[1]Min Zhang

Lunsen Zou

Zhiqiang Wang

Kexin Liu

Junyu Zhu

Optimization of Charging or Discharging Strategy of Energy Storage in Multi-Objective Market Transactions Based on Quantum Genetic Algorithm

JES

Journal of Electrical Systems

Abstract: - Multi-objective energy optimization is critical for ensuring stable and power system operation securely. Though, multi-objective energy optimization is difficult because of an interdependence and opposing goals. To address conflicting objectives, a multi-objective optimization model is required, hence Monarch Butterfly African Vulture Optimization Algorithm (MBAVOA) is newly proposed for resolving multi objective issues. MBAVOA is the hybridized of two optimization algorithms, which includes Monarch Butterfly Optimization (MBO), and African Vulture Optimization Algorithm (AVOA). Here, charging cost, distance, and the user convenience are optimized while taking Renewable Energy Sources (RES) into consideration using MBAVOA. In addition, a load is computed using a Quantum Genetic Algorithm (QGA), describes intermittent and uncertain RES, such as wind and solar. The QGA-MBAVOA outperformed with the least charging cost 63%, fitness 0.010, and user convenience 0.819.

Keywords: Monarch Butterfly optimization, Charging or discharging, Quantum Genetic Algorithm, Energy Storage, Energy Management.

1. Introduction

To meet the increased demand for electricity, RESs like wind and solar energy must be integrated into the distribution grid. Furthermore, adopting renewable energy sources contributes to lowering global temperatures by reducing greenhouse gas emissions. However, RESs generate fluctuating electricity depending on location, time, and a nature of weather where they are attached [10]. This volatility in generated power complicates the distribution side's control and energy management (EM) [2]. With a rapid growth of energy storage, traditional power systems that were previously functioned by real-time balancing of demand and supply are transitioning to use such methods. Many potentials use for Energy Storage (ES) in power systems have been examined [11]. The goal of using ES is to contribute to the development of a dependable and effective smart grid [6].

The primary advantages of an ES are the ability to time-shift electric energy, regulate frequency, and relieve transmission congestion [12][6]. An ideal energy management control must be implemented to reduce costs and improve network stability [13][2]. The control unit of a microgrid is designed to achieve energy management efficiently by optimally utilizing the energy storage system (ESS) when the microgrid is in isolated and/or grid-connected mode. The ESSs are used in a microgrid to grip excess electricity and subsequently supply it when there are no RESs available. The central control unit's primary goal is to manage the charging and discharging of ESSs [14]. To generate a profit, the ESSs' is retailed when peak electricity hours. When the cost of electricity is cheap, they can store energy, lowering operating costs and achieving robust, malleable, and dependable energy management for an interconnected microgrid system [2].

Many scholars have investigated various features and techniques to value energy optimization [1]. In [15][4], the dual-layer control technique for a Battery Energy Storage Systems (BESS) was introduced to reduce wind power fluctuations. Most of the existing studies use dynamic programming-based methods [9], Model Predictive Control

[1] [1]Cgs Power Generation(Guangdong)Energy Storage Technology Co.,Ltd, Guangzhou,Guangdong, 510630, China

*Corresponding author's e-mail: **cnkjzhangmin@126.com**

Lunsen Zou：cnkjzoulunsen@126.com

Zhiqiang Wang：cnkjwangzhiqiang@126.com

Kexin Liu：xkllkx@dingtalk.com

Junyu Zhu：15927653235@163.com

[16][9], or a Neural Networks to identify optimum storage plans in real-time or Time of Use (ToU) pricing. Research on the best demand-side reaction to electricity spot pricing for storage-type consumers is one of the initiatives focused on using ES to increase economic benefits. The authors in [7] report experiments on price-based real-time control of thermal storage systems to save costs. However, most of the studies on ES design issues consider an influence of ES capacity and electricity price [10].

The intention is to create a model that optimizes three objective functions to increase microgrid performance and profitability by optimizing storage system charging/discharging cycles. The ES is maintained in EMS using a newly developed MBAVOA. The MBAVOA was developed by combining MBO with AVOA. A novel multi-objective fitness measure has been designed, with factors including user preference, distance parameters, and charging cost. Moreover, QGA is utilized to evaluate load that increase voltage fluctuations, system reliability, power quality, and a grid utility stability. The Distribution System Operator (DSO) efficiently transfers power to end users over a transmission network with minimal losses. RES present new potential for DSOs to provide affordable power to end consumers.

The paper's primary contributions are:

- Using the MBAVOA, multi-objective energy optimization problems are solved for commercial, residential, and the industrial users. In addition, the Pareto fronts and the optimize solutions are identified using multi-criteria decision-making. The MBAVOA was developed by combining MBO with AVOA that optimizes the charging or the discharging of an ES units. In addition, the load is computed using QGA.
- New parameters, including user choice, charging cost, and distance parameters, are used to model the multi-objective fitness function that identify renewable energy generation accurately.

The following is the arrangement of the remaining sections: Section 2 covers a literature study charge or discharging of ES system. Section 3 describes a system paradigm for EM system. Section 4 discusses the MBAVOA for EM system. Section 5 calculates a QGA_MBAVOA efficiency compared to classical methodologies. Section 6 presents the conclusion.

