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Research Article

Optimization of Electric Vehicle Charging or Discharging Scheduling and Energy Storage in Multi-Objective Market Transactions Based on Quantum Genetic Algorithm

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ABSTRACT

Electric Vehicles (AEVs) may play an essential role in the future of transportation as the use of electric vehicles grows and new transportation network services evolve. AEVs can automatically plan their routes, park at charging stations, and provide vehicle-to-grid (V2G) services. However, V2G services may disappoint customers due to work delays. EVs hold massive promise for future transportation systems, and effective charge scheduling tactics are vital to growing EV profitability. Two difficulties arise when charging/discharging EVs: how to reduce load and charging costs. The goal is to discover the most convenient EV charging station using VANET. This paper uses Monarch Butterfly African Vulture Optimization Algorithm (MBAVOA) for charge scheduling in EVs. The initial stage is to simulate EVs in the Vehicular Ad-hoc Network (VANET) model. Here, the shifting requests from EVs and accessible charging stations are identified. In addition, the load is computed using a Quantum Genetic Algorithm (QGA). Moreover, the multi-objective fitness parameters, like distance, charging cost, and user preference is considered for a charge or discharging schedule. The QGA-MBAVOA outperformed with the lowest charging cost of 66%, fitness of 0.010, and user convenience of 0.779.

Keywords: Monarch Butterfly optimization, Charging or discharging scheduling, Quantum Genetic Algorithm, Electric Vehicle, Energy Management.

1. Introduction

The use of electric vehicles (EVs) is a possible solution to transportation exhaust gas emission problems. With the integration of large-scale renewable sources into power grids, more clean energy utilized by EVs might significantly cut exhaust gas emissions from electricity generation. Other advantages of electric vehicles include less noise. In this scenario, the use of EVs has increased fast in recent years [1. EVs use electricity from the grid to meet power demands, and idle EVs can discharge electricity back into the grid to enable vehicle-to-grid (V2G) services [9][3]. The upcoming V2G services can assist the power grid to minimize power costs and to improve power system stability [10][3]. As the number of EVs on the road increases, more Charging Stations (CS) are being designed to address the EV charging problem. Some renewable energy CS, such as solar and wind, have been created to increase the use of green energy. EV behavior is challenging to predict accurately, which impedes electric vehicle charging optimization [3][11].

The platform of power distribution networks needs to be improved to accommodate the massive spread of EVs. The first requirement, however, is a thorough understanding of EV charging over a distributed network. The paradigm shift in load profile occurs when distribution networks are regarded to acquire EV penetration. The unstable three-phase load and flow simulation of microgrids is adapted for analyzing system performance with EV charging loads [12]. Even though the EV is regarded as a well-known technology capable of solving a million problems, there are still some battery-related issues. EV have short driving range, which is limited due to poor battery technologies, reducing their dependability and efficiency. Second, there were remarkably few charging bases, which were unevenly distributed [13]. As the number of EVs on the road increases, controlling their charging and discharging becomes increasingly complex quickly. Uncoordinated EV integration into the network may pose problems with the power system's control, management, and operation, putting its stability at risk by creating a new peak demand. As a result, various studies have been undertaken to date on managing EV charging and discharging for optimal network integration, and this topic continues to pique academics' interest [15][14].

In addition to generating money, EVs can effectively promote the usage of renewable energy sources in the power grid by charging during off-peak times when renewable energy output is high and discharging during peak hours [14]. Drivers and power grid operators must handle EV charging optimally. Several studies have recently been conducted on EV charging and smart charging technologies. The majority of techniques concentrated on EV charging methods, both controlled and uncontrolled. Uncontrolled EV charging exacerbates grid issues such as power losses, voltage variations, and substation overload. Synchronized charging systems are designed to address difficulties with existing approaches such as centralized and distributed control and time of use (TOU) [16][3]. In [17], the EV level is optimized, and the coordinated scheduling of wind power and EV charging is examined. The model, on the other hand, considers node voltage and transmission power into account when charging electric vehicles.

