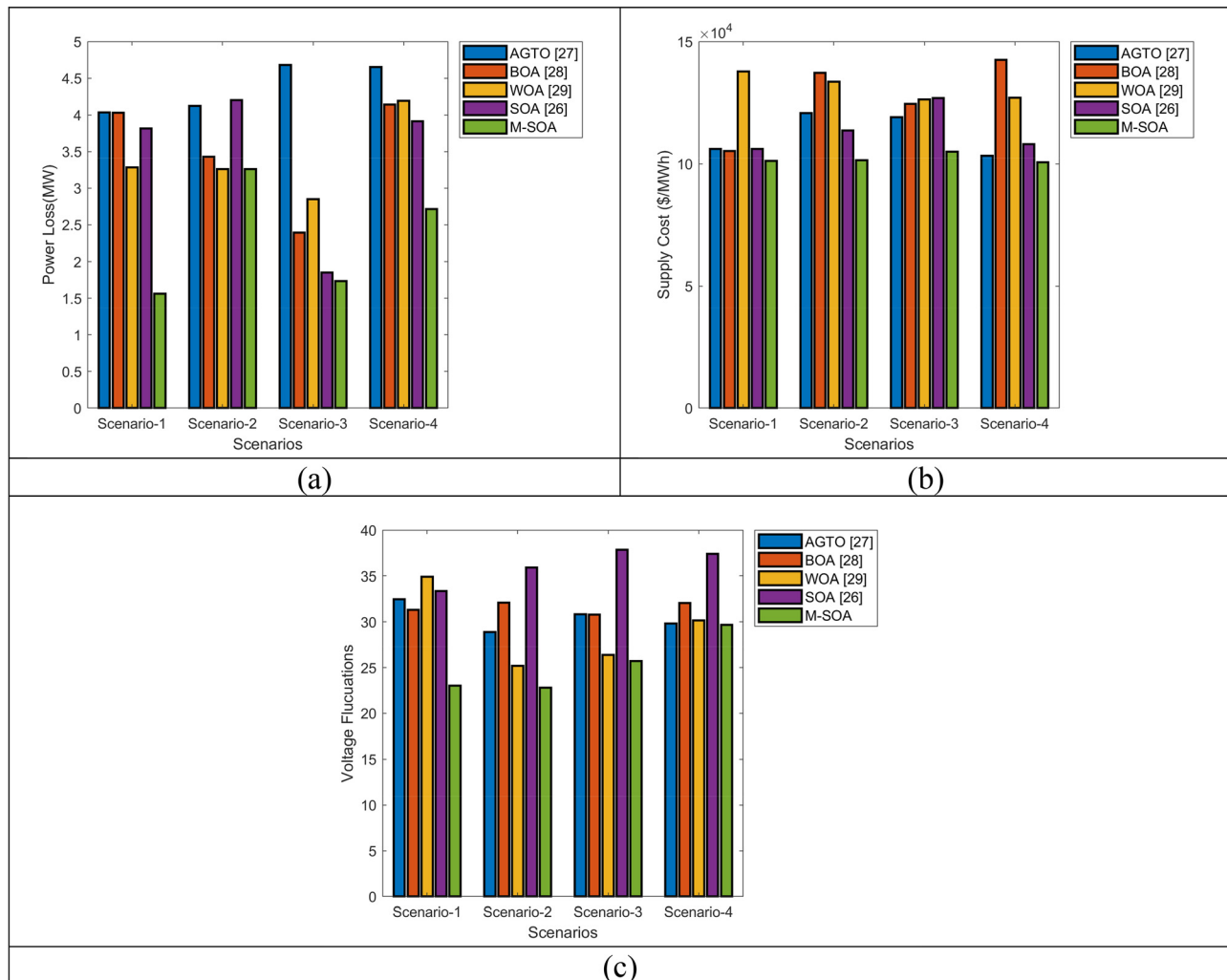

Figure 7: Different scenarios-based power loss, supply cost, and voltage fluctuations analysis on developed techno-economic optimization in microgrid with demand side management model.

Table 6: Statistical Analysis of Developed techno-economic Optimization in Microgrid with demand side management.