2. Literature survey

Ahmad Alzahrani *et al.* [1] have presented a non-dominated genetic sorting method to maximize objectives, such as operation cost, pollution emission, and a Loss of Load Expectation (LOLE) while taking Renewable Energy Sources (RES) into account. A Probability Density Function (PDF) is used to describe RES, which are uncertain and intermittent like sun and wind. The method resulted in lower operation costs and environmental emissions, making it appropriate for addressing multi-objective issues but does not electrify the load, causing load shedding.

Yomna O. Shaker *et al.* [2] devised a multi-objective hunger game search algorithm (MOHGS) is applied to minimize operating costs, ensuring a continuity of the feeding load, and a profit for a customer. The key goals of the MOHGS are to maintain uninterruptible power to the load with low running costs and low emissions from a storage systems while obtaining the high renewable factor. The method reduces emissions and improving Renewable Factor (RF) performance. However, an extra energy was needed to the grid for obtaining high profit.

Tom Terlouw *et al.* [3] have presented two options for Community ES (CES) ownership. i) an Energy Arbitrage (EA) scenario in which the aggregator tries to reduce costs and a CO2 emission from the energy portfolio. ii) The Energy Arbitrage - Peak Shaving (EA-PS) scenario was evaluated using shared ownership model among Distribution System Operator (DSO) and the aggregator. In addition, a Mixed Integer Linear Programming (MILP) was introduced to reduce expenses and the CO2 emissions for the neighborhood in Cernier, Switzerland, by utilizing several battery methods in a CES system. The method delivers superior economic and environmental performance, but focus on integrating additional storage technologies for CES systems, taking into account costs and environmental effect indicators.

Feng Zhang *et al.* [4] have developed a better sizing and control approach for the wind ESS to smooth wind. In addition, a cycle control technique was introduced with a progressive cycle time that includes one charge and discharge period, taking into account power market trading restrictions. Furthermore, the multi-objective

optimization model was employed to calculate a reference output and cycle control period duration, taking into account both the maximum time duration and the minimal power variance between discharge and charge intervals. Here, the method increases the dispatchability and trade reliability, but the seasonal changes in wind power have minimal impact.

Elham Mokaramian *et al.* [5] employed multi-objective energy hub model to reduce operational costs and pollutant emissions. Moreover, the day-ahead scheduling paradigm for the energy hubs (EH) was introduced in reserve and energy markets focuses on balancing economic and environmental goals. The Mont-Carlo method was then used to account for variation in load, wind speed, and photovoltaic irradiation. In addition, a conditional value at risk (CVaR) assesses the risk level of energy hubs in order to improve their operational efficiency. Here, the environmental emissions and operational costs was minimized, it suffers from high storage costs.

An improved multi-objective Particle Swarm Optimization (PSO) was presented by Yixing Xu, and Chanan Singh [6] for addressing ES design in the distribution systems. The PSO delivers a Pareto front to help decision makers and to determine a desired tradeoff among several objectives. An ES design factors encompass not only capacity and the power rate, but also the operation strategy. The method minimizes unserved energy and prevent load loss within operating limitations. However, several ES variables need to be included, and the to be applied to transmission networks.

Qinhao Xing *et al.* [7] developed an energy aggregator model that optimizes and dispatches DERs, including generators, energy storages, and flexible charging loads to integrate renewables while evaluating the advantages of all energy resources under time-of-use tariff. A multi-objective optimal dispatch was utilized that takes into account power network flows, DER operational needs, and a user comfort. Meanwhile, conventional generators had less frequent regulation. A sensitivity analysis found that the starting state of charge for the storage affects charging and discharging, potentially impacting yield of storage owners participating in a dispatch.

Rui Li, and Su Su *et al.* [8] have introduced a unique day-ahead operation method for ESSs using a fuzzy multi-objective model that adheres to operational limitations. This model balances three objectives: operational friendliness, reliability, and an economic efficiency. To align these objectives, a fuzzy mathematical technique was used, thus attained slow rate convergence. The uncertainties of the renewable energy sources and the load needs need to be more effectively considered.

The following are the issues experienced in the relevant job,

The current global condition of the energy consumption and generation, in which several countries rely on the fossil fuels to supply their energy needs, presents enormous problems using energy security and the environmental deterioration. Moreover, renewable energy generators face installation limits in modern power grids for technological and policy reasons, complicating their integration into energy mix models. Energy production and the consumption around a world faces major difficulties by environmental degradation and the energy security. RES can help these problems can be solved to a large extent, so it has become widespread in recent years. Though, to fully switch to renewable energy, energy produced must be kept and utilized when there is a lack of renewable resources. In these instances, the significance of ESS and smart grid systems in the modern world cannot be underestimated.

3. System model

Figure 1 shows the ESS model for charging as well as discharging. The future power system is an Integrated Energy System (IES), which considers the best use of ES and flexible demand while fostering positive interaction between the generation source, load, and energy storage. Most IESs are now functioned by the aggregators, host a variety of generating and flexible resources, providing power to the load within regions while maximising revenues. In order to increase the degree of efficient and cost-effective use of renewable energy, the energy internet is applied beneath energy dispatch of the aggregators that allows load, generation, and an ES to engage in the energy system and trading operations. Let us consider that the ES battery is managed by aggregator or a Distributor system operator (DSO). Moreover, consider that every family has a Photovoltaic Panels (PV) system, resulting maximal renewable electricity penetration level. The community's total electricity and electric heat requirement can be met via electricity absorption from grid, direct consumption of the rooftop PV, or depleting

ES battery $g_u^{batt,dischar}$. The locally generated PV-electricity Q_u^{PV} can be consumed directly, stored in ES battery by charging battery $g_u^{batt,char}$, or injected into electricity grid $g_u^{GRID,INJ}$.