The goal is to find the appropriate charging station for EVs using VANET. The goal is to develop a model that focuses on scheduling the charging outlets of electric vehicles. Initially, the EV is simulated using the VANET model. Here, charging requests from EVs and accessible charging stations are detected. The charge scheduling algorithm is then called to schedule the EV, a newly created charge scheduling technique MBAVOA. The MBAVOA was developed by combining MBO with AVOA. A new multi-objective fitness function has been designed, with factors including charging cost, user preference, remaining power, and distance parameters.

The paper's primary contributions are:

- The charge scheduling algorithm is called to schedule the EV, and it was built utilizing the MBAVOA. The MBAVOA was developed by combining MBO with AVOA. In addition, the load is computed using QGA.
- The multi-objective fitness function is newly modeled utilizing specific parameters, such as charging cost, user preference, and distance parameters.

The remainder of the sections are organized as follows: Section 2 covers the traditional charge scheduling algorithm. Section 3 describes the system paradigm for EV charge scheduling. Section 4 discusses the MBAVOA for charge scheduling. Section 5 calculates the QGA_MBAVOA efficiency compared to classical methodologies. Section 6 presents the conclusion.

2. Literature survey

Shaofeng Lu *et al.* [1] introduced two multi-objective optimization approaches to model the economic relationship between aggregator profit and EV owners' charging fees. Moreover, an EV charging and discharging approach was employed to establish a settlement price between the aggregator and owners, enabling involvement from both EV owners and stakeholders in energy markets. Here, the aggregator maximizes profits while minimizing economic inconsistency among stakeholders. However, this approach could have avoided from high storage costs.

Haozhe Xu *et al.* [2] have developed a Multi-Objective Particle Swarm optimization (MOPSO) to solve the multi-objective Stackelberg problem and analyze optimization outcomes for varied preferences. In addition, the Stackelberg game is offered to mitigate the negative impact of large-scale EV charging on the power grid. Participating in V2G can minimize expenses for electric vehicles, while the grid can guide charging and discharging to achieve peak reduction and valley filling. However, the economy is the worst.

To handle the nonconvex optimization problem, Yongsheng Cao *et al.* [3] created a suboptimal charging method with some constraints (SCAC) using the Lyapunov optimization technique to strike a balance between overall cost and consumer discontent. Furthermore, to obtain a worldwide charging schedule, the SCAC algorithm's criterion was used as a priori knowledge to create a Charge Scheduling Reinforcement-Learning (CSRL) algorithm, which was more efficient than a reinforcement learning (RL) technique with no specific criterion. However, the system failed to account for other practical charging waiting lists.

Vishu Gupta *et al.* [4] have presented a multi-aggregator, mobility-aware, and collaborative EV charging scheduling system for a PV-supported charging station (PVCS) with BS. Collaborative scheduling and PV/Battery support for energy supply were introduced to maximize aggregator revenues. In addition, the CS can use solar energy or connect to the grid as needed. Here, increased PV energy generation leads to higher earnings but fails to consider variations in aggregator profits when implementing various penalty functions.

James Dixon *et al.* [5] have developed a model for coordinated EV charging to reduce CO2 emissions using grid carbon intensity (gCO2/kWh). The method used time-coupled linearized optimum power to absorb high wind generation while reducing carbon intensity. The Schedules were created with accurate half-hourly grid intensity data and carbon intensity. Distribution restrictions, such as thermal and voltage, may limit the flexibility of transmission systems.

Sean Anderson and Vineet Nair [6] have introduced a technique for optimally scheduling the charging of long-range battery EVs (BEVs) across highway networks to reduce the aggregate cost of the entire system employing utilities and other platforms. As a result, the problem was modeled utilizing a hybrid systems approach. However, the system failed to use real roadway networks for additional investigation.

