EVs Coordination to Maximize the Usage of Local Renewable Energy

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ABSTRACT
The intermittent nature of renewable energy sources poses challenges for their integration at the edge of the grid leading to mismatching between the demand and supply. In this paper we examine the potential of electrical vehicle charging and discharging coordination for demand side management. We define a lightweight EVs coordination strategy based on Whale Optimization Algorithm that optimizes the charging and discharging schedule of a fleet of EVs to follow a renewable energy generation curve and maximize its usage in the local microgrid. In this process, individual whales are represented as a scheduling matrix, and element-wise mathematical operations are applied to the energy values to explore and exploit the search space. This is done while considering constraints such as charging station capacities, EV battery levels, and driver preferences. The fitness function is defined to align the EVs operation with the availability of local renewable energy while penalizing violations of constraints. The initial findings are promising, indicating that the algorithm effectively schedules EVs to closely align with renewable energy profiles, with a Pearson coefficient > 0.97. It features good convergence properties, the fitness stabilizing in relatively a low number of iterations, making it suitable for deployment directly on EVs or even on low-resource devices, such as IoT smart meters used in microgrids.

CCS Concepts
• Computing methodologies → Distributed computing methodologies → Distributed algorithms • General and reference → Cross-computing tools and techniques → Design

Keywords
Electric vehicles, coordination; whale optimization algorithm