Every family also has a localized EMS that they use to plan and manage both shiftable and the non-shiftable loads. In order to maximize the community's load and schedule, localized EMSs interact with a community EMS. It is possible to assess how the community affects transformer in the distribution network by looking at the transformer's capacity Q^{TRANS}. A battery's size is then determined. To begin, battery is expanded to ensure requisite storage capacity $D^{batt,requ}$ at end of its life. Equation. (1) determines the installed energy size of ES battery $D^{batt,ES}$, taking into account the discharge efficiency $\gamma^{dischar}$, depth-of-discharge (DoD), and a rated energy capacity at the End of the Life (EoL).

$$D^{batt,ES} = \frac{D^{batt,requ}}{\gamma^{dischar}.A.G} \tag{1}$$

where, A be the DoD, and the term G denotes the EoL. Next, battery deterioration is included in a optimization issue because battery degrades with each discharging/charging cycle (cycle losses) and over time (calendar losses). This can have the significant impact on the economic profitability, as decreasing battery performance might reduce the economic feasibility of a system layout, resulting in increased expenses. As a result, battery degradation is the simple way by oversizing batteries and introducing limitation to ensure battery's longevity. To include battery degradation in optimization issue, first, the average battery capacity $D^{batt,average}$ is calculated across the battery lifespan, taking into account the needed CES battery capacity at end.

$$D^{batt,average} = \frac{(G+1)}{2}.D^{batt,ES} \tag{2}$$

Furthermore, we assume that the battery's health diminishes linearly over its lifetime. As a result, we employ each battery technology's average battery capacity $D^{batt,average}$ in optimization impact to improve comparability. In actuality, battery degradation is more intricate and significantly influenced by several stress parameters, like C-rate, temperature and DoD, resulting in nonlinear relationship.
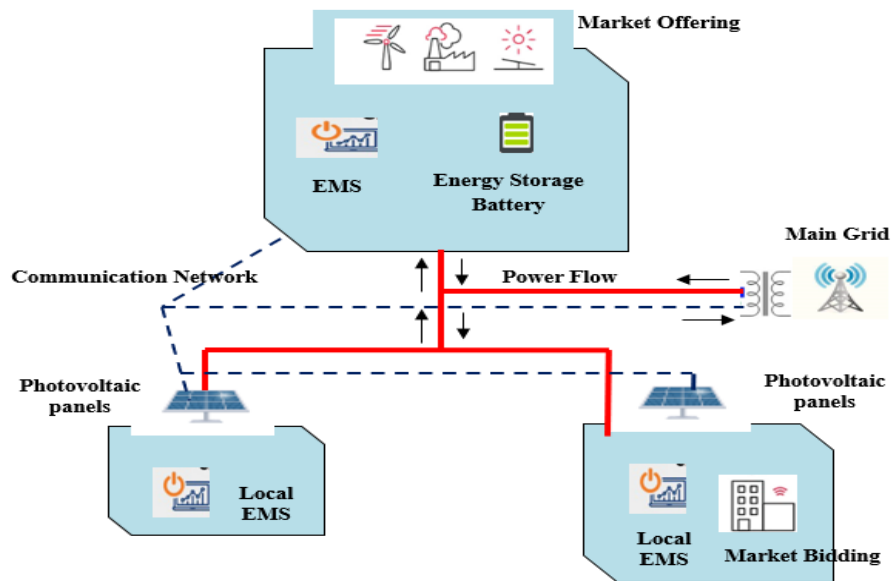

Figure 1. System model of charging or discharging strategy of ESS

4. Proposed Methodology

The distribution system operator (DSO) in the power network is in charge of sending power to the load of the final customer through transmission network with a high degree of efficiency as well as minimal losses. RES are alternative power sources that provide potential for DSO to offer cheap power to the end users' loads and satisfy its demand while minimizing operation costs, pollution emissions, and the load expectation loss. DSO, on the other hand, uses DSM methods to achieve effective load control. Implementing such infrastructure is achievable in the smart power grid (SPG), which has real-time monitoring, control, and two-way communication infrastructures between utilities and customers. The MBAVOA used to evaluate the performance of energy management system. Here, a MBAVOA combines AVOA [1] and MBO [2]. In addition, a charging cost, user preference, and distance parameters are used as the fitness measures. The model parameters will then be tweaked to demonstrate the method's efficacy. Figure 2 shows the MBAOA schematic view.
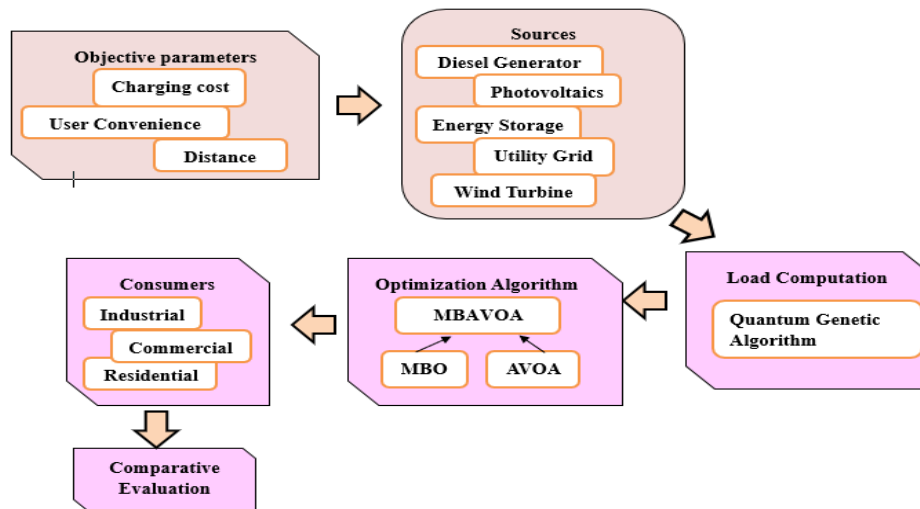