Hwei-Ming Chung *et al.* [7] have devised a fee scheduling issue for EV charging on a microgrid scale. The problem involved a group of CS managed by a central aggregator. The primary stakeholder is the charging station operator, motivated to lower charging station costs, and the secondary stakeholder is the vehicle owner, who wants to charge the vehicle fully. Here, an online centralized scheduling strategy is developed to reduce the data transmission rate and the system's computing complexity. Although, the centralized scheduling strategy provides good performance, it suffers from high storage costs.

Riccardo Iacobucci *et al.* [8] devised a technique for optimizing EV charging in parallel, considering optimal relocation and routing. The approach was developed for charge optimization. By taking predictive control into account, the model maximized transport service and billing across different time scales. The strategy effectively optimized both system function parameters. The problem was tackled using a mixed-integer linear program. However, the approach failed to explore the services using global optimization.

The following are the issues experienced in the relevant job,

One of the most challenging components of modeling future electrified transportation scenarios is the impact of human behavior, such as how people determine when to charge their vehicles. However, the scheduling problem presents two fundamental obstacles. First, it is difficult to identify the globally optimal scheduling method that minimizes total cost. Second, creating a distributed scheduling mechanism capable of handling a significant population and EV arrivals at random is challenging. The large number of EVs results in high-dimensional scheduling optimization variables, frequently leading to the 'curse of dimensionality'; fluctuations within the energy system and the uncertainty of EV user demand make accurate models challenging to establish, limiting the algorithm's control effectiveness and performance.

3. System model

Effective battery charging is becoming a big issue because of the large number of electric vehicles on the road. Coordinated charging is generally preferred over uncoordinated charging, as it can negatively impact the power grid by increasing peak load and overall expenses. Here, a coordinated charging procedure is examined, in which a central aggregator controls a large number of parking stations. A sub-aggregator (SA) is installed in the charging station to exchange information with the CA. The CA is responsible for EV charge scheduling by managing charging prices and monitoring charging start and finish times. The scheduling is carried out by gathering the necessary information, such as charge demands, time of arrival, and deadlines set by SA.

Let us assume K, which indicates the number of CS. In addition, J is the number of EVs in a microgrid, whereas G represents the number of SAs for CSs and a CA for managing SA. The time slots are denoted as $s = \{1,2,\ldots,S\}$.

The charge level of an EV_x^y where x^{th} EV under under y^{th} CS is designated as SOC_x^y, which ranges from [0, 1], with 1 representing a full battery and 0 representing an empty battery. The arrival time b_x^y relates to EV_x^y arrival time, the EV_x^y deadline is q_x^y, the battery capacity of EV_x^y is $D_{x,y}^{cap}$, the initial battery energy level at arrival time is $D_{x,y}^{ini}$, and the battery energy level at finish time is stated as $D_{x,y}^{fin}$. The starting battery energy level at arrival time is calculated as follows:

$$D_{x,y}^{ini} = SOC_{x,s}^y \times D_{x,y}^{cap} \tag{1}$$

The fit factor value $g_{x,s}^y$ is presented as follows:

$$g_{x,s}^y = \begin{cases} 1 & ; \quad If \ EV_x \ is \ in \ station \, y \ at \, t^{th} \ time \\ 0 & ; \quad Otherwise \end{cases} \tag{2}$$

The formula for the power present in EV_x^y is as follows,

$$Q_{x,s}^y = \sum_{y=1}\sum_{x=1}\left(SOC_{x,y}^{fin} - SOC_{x,s}^y\right)D_{x,y}^{cap} \tag{3}$$

where, SOC's finish time of EV_x is denoted as $SOC_{x,y}^{fin}$ in which the value of power relies on $Q_{x,\min}^y \leq Q_{x,s}^y \leq Q_{x,\max}^y$. The charge of EV_x^y is given by,

$$SOC_{x,s+1}^y = SOC_{x,s}^y + \frac{Q_{x,s}^y}{D_{x,y}^{cap}} \tag{4}$$

Figure 1 shows the system paradigm for EV charging scheduling.