Analysis constraints	AGTO (Singh et al. 2022)	BOA (Qazani et al. 2020)	WOA (Zhai et al. 2020)	SOA (Kaur, Jain, and Goel 2020)	M-SOA
			Analysis of 3 h		
Best	$1.10 \times 10^{+05}$	$1.08 \times 10^{+05}$	$1.11 \times 10^{+05}$	$1.02 \times 10^{+05}$	99,371
Worst	$1.22 \times 10^{+05}$	$1.22 \times 10^{+05}$	$1.26 \times 10^{+05}$	$1.21 \times 10^{+05}$	$1.14 \times 10^{+05}$
Mean	$1.12 \times 10^{+05}$	$1.11 \times 10^{+05}$	$1.12 \times 10^{+05}$	$1.09 \times 10^{+05}$	$1.02 \times 10^{+05}$
Median	$1.12 \times 10^{+05}$	$1.10 \times 10^{+05}$	$1.11 \times 10^{+05}$	$1.10 \times 10^{+05}$	99,371
Standard deviation	2898.2	3429.7	3058.1	2972.6	4643.2
			Analysis of 6 h		
Best	$1.13 \times 10^{+05}$	$1.06 \times 10^{+05}$	$1.06 \times 10^{+05}$	$1.02 \times 10^{+05}$	97,157
Worst	$1.25 \times 10^{+05}$	$1.10 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.14E \times 10^{+05}$	$1.18 \times 10^{+05}$
Mean	$1.15 \times 10^{+05}$	$1.08 \times 10^{+05}$	$1.07 \times 10^{+05}$	$1.04 \times 10^{+05}$	$1.01 \times 10^{+05}$
Median	$1.13 \times 10^{+05}$	$1.09 \times 10^{+05}$	$1.06 \times 10^{+05}$	$1.03 \times 10^{+05}$	99,066
Standard deviation	2938.7	1330.6	3476.6	3874.1	5101.2
			Analysis of 9 h		
Best	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.17 \times 10^{+05}$
Worst	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$
Mean	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.17 \times 10^{+05}$
Median	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.17 \times 10^{+05}$
Standard deviation	39.323	8.9	18.139	15.177	61.661
			Analysis of 12 h		
Best	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.17 \times 10^{+05}$
Worst	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$
Mean	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.17 \times 10^{+05}$
Median	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.17 \times 10^{+05}$
Standard deviation	95.558	19.785	77.854	42.515	15.92

expenses on the operational cost have been reduced through the developed model based on the proposed M-SOA.

6.8 Time analysis of implemented model

The developed techno-economic optimization in microgrid with demand side management model is evaluated based on the time analysis as displayed in Table 7. The developed M-SOA obtains 3.84 %, 0.98 %, 5.72 %, and 4.63 % better performance with less latency than the AGTO, BOA, WOA, and

SOA, respectively. This shows that the developed model has scored a better performance rate on reducing the objective constraints with less time consumption.

6.9 Power loss, supply cost, and voltage fluctuations analysis on implemented model

The developed techno-economic optimization in microgrid with demand side management model is analyzed based on power loss, supply cost, and voltage fluctuations are mentioned in Table 8.

Table 7: Time Analysis on developed techno-economic optimization in microgrid with demand side management.

Hours	AGTO (Singh et al. 2022) (sec)	BOA (Qazani et al. 2020) (sec)	WOA (Zhai et al. 2020) (sec)	SOA (Kaur, Jain, and Goel 2020) (sec)	M-SOA (sec)
3	3.5774	3.7498	3.5755	3.5641	3.5562
6	3.8133	3.7033	3.8893	3.8449	3.6668
9	3.6393	3.6308	3.6186	3.6538	3.6133
12	3.6852	3.7931	3.7064	3.6553	3.6287

Table 8: Power Loss, Supply Cost, And Voltage Fluctuations-based Analysis on developed techno-economic optimization in microgrid with demand side management.