Figure 2. Schematic view of MBAOA

The model's primary elements are discussed below.

 -Communication

Optimal load management requires participation in Demand Side Management (DSM) and Demand Response (DR) programs in the electrical market. A bidirectional communication infrastructure between customers and DSO is necessary for active involvement in the electricity market. Smart power grid (SPG's) Distribution system operator (DSO) utilizes communication infrastructure to coordinate consumer loads with Distributed Energy Resources (DERs) and the power grid, resulting in optimal load operations.

-Distributed Energy Resources

DERs are the sources that are close to the load and produce distributed energy control. This work focuses on two categories of DERs: certain and uncertain energy sources. The first sort of energy source includes diesel generators (DGs). The second class includes RES, such as solar and wind. BESS are used to manage the intermittent nature of RES. In addition to DERs, the electricity grid is connected for increased reliability.

-Load Side (End Users)

The MBAVOA optimizes energy for three types of consumers: industrial (IC), commercial (CC), and the residential (RC). Shifting and scheduling consumers' deferrable and responsive loads optimizes charging cost, distance and the user convenience.

4.1. Computing Load

Utilizing a forecasting technique can enhance scheduling performance when the load of a charging station is uncertain, as it guarantees that the load generated at each instance is not amplified. Therefore, load forecasting, which boosts the precision and efficacy of scheduling methods. With the SOC target fixed to 1, the SOC preliminary values are created uniformly and arbitrarily in interval [0, 1]. Based on the outcomes of the load forecast, the base load data is produced. Hence, the base load unit is altered by,

$$A_s^{base} = \frac{A_s^{fore} \times A^{peak}}{\max_s \left(A_s^{fore} \right)}$$

(3)

where, the peak load under various EV configurations is denoted as A^{peak}, and the forecasted load is represented by A^{fore}, in which the forecasted load is determined using Quantum Genetic algorithm.

4.2. QGA architecture

To efficiently enhance the global search capabilities of quantum algorithms, QGA leverages the coding mechanism of quantum probability vectors, the crossover operator from genetic algorithms and the update method from quantum computing. The steps of the QGA are outlined below.

Step 1: Chromosome representation as a qubit population

A population of quantum bits, or qubits, represents the chromosomes. A quantum bit is a least information held in two-state quantum computer. A qubit can be "1" or "0" state or any combination of atwo. The state of a qubit is described by,

$$|\gamma\rangle = \beta|0\rangle + \alpha|1\rangle$$

(4)

where, the complex numbers β and α indicate a probability of qubit in "0" or "1" states, respectively.

Step 2: Decoding and encoding strategy

Consider developing an encoding and decoding system for scheduling process applications in EV. The chromosome is denoted as $W_u(s)$. The chromosomal size refers to the total modules in an U-sized jobs. Every module will be assigned to nodes 0 through $L-1$. $W_u(s)$ is derived from the population of qubits $Y_u(s)$, where $u = 1,2,...,T$. Here, T represents the number of chromosomes). If the system has L nodes, each qubit population requires v qubits to represent those nodes. The node identifier is defined by its population of individual qubits.

Step 3: Gate for Quantum Rotation

The qubit can be modified using quantum gates. The operation is reversible and represented by a single operator X, which operates on a qubit basic state that meet: $X^*X = XX^*$.

Step 4: Generation of dynamic Rotation Angle

The rotational angle $\Delta\theta_u$ has minimum for a fine refinement and maximum for coerce refinement. The dynamic angle for rotation maintains a solution's convergence rate based on changing fitness values. The value of $\Delta\theta_u$ changes is on a basis of fitness of a present generation's n^{th} objective is compared to a preceding generation. An objective function with the most significant percentage change is chosen for adjusting a rotation angle. Initially, a value of $\Delta\theta_u$ is fixed as previously indicated. As fitness approaches the optimal solution, $\Delta\theta_u$ changes correspondingly.

Step 5: NOT Gate (Mutation Operator)

The NOT gate functions operate for quantum mutation. Mutation enhances individual diversity and minimizes immature convergence. It also improves the capacity to search locally. The NOT gate is used to reverse the probabilities of the qubit population, allowing for mutation.

Step 6: Comparison for Crowd Operator

This operator is employed in non-dominated sorting to ensure diversity and uniformity in a Pareto front. If two people are in the same front, they are selected based on their rank in front, then on the crowding distance. Choose the answer with a lower rank if two solutions have different non-domination ranks based on front value. Based on crowding distance, select the less crowded option if both solutions are part of the same front.