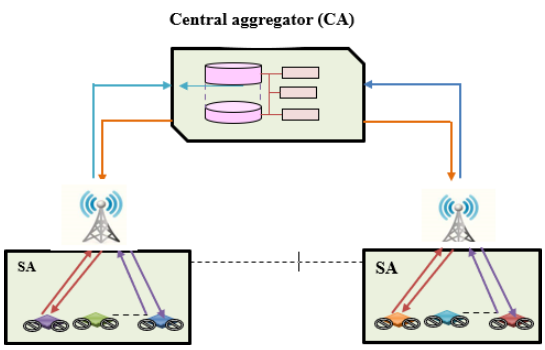


Figure 1. EV Charging scheduling system model

4. Proposed Methodology

The main purpose is to develop a technique for scheduling EV charging stations. First, the VANET model is used to simulate the EV, and then the changing EV requests and available charging stations are detected here. The charge scheduling algorithm constructed using MBAVOA, is then invoked to schedule the EV. Here, the MBAVOA combines

AVOA [1] and MBO [2]. In addition, a multi-objective fitness function is created using specific criteria, such as charging cost, user preference, and distance parameters. The EVs are then assigned to a CS based on the scheduling approach. The EV charging scheduling model parameters will then be tweaked to demonstrate the method's efficacy. Figure 2 depicts the architecture of the MBAVOA, and the EV charging scheduling technique.

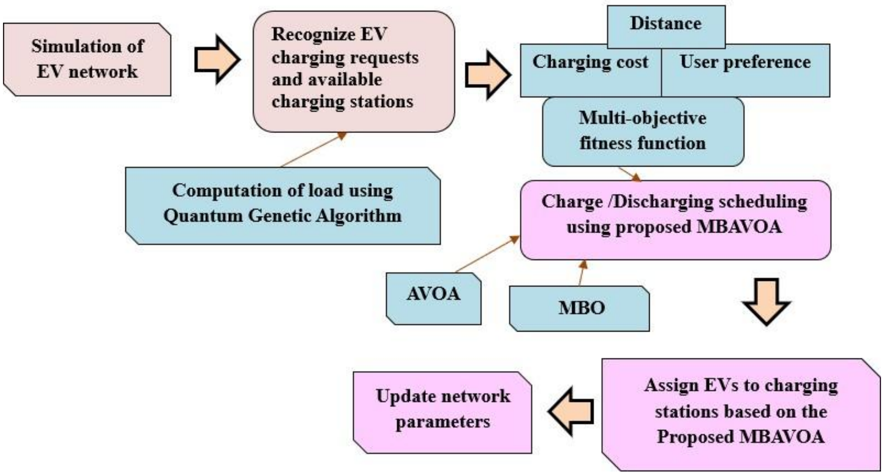


Figure 2. EV charging scheduling architecture based on MBAVOA

4.1. Steps to schedule EV charging/discharging

1. Network simulation based on electric vehicles and computation load
2. Finding the available CS and the charging request from the EV
3. Call charge/discharging scheduling technique with MBAVOA
4. Allocate EVs to CS's using MBAVOA
5. Update $SOC_{x,s+1}^{y}$ and energy

The stages are briefly described below.

A network is run as a linked graph $B=(F,G,H)$, where $F=\{1,\ldots,E\}$ representing a non-empty set of E nodes that discloses intersection of road and capable site of EV charging station, G represents a set of edges that reflect length of road segment, and H represents an adjacency matrix that indicates if nodes are associated. The term $a^{k,n} > 0$ represents a positive-weighted transition from node k to node n for a collection of edges. The graph represents a highway, with traffic expected to flow in both directions without sacrificing generality.