Hours	AGTO (Singh et al. 2022)	BOA (Qazani et al. 2020)	WOA (Zhai et al. 2020)	SOA (Kaur, Jain, and Goel 2020)	M-SOA
			Power loss		
1	1.1709	3.6558	1.0502	1.083	1.0313
2	4.5303	2.987	1.1788	1.4368	1.0927
3	1.5854	1.5146	1.4343	1.2578	1.0496
4	1.7012	1.7692	1.8027	2.0276	1.073
5	1.9012	1.8691	1.8901	2.24	1.1933
6	2.0631	3.5914	1.9365	2.6319	1.1945
7	2.3986	1.8921	2.0649	3.1603	1.4345
8	2.4397	1.9352	2.1142	3.9899	1.4735
9	2.444	2.2291	2.2449	2.8992	1.6478
10	2.6818	4.9138	2.3311	3.1164	1.9156
11	3.9732	3.4042	4.6879	3.1603	2.9501
12	2.4653	2.0983	2.3504	3.1719	1.7012
13	3.0949	2.6179	2.4396	3.7457	2.2616
14	4.0982	2.9576	2.4396	3.9754	2.3156
15	3.3063	2.3353	2.7319	3.9899	2.3311
16	3.5597	2.3865	1.9352	4.0071	1.4343
17	3.6869	2.9243	2.8002	4.0736	2.7244
18	3.9538	2.987	2.8229	4.1001	2.7874
19	4.0982	3.1785	2.849	2.9371	2.24
20	4.823	3.4042	2.9576	4.2046	2.9214
21	4.3442	3.4246	3.8216	4.2655	3.3693
22	4.5303	3.5227	2.2449	4.3455	1.4345
23	4.5975	3.5914	3.882	4.793	2.0983
24	3.3063	3.4845	3.9496	3.6098	1.0927
			Supply cost		
1	147,110	$1.02 \times 10^{+05}$	$1.47 \times 10^{+05}$	$1.03 \times 10^{+05}$	$1.00 \times 10^{+05}$
2	$1.01 \times 10^{+05}$	$1.02 \times 10^{+05}$	$1.04 \times 10^{+05}$	$1.10 \times 10^{+05}$	$1.00 \times 10^{+05}$
3	$1.03 \times 10^{+05}$	$1.08 \times 10^{+05}$	$1.04 \times 10^{+05}$	$1.05 \times 10^{+05}$	$1.01 \times 10^{+05}$
4	$1.03 \times 10^{+05}$	$1.09 \times 10^{+05}$	$1.07 \times 10^{+05}$	$1.25 \times 10^{+05}$	$1.03 \times 10^{+05}$
5	$1.08 \times 10^{+05}$	$1.09 \times 10^{+05}$	$1.09 \times 10^{+05}$	$1.06 \times 10^{+05}$	$1.05 \times 10^{+05}$
6	$1.43 \times 10^{+05}$	$1.12 \times 10^{+05}$	$1.39 \times 10^{+05}$	$1.10 \times 10^{+05}$	$1.09 \times 10^{+05}$
7	$1.10 \times 10^{+05}$	$1.13 \times 10^{+05}$	$1.33 \times 10^{+05}$	$1.07 \times 10^{+05}$	$1.05 \times 10^{+05}$
8	$1.13 \times 10^{+05}$	$1.16 \times 10^{+05}$	$1.10 \times 10^{+05}$	$1.11 \times 10^{+05}$	$1.10 \times 10^{+05}$
9	$1.14 \times 10^{+05}$	$1.19 \times 10^{+05}$	$1.14 \times 10^{+05}$	$1.11 \times 10^{+05}$	$1.10 \times 10^{+05}$
10	$1.34 \times 10^{+05}$	$1.11 \times 10^{+05}$	$1.14 \times 10^{+05}$	$1.12 \times 10^{+05}$	$1.08 \times 10^{+05}$
11	$1.13 \times 10^{+05}$	$1.45 \times 10^{+05}$	$1.14 \times 10^{+05}$	$1.16 \times 10^{+05}$	$1.13 \times 10^{+05}$
12	$1.17 \times 10^{+05}$	$1.20 \times 10^{+05}$	$1.14 \times 10^{+05}$	$1.17 \times 10^{+05}$	$1.01 \times 10^{+05}$
13	$1.16 \times 10^{+05}$	$1.22 \times 10^{+05}$	$1.19 \times 10^{+05}$	$1.37 \times 10^{+05}$	$1.16 \times 10^{+05}$
14	$1.46 \times 10^{+05}$	$1.23 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.21 \times 10^{+05}$	$1.01 \times 10^{+05}$
15	$1.21 \times 10^{+05}$	$1.23 \times 10^{+05}$	$1.18 \times 10^{+05}$	$1.25 \times 10^{+05}$	$1.17 \times 10^{+05}$
16	$1.20 \times 10^{+05}$	$1.28 \times 10^{+05}$	$1.19 \times 10^{+05}$	$1.23 \times 10^{+05}$	$1.17 \times 10^{+05}$
17	$1.23 \times 10^{+05}$	$1.31 \times 10^{+05}$	$1.46 \times 10^{+05}$	$1.46 \times 10^{+05}$	$1.07 \times 10^{+05}$
18	$1.16 \times 10^{+05}$	$1.32 \times 10^{+05}$	$1.22 \times 10^{+05}$	$1.25 \times 10^{+05}$	$1.10 \times 10^{+05}$
19	$1.25 \times 10^{+05}$	$1.38 \times 10^{+05}$	$1.30 \times 10^{+05}$	$1.28 \times 10^{+05}$	$1.10 \times 10^{+05}$
20	$1.29 \times 10^{+05}$	$1.32 \times 10^{+05}$	$1.33 \times 10^{+05}$	$1.28 \times 10^{+05}$	$1.27 \times 10^{+05}$
21	$1.32 \times 10^{+05}$	$1.34 \times 10^{+05}$	$1.49 \times 10^{+05}$	$1.29 \times 10^{+05}$	$1.03 \times 10^{+05}$
22	$1.35 \times 10^{+05}$	$1.38 \times 10^{+05}$	$1.36 \times 10^{+05}$	$1.27 \times 10^{+05}$	$1.06 \times 10^{+05}$
23	$1.34 \times 10^{+05}$	$1.37 \times 10^{+05}$	$1.30 \times 10^{+05}$	$1.11 \times 10^{+05}$	$1.04 \times 10^{+05}$
24	$1.25 \times 10^{+05}$	$1.30 \times 10^{+05}$	$1.19 \times 10^{+05}$	$1.29 \times 10^{+05}$	$1.12 \times 10^{+05}$
			Voltage fluctuations		
1	22.317	33.572	22.492	22.545	22.266
2	22.518	22.75	23.551	22.809	22.42
3	29.696	28.721	30.445	23.881	22.901