4.3. Computation of multi-objective fitness

The fitness measure is illustrated using MBAVOA for solving EM issues. The fitness feature of the MBAVOA is a new design for choosing the optimal charging system. The fitness function containing distance, charging cost, and user convenience, which is expressed as,

$$Fit = \sum_{y=1}^{K} Z_{x,s}^{y} + \left(1 - V_{x,s}^{y}\right) + C_{x,s}^{y} \tag{5}$$

where, the charging cost of EV_x^y is denoted as $Z_{x,s}^{y}$, the convenience of user is indicated as $V_{x,s}^{y}$, $C_{x,s}^{y}$ be the distance, and the available power is represented as $R_{x,s}^{y}$. The charging cost [7] expression is provided by,

$$Z_{x,s}^{y} = \sum_{s=1}^{S} \left[h_0 \left(u_s^{x,y} - A_s^{base} \right) + h_1 \left(u_s^{x,y^2} - A_s^{base^2} \right) \right] \tag{6}$$

where, h_0 and h_1 be constants, which is the minimization parameter.

The expression of convenience for user [7] is,

$$V_{x,s}^{y} = \frac{1}{w_{x,s}^{y*} w_{x,s}^{t}} \tag{7}$$

where, $w_{x,s}^{y*} = \dfrac{\left(SOC_{x,s}^{fin} - SOC_{x,s}^{y}\right) D_{x,y}^{cap}}{Q_{x,max}^{y}}$ and $w_{x,s}^{y} = q_x^{y} - s$, which be the maximization function.

The expression of distance is,

$$R_{x,s}^{y} = \frac{1}{J \times g} \sum_{x=1}^{J} \| k_{x,y}^{s} - k_e \| \tag{8}$$

where, the normalizing factor is denoted as g, the CS position be k_e, and $k_{x,y}^{s}$ be EV_x^y position. It is a minimization parameter.

4.4. Monarch Butterfly African Vulture Optimization Algorithm

The hybrid algorithm MBAVOA, which was developed by merging AVOA [17] and MBO [19] is utilized to solve the optimization issue of EM system. The MBO is a nature-inspired meta-heuristic algorithm, which operates imitating migration behavior. MBO is more significant for parallel processing and producing trade-offs among diversification and intensification. AVOA is based on the simulation of African vulture navigation and foraging habits, which has been customized to find the optimal solution. It can address a various engineering design issue, has lower computing complexity, and is more trustworthy than other techniques. Furthermore, it effectively

balances variability and resonance and has demonstrated the ability to achieve critical aspects in large-scale situations. It has a lower operating time and computational complexity. The algorithmic steps for the MBAVOA algorithm are explained below.

Initialization

Consider the Cth population with the MB individuals, representing the highest generation I_{max}. Even though the counter for generation is defined by $f = 1$, the MB count in land-A is specified as X_1, the MB in land-B is denoted as X_2, the highest step is marked as V_{max}, p represents the adjustment rate of butterfly, n represents a migration duration, and a migration ratio.

Computation of fitness

The fitness function is used to find the optimal solution, which is regarded as a minimization impact. Thus, a solution that produces a least fitness is chosen as an optimal solution. Section 4.3 describes the fitness function.

Updating migration operator

MB are often present in land-A from April to August and in land-B from September to March. MB on land-A is referred to as sub-population-A, whereas butterflies on land-B are known as subpopulation-B.

Updating adjusting operator of butterfly

A butterfly's position is upgraded via an adjusting operator where the butterfly every component m, if $ran \le 1$, then update position is,

$$Y_{m,r}^{d+1} = Y_{best,r}^{d} \qquad (9)$$

where, $Y_{m,r}^{d}$ is the element r of Y_m at $d+1$ generation, which depicts m^{th} butterfly location, and $Y_{best,m}^{d}$ be element r of Y_{best} that means optimal butterfly placed in land-1 and 2. If $ran > v$, then the updated position is,

$$Y_{m,r}^{d+1} = Y_{c2,r}^{d} \qquad (10)$$

where, $Y_{c2,r}^{d}$ be element r^{th} of Y_{best}, which is chosen randomly from land-2, $u2 \in \{1,2,...,X_2\}$. If $ran > p$, then the position is updated by,

$$Y_{mr}^{d+1} = Y_{mr}^{d+1} + \gamma(aY_r - 0.5) \qquad (11)$$

$$Y_{mr}^{d+1} = Y_{mr}^{d} + \gamma(aY_r - 0.5) \qquad (12)$$

The revised equation from AVOA is as follows:

$$Y_{mr}^{d+1} = U_{mr}^{d} - R_{mr} * Z \qquad (13)$$

where, Y_{mr}^{d+1} represents the next iteration vulture's position vector, U_{mr}^{d} denotes the best vulture of the current iteration, Z be the vulture rate, To keep their prey safe from other vultures, the vultures move at random is denoted by O.