4.2. Load computation

If the charging station's load is unknown, a forecasting technique can be used to improve scheduling performance by ensuring that the load generated at each instance is not exceeded. Thus, load forecasting is required, which is utilized to improve the accuracy and performance of scheduling techniques. The preliminary SOC values are generated arbitrarily and uniformly in the range [0, 1], with the SOC target set to 1. The base load information is created based on the results of the load forecast. Thus, the unit of base load is changed by,

$$A_s^{base} = \frac{A_s^{fore} \times A^{peak}}{\max_s \left(A_s^{fore}\right)} \tag{5}$$

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.

4.2.1. 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 the smallest unit of information held in a two-state quantum computer. A qubit can be in the "1" or "0" state or any combination of the two. A qubit's state can be represented as

$$|\gamma\rangle = \beta|0\rangle + \alpha|1\rangle \tag{6}$$

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

Step 2: Decoding and encoding strategy

Quantum bits can represent a linear superposition of solutions in probability, but cannot directly calculate fitness values. 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 number of modules in an U -sized batch of jobs. Each module will be assigned to nodes 0 through $L-1$. $W_u(s)$ is derived from the population of qubits $Y_u(s)$, where $u = 1,2,\ldots,T$. 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: Quantum Rotation Gate

The state of a qubit can be modified using quantum gates. The operation is reversible and represented by a unitary operator X. This operator operates on qubit basic states that meet the following condition: $X^*X = XX^*$.

Step 4: Generation of dynamic Rotation Angle

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

Step 5: NOT Gate (Mutation Operator)

The NOT gate functions as a quantum mutation operator. Mutation enhances individual diversity and minimizes immature convergence. It also improves the capacity to search locally. It prevents the solution from becoming caught in local minima. The NOT gate is used to reverse the probabilities of the qubit population, allowing for mutation.

Step 6: Crowd Comparison Operator

The crowded-comparison operator is employed in non-dominated sorting to ensure uniformity and diversity in the Pareto front. Individuals are selected based on their rank in the front, followed by the crowding distance if they are in the same front. If two solutions have differing non-domination ranks based on front value, we prefer the one with a lower rank. If both solutions belong to the same front, choose the less packed solution based on crowding distance.

4.3. Computation of multi-objective fitness

The fitness function is illustrated using MBAVOA for charge scheduling. The fitness feature of the MBAVOA is a new design for choosing the best charging system. In this case, the fitness function includes user convenience, distance, and charging cost, which is expressed as,

$$Fit = \sum_{y=1}^{x} Z^{y}_{x,s} + \left(1 - V^{y}_{x,s}\right) + C^{y}_{x,s} \tag{7}$$

where, the charging cost of EV^{y}_{x} is denoted as $Z^{y}_{x,s}$, the convenience of user is indicated as $V^{y}_{x,s}$, $C^{y}_{x,s}$ be the distance, and the available power is represented as $R^{y}_{x,s}$. The charging cost [7] expression is provided by,

$$Z^{y}_{x,s} = \sum_{s=1}^{S}\left[h_0\left(u^{x,y}_{s} - A^{base}_{s}\right) + h_1\left(u^{x,y^2}_{s} - A^{base^2}_{s}\right)\right] \tag{8}$$

where, h_0 and h_1 be constants, which is a minimization function.

The expression of user convenience [7] is,

$$V^{y}_{x,s} = \frac{1}{w^{y*}_{x,s} w^{t}_{x,s}} \tag{9}$$

where, $w^{y*}_{x,s} = \dfrac{\left(SOC^{fin}_{x,s} - SOC^{y}_{x,s}\right) D^{cap}_{x,y}}{Q^{y}_{x,\max}}$ and $w^{y}_{x,s} = q^{y}_{x} - s$, which be the maximization function.