Table 8: (continued)

Hours	AGTO (Singh et al. 2022)	BOA (Qazani et al. 2020)	WOA (Zhai et al. 2020)	SOA (Kaur, Jain, and Goel 2020)	M-SOA
4	25.009	28.704	35.711	24.667	22.547
5	24.029	32.871	24.724	23.004	22.516
6	33.881	35.976	28.916	23.574	23.158
7	26.141	24.677	31.841	37.616	24.034
8	31.676	26.419	28.342	22.901	22.547
9	24.512	33.184	34.35	26.426	23.699
10	34.33	24.776	22.516	33.114	22.266
11	25.009	25.671	28.47	24.227	22.65
12	26.253	25.987	33.287	37.328	23.158
13	32.683	25.987	28.626	24.227	23.551
14	34.531	37.843	37.854	28.47	24.667
15	25.069	28.702	24.49	28.704	22.809
16	26.253	28.721	37.55	28.916	23.699
17	28.017	25.671	27.394	34.938	24.951
18	29.047	24.677	27.762	33.473	24.034
19	28.909	30.587	33.377	25.394	24.724
20	29.549	29.356	27.781	30.863	27.484
21	24.029	29.466	28.342	30.482	23.881
22	29.549	30.587	33.814	31.803	29.122
23	29.696	30.998	29.345	26.141	23.004
24	30.66	32.871	29.91	28.626	23.574

7 Conclusions

This paper has investigated the problem of demand-side management in microgrids by performing techno-economic optimization over the parameters of microgrids. A new enhanced heuristic algorithm named M-SOA has been developed for optimizing the parameters like PV capacity, wind turbine capacity, ESS capacity, PV bus location, wind turbine bus location, and ESS bus location of the microgrid. This was done for attaining the objectives of reducing the constraints like network power losses, voltage fluctuations, electricity supply costs, initial costs, operation costs, and fuel costs in the microgrid system. With the consideration of power loss analysis, the proposed model sudden variations in the power loss between 10 and 20 h and finally, get reduced the power loss. Through the experimental analysis, the developed M-SOA has secured a better performance rate in reducing the voltage fluctuations, power losses, and electricity supply costs of the microgrid system.

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