$$R_{mr} = |O * U_{mr}^{d} - Y_{mr}^{d}| \qquad (14)$$

$$Y_{mr}^{d+1} = U_{mr}^{d} - |O * U_{mr}^{d} - Y_{mr}^{d}| * Z \qquad (15)$$

$$Y_{mr}^{d+1} = U_{mr}^d - \left(O * U_{mr}^d - Y_{mr}^d\right) * Z \tag{16}$$

$$Y_{mr}^d = \frac{Y_{mr}^{d+1} - U_{mr}^d\left[1 - OZ\right]}{Z} \tag{17}$$

The above expression is substituted in equation (11),

$$Y_{mr}^{d+1} = \frac{Y_{mr}^{d+1} - U_{mr}^d\left[1 - OZ\right]}{Z} + \gamma\left(aY_r - 0.5\right) \tag{18}$$

$$Y_{mr}^{d+1} - \frac{Y_{mr}^{d+1}}{Z} = \frac{-U_{mr}^d\left[1 - OZ\right]}{Z} + \gamma\left(aY_r - 0.5\right) \tag{19}$$

$$Y_{mr}^{d+1}\left[\frac{Z-1}{Z}\right] = \frac{-U_{mr}^d\left[1 - OZ\right]}{Z} + \gamma\left(aY_r - 0.5\right) \tag{20}$$

$$Y_{mr}^{d+1} = \frac{-U_{mr}^d\left[1 - OZ\right]}{Z} + \gamma\left(aY_r - 0.5\right) * \left[\frac{Z}{Z-1}\right] \tag{21}$$

Thus, from the above MBAVOA update equation, the EM issues are solved efficiently.

Check the feasibility of the solution

The feasibility of a solution is assessed to determine the optimal solution using the fitness equation. If a new solution improves on the prior one, the solution is updated with a new value.

End

The processes above are repeated until the optimal solution is achieved. Thus, the integration of MBO with the AVOA technique effectively charging/discharging of EM system. Algorithm 1 shows the MBAVOA pseudocode.

Algorithm 1. Pseudo code of MBAVOA

Input: Parameters are initialized
Output: Optimal solution
Start
Population is initialized
Compute fitness function
while $d < V_{max}$ **or best solution is not found**
do
Organize each monarch butterfly according to its fitness function
Divide individual butterflies into land-A and land-B
Generate random integers using a uniform distribution
Select a butterfly at random from subpopulation A
Produce r^{th} **element of** Y_m^{d+1} **by equation (9)**
else
Pick a monarch butterfly at random from subpopulation B
Produce r^{th} **element of** Y_m^{d+1} **by equation (10)**
end
do
for $r = 1 \, to \, K$

do
Randomly generated ran **using a uniform distribution.**
if $ran > p$
Produce r^{th} **element of** Y_m^{d+1} **by equation (9)**
else
Select a monarch butterfly at random from subpopulation B
Produce r^{th} **element of** Y_m^{d+1} **by equation (10)**
If $ran > p$
Update the MBAVOA solution by equation (21)
end if
end if
end for
end for
Combine two subpopulations into a single one
Use the updated location to estimate the subpopulation
$d = d + 1$
end while
Return the optimal solution

5. Results and discussion

This section describes a GQA+MBAVOA's outcomes and analysis for charging or discharging strategy of energy storage. The efficiency is assessed by comparing charging costs, fitness, and user convenience.

### 5.1. Experimental setup

GQA+MBAVOA is conducted in MATLAB using a Windows 10 operating system.

5.2 Performance metrics

The GQA+MBAVOA performance is measured in terms of user fitness, charging cost, and convenience, and the metrics are clearly mentioned in section 4.3.

5.3. Competing methods and assessment

This section compares the GQA+MBAVOA to other approaches, such as Genetic Sorting Method [1], MOHGS [2], MILP [3], and PSO [6] in terms of performance measures.
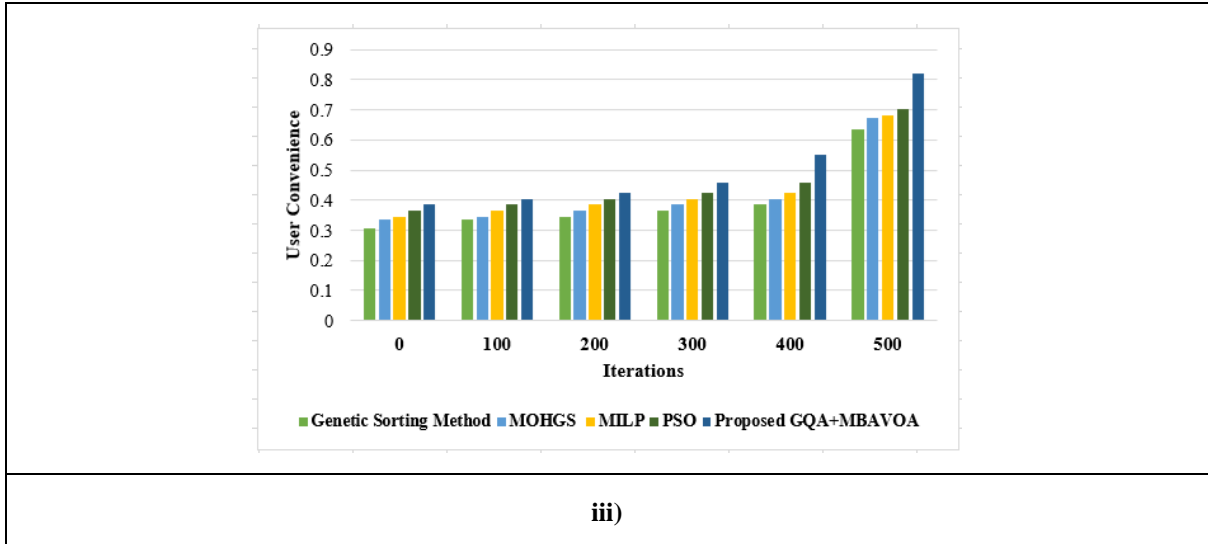
i)	ii)