The expression of distance is,

$$R^{y}_{x,s} = \frac{1}{J \times g} \sum_{x=1}^{J} \| k^{s}_{x,y} - k_e \| \tag{10}$$

where, the normalizing factor is denoted as g, the CS position be k_e, and $k^{s}_{x,y}$ be EV^{y}_{x} position. It is a minimization function.

4.4. EV Charging/ discharging scheduling

Here, the parked EV waits until CS schedules it to charge, which is carried out by the hybrid algorithm MBAVOA, which is created by combining MBO [19] and AVOA [20]. The MBO is nature-inspired meta-heuristic optimization, which operates by imitating migration behavior. MBO is more effective for parallel processing and producing trade-offs between intensification and diversification processes. 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 C^{th} population with the most monarch butterfly individuals, representing the maximum generation $I_{\max}$. Even though the generation counter is defined as $f = 1$, the number of monarch butterflies in land-1 is specified as X_1, the number of monarch butterflies in land-2 is denoted as X_2, the maximum step is marked as $V_{\max}$, p represents the butterfly adjustment rate, n represents the migration duration, and the migration ratio is stated as.

Computation of fitness

The optimum solution is obtained using the fitness function and is considered as a minimization problem. Thus, the solution that produces the least fitness is chosen as the optimal solution. The fitness function has already been described in Section 4.3.

Updating migration operator

Monarch butterflies are often present in land-1 from April to August and in land-2 from September to March. As a result, the number of butterflies in land-1 and land-2 is defined as and, respectively. Monarch butterflies on land-1 are referred to as subpopulation-1, whereas butterflies on land-2 are known as subpopulation-2.

Updating butterfly adjusting operator

The butterfly's location is updated via an adjusting operator where the butterfly every component m, if $ran \leq 1$, then update position is,

$$Y_{m,r}^{d+1} = Y_{best,r}^{d} \tag{11}$$

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,

$$Y_{m,r}^{d+1} = Y_{c2,r}^{d} \tag{12}$$

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,

$$Y_{mr}^{d+1} = Y_{mr}^{d+1} + \gamma\left(aY_r - 0.5\right) \tag{13}$$

$$Y_{mr}^{d+1} = Y_{mr}^{d} + \gamma\left(aY_r - 0.5\right) \tag{14}$$

The revised equation from AVOA is as follows:

$$Y_{mr}^{d+1} = U_{mr}^{d} - R_{mr} * Z \tag{15}$$

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, O means the vultures move randomly to protect their prey from other vultures.

$$R_{mr} = | O * U_{mr}^{d} - Y_{mr}^{d} | \tag{16}$$

$$Y_{mr}^{d+1} = U_{mr}^{d} - | O * U_{mr}^{d} - Y_{mr}^{d} | * Z \tag{17}$$

$$Y_{mr}^{d+1} = U_{mr}^{d} - \left(O * U_{mr}^{d} - Y_{mr}^{d}\right) * Z \tag{18}$$

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

The above expression is substituted in equation (14),

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

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

$$Y_{mr}^{d+1}\left[\frac{Z-1}{Z}\right] = \frac{-U_{mr}^{d}\left[1-OZ\right]}{Z} + \gamma\left(aY_r - 0.5\right) \tag{22}$$

$$Y_{mr}^{d+1} = \frac{-U_{mr}^{d}\left[1-OZ\right]}{Z} + \gamma\left(aY_r - 0.5\right) * \left[\frac{Z}{Z-1}\right] \tag{23}$$

Thus, from the above MBAVOA update equation, the EVs are used for charging/discharging schedule.

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 schedules the charging/discharging of EVs.

5. Results and discussion

This section describes the GQA+MBAVOA's results and analysis for scheduling EV charging and discharging. The efficiency is assessed by comparing charging costs, fitness, and user convenience over 100 vehicles.

5.1. Experimental setup

The GQA+MBAVOA is conducted in MATLAB using a Windows 10 operating system with an Intel core processor and 2GB of RAM.