iii)
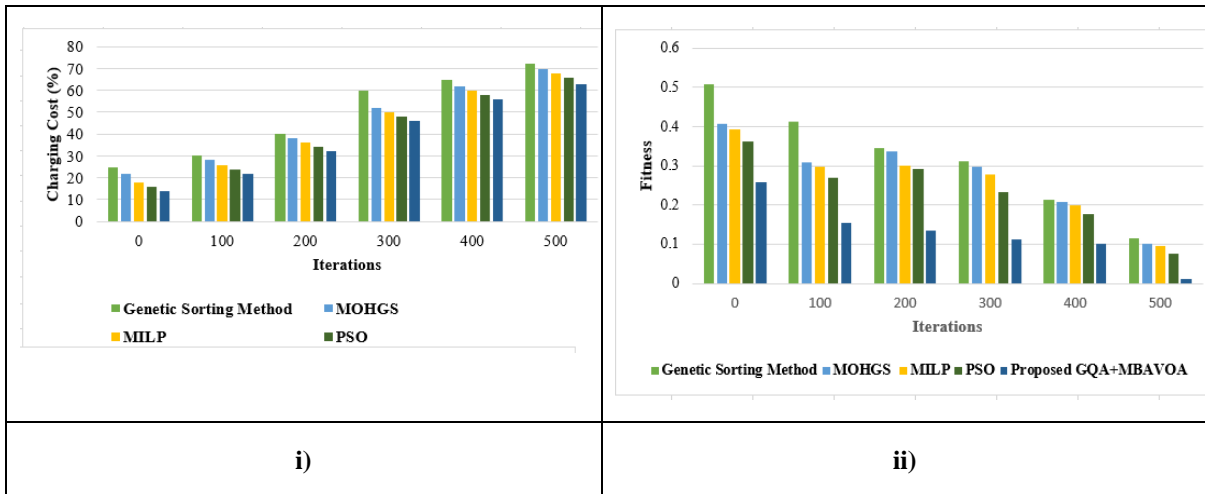
Figure 2. Comparative evaluation of GQA+MBAVOA i) Charging Cost, ii) Fitness, iii) User Convenience

Figure 2 depicts a comparative examination of GQA+MBAVOA based on the number of iterations and several performance measures. Figure 2i) demonstrates charging cost. For 100 iterations, the charging cost assessed by Genetic Sorting Method, MOHGS, MILP, and PSO are 30%, 28%, 26%, 24%, and 22%, respectively. Figure 2ii) shows an assessment of approaches with fitness. The fitness values for Genetic Sorting Method, MOHGS, MILP, PSO, and GQA+MBAVOA for 200 iterations are 0.345, 0.187, 0.167, 0.351, and 0.134, respectively. In addition, for 400 iterations, the fitness evaluated by Genetic Sorting Method, MOHGS, MILP, PSO, and GQA+MBAVOA are 0.213, 0.209, 0.1, 0.107, and 0.101. Figure 2iii) displays the user convenience of various techniques compared to the GQA+MBAVOA. When 100 iterations are considered, the user convenience values of Genetic Sorting Method are 0.336, MOHGS is 0.342, MILP is 0.365, PSO is 0.385, and GQA+MBAVOA is 0.405.

5.6. Comparative discussion

Table 1 compares charging/discharging of energy management systems based on user convenience, fitness, and charging cost. The GQA+MBAVOA has the lowest % charging cost of 63%, while Genetic Sorting Method, MOHGS, MILP, and PSO have of 72%, 70%, 68%, 66%, respectively. The GQA+MBAVOA has the lowest fitness of 0.010, while Genetic Sorting Method, MOHGS, MILP, and PSO have fitness values of 0.114, 0.012, 0.035, 0.025, respectively. The GQA+MBAVOA has the maximum user convenience of 0.819, while Genetic Sorting Method, MOHGS, MILP, and PSO have values of 0.636, 0.691, 0.703, and 0.752, respectively.

Table 1. Comparative analysis

Metrics	Genetic Sorting Method	MOHGS	MILP	PSO	GQA+MBAVOA
Charging cost (%)	72	70	68	66	**63**
Fitness	0.114	0.012	0.035	0.025	**0.010**
User convenience	0.636	0.691	0.703	0.752	**0.819**

6. Conclusion

This research presents GQA+MBAVOA for scheduling energy and load in EM system. The ES is maintained for charging or discharging using the MBAVOA, with a newly built algorithm. The suggested MBAVOA was created by combining MBO and AVOA. Here, user preference, charging cost, and distance, regarded as a minimization

function are used to create a new model of a multi-objective fitness function. According to MBAVOA, the EVs are allocated to a CS. The GQA_MBAVOA can yield the lowest possible charging cost while minimizing charging time. The GQA_MBAVOA showed exceptional performance, with the minimal charging cost of 63%, the fitness of 0.010, and the maximal user convenience of 0.819. Later on, examining the GQA_MBAVOA flexibility using other sophisticated optimization techniques.