5.2. Experimental outputs

The simulation results for GQA+MBAVOA are investigated here. Figure 3 depicts the results of the GQA+MBAVOA simulation based on the number of vehicles and simulation time. Figure 3 shows red nodes in the network representing automobiles going west-east. The simulated model of an EV at different simulation times is shown. CS represents a CS where each EV with a battery shortfall battery can recharge its battery at the nearest CS. Figure 3 shows the VANET model with 100 vehicles and a time interval of 10 seconds. Initially, the CS is idle, and after a few seconds, the EV is connected to the appropriate CS to charge its EV.

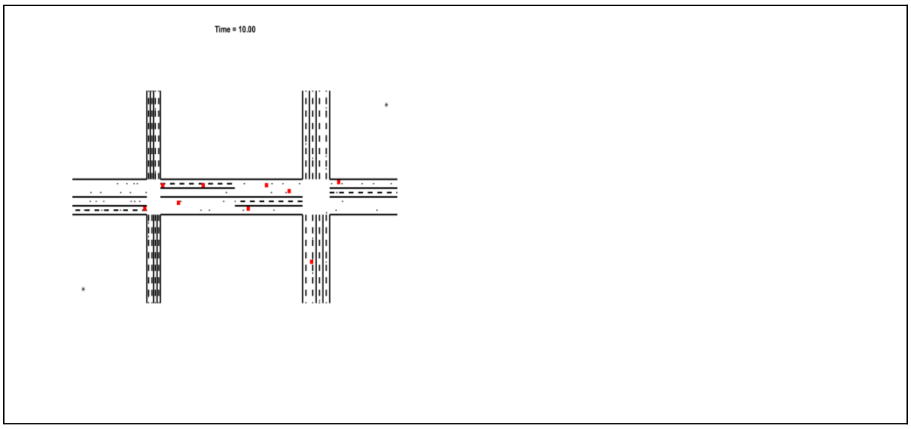


Figure 4. Experimental Output of GQA+MBAVOA for 100 Vehicles

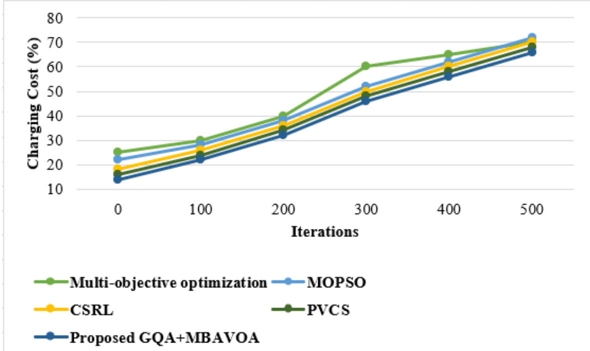
5.3 Performance metrics

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

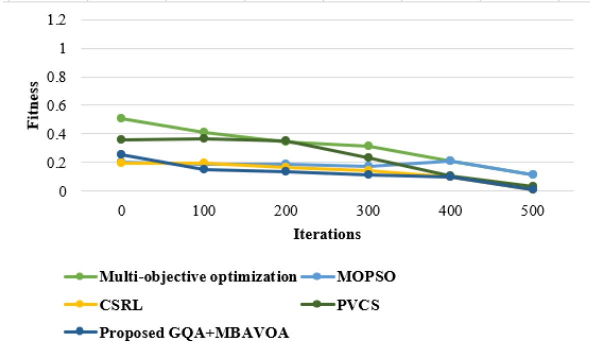
5.4. Competing methods

This section compares the GQA+MBAVOA to other approaches, such as Multi-objective optimization [1], MOPSO [2], CSRL [3], and PVCS [4], in terms of performance measures. The comparison is carried out using 100 vehicles.

Comparative assessment for 100 vehicles



a)



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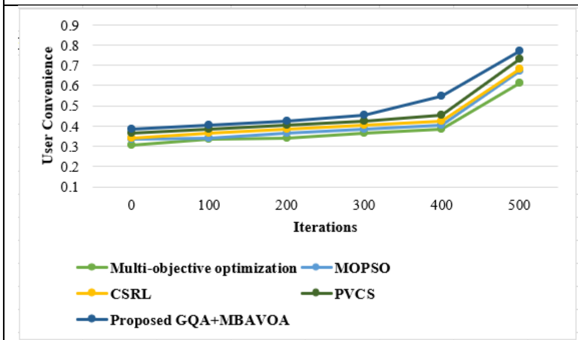

c)

Figure 5. Comparative evaluation of GQA+MBAVOA a) Charging Cost, b)Fitness, c) User Convenience

Figure 5 depicts a comparative examination of GQA+MBAVOA based on the number of iterations and several performance measures. Figure 5a) demonstrates charging cost. For 100 iterations, the charging cost assessed by Multi-objective optimization, MOPSO, CSRL, PVCS, and GQA+MBAVOA are 30%, 28%, 26%, 24%, and 22%, respectively. Figure 5b) shows an assessment of approaches with fitness. The fitness values for Multi-objective optimization, MOPSO, CSRL, PVCS, 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 Multi-objective optimization, MOPSO, CSRL, PVCS, and GQA+MBAVOA are 0.213, 0.209, 0.1, 0.107, and 0.101. Figure 5c) displays the user convenience of various techniques compared to the GQA+MBAVOA. When 100 iterations are considered, the user convenience values of Multi-objective optimization are 0.336, MOPSO is 0.342, CSRL is 0.365, PVCS is 0.385, and GQA+MBAVOA is 0.405.

5.6. Comparative discussion

Table 1 compares 100 vehicles based on user convenience, fitness, and charging cost. Using 100 vehicles, the GQA+MBAVOA has the lowest % charging cost of 66 %, while Multi-objective optimization, MOPSO, CSRL, and PVCS have of 70%, 72%, 70%, and 68%, respectively. The GQA+MBAVOA has the lowest fitness of 0.010, while Multi-objective optimization, MOPSO, CSRL, and PVCS have fitness values of 0.116, 0.114, 0.012, and 0.035, respectively. The GQA+MBAVOA has the maximum user convenience of 0.779, while Multi-objective optimization, MOPSO, CSRL, and PVCS have values of 0.625, 0.682, 0.693, and 0.741, respectively.

Table 1. Comparative analysis

Vehicles	Metrics	Multi-objective optimization	MOPSO	CSRL	PVCS	GQA+MBAVOA
100 vehicles	Charging cost (%)	70	72	70	68	66
	Fitness	0.116	0.114	0.012	0.035	0.010
	User convenience	0.625	0.682	0.693	0.741	0.779

6. Conclusion

This research presents GQA+MBAVOA for charge scheduling in electric vehicles. The simulation of EV in the VANET architecture is the first stage. The detection of changing EV requests and available charging stations occurs here. The charge scheduling approach is then called to schedule the EV, with the charge scheduling algorithm newly designed utilizing the MBAVOA. The suggested MBAVOA was created by combining MBO and AVOA. Here, charging cost, user preference, and distance parameters, regarded as a minimization function are used to create a new model of a multiobjective fitness function. According to the scheduling technique, the EVs are assigned to the charging station. The EV charging schedule model's parameters are then changed to demonstrate the method's success. The GQA_MBAVOA can yield the lowest possible charging cost while minimizing charging time. The GQA_MBAVOA showed exceptional performance, with the lowest charging cost of 66%, the lowest fitness of 0.010, and the highest user convenience of 0.779. Later on, examining the GQA_MBAVOA flexibility using other sophisticated optimization techniques.

Compliance with ethical standards
Conflict of interest
The authors declare that they have no conflict of interest.
Human and Animal Rights
No human or animal research has been conducted by any author.
Informed Consent
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