References

[1] Ahmad Alzahrani, Mujeeb Ur Rahman, Ghulam Hafeez, Gul Rukh, Sajjad Ali, Sadia Murawwat, Faiza Iftikhar, Syed Irtaza Haider, Muhammad Iftikhar Khan, and Azher M. Abed, "A Strategy for Multi-Objective Energy Optimization in Smart Grid Considering Renewable Energy and Batteries Energy Storage System", IEEE Access, vol.11, pp.33872-33886, 2023.

[2] Yomna O. Shaker, Dalia Yousri, Ahmed Osama, Ahmed Al-Gindy, Elsayed Tag-Eldin, and Dalia Allam, "Optimal Charging/Discharging Decision of Energy Storage Community in Grid-Connected Microgrid Using Multi-Objective Hunger Game Search Optimizer", IEEE Access, vol.9, pp.120774-120794, 2021.

[3] Tom Terlouw, Tarek AlSkaif, Christian Bauer, and Wilfried van Sark, "Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies", Applied energy, vol.239, pp.356-372, 2019.

[4] Feng Zhang, Guibin Wang, Ke Meng, Junhua Zhao, Zhao Xu, Zhaoyang Dong, and Jun Liang, "Improved Cycle Control and Sizing Scheme for Wind Energy Storage System Based on Multi-objective Optimization", IEEE Transactions on Sustainable Energy, vol.8, no.3, pp.966-977, 2016.

[5] Elham Mokaramian, Hossein Shayeghi, Farzad Sedaghati, Amin Safari, and Hassan Haes Alhelou,"A CVaR-Robust-Based Multi-Objective Optimization Model for Energy Hub Considering Uncertainty and E-Fuel Energy Storage in Energy and Reserve Markets", IEEE Access, vol.9, pp.109447-109464, 2021.

[6] Yixing Xu, and Chanan Singh, "Multi-Objective Design of Energy Storage in Distribution Systems Based on Modified Particle Swarm Optimization", In proceedings of 2012 IEEE Power and Energy Society General Meeting, IEEE, pp. 1-8, 2012.

[7] Qinhao Xing, Meng Cheng, Shuran Liu, Qianliang Xiang, Hailian Xie and Tailai Chen,"Multi-Objective Optimization and Dispatch of Distributed Energy Resources for Renewable Power Utilization Considering Time-of-Use Tariff", Frontiers in Energy Research, vol.9, pp.647199, 2021.

[8] Rui Li, and Su Su,"A Fuzzy Multi-objective Operation Strategy of Energy Storage System based on Gravity Search Algorithm", In proceedings of IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia), IEEE, pp. 480-485, May 2019.

[9] Reza Kamyar and Matthew M. Peet,"Multi-objective Dynamic Programming for Constrained Optimization of Non-separable Objective Functions with Application in Energy Storage", In proceedings of IEEE 55th Conference on Decision and Control (CDC),IEEE, pp. 5348-5353,2016.

[10] Jos´e R. Andrade and Ricardo J. Bessa,"Improving Renewable Energy Forecasting with a Grid of Numerical Weather Predictions",IEEE Transactions on Sustainable Energy, vol.8, no.4, pp.1571-1580, 2017.

[11] Yixing Xu, and Chanan Singh,"Distribution Systems Reliability and Economic Improvement with Different Electric Energy Storage Control Strategies", In proceedings of IEEE Power and Energy Society General Meeting, IEEE, pp. 1-8, 2011

[12] Hafeez Ahmad, Ayaz Ahmad, and Sadiq Ahmad, "Efficient Energy Management in a Microgrid", In proceedings of 2018 International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET), IEEE, pp.1-5, 2018.

[13] Md Alamgir Hossain, Hemanshu Roy Pota, Stefano Squartini and Ahmed Fathi Abdou," Modified PSO Algorithm for Real-time Energy Management in Grid-connected Microgrids",Renewable energy, vol.136, pp.746-757, 2019.

[14] Quanyuan Jiang, Yuzhong Gong, and Haijiao Wang, "A Battery Energy Storage System Dual-Layer Control Strategy for Mitigating Wind Farm Fluctuations", IEEE Transactions on power systems, 28(3), pp.3263-3273, 2013.

[15] Alessandro Di Giorgio, Laura Pimpinella and Francesco Liberati,"A Model Predictive Control Approach to the Load Shifting Problem in a Household Equipped with an Energy Storage Unit", In 2012 20th Mediterranean Conference on Control & Automation (MED), pp. 1491-1498, IEEE, July 2012.

[16] Matteo Boaro, Danilo Fuselli, Francesco De Angelis, Derong Liu, Qinglai Wei, and Francesco Piazza, "Adaptive Dynamic Programming Algorithm for Renewable Energy Scheduling and Battery Management", Cognitive Computation, 5, pp.264-277, 2013.

[17] Abdollahzadeh, B., Gharehchopogh, F.S. and Mirjalili, S, "African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems," Computers & Industrial Engineering, vol.158, pp.107408, 2021.

[18] Taj Alam , Zahid Raza,"Quantum Genetic Algorithm based Scheduler for Batch of Precedence Constrained Jobs on Heterogeneous Computing Systems", Journal of Systems and Software, vol.135, pp.126-142, 2018.

[19] Wang GG, Deb S, Cui Z. "Monarch butterfly optimization", Neural computing and applications, vol.31, no.7, pp.1995-2014, July 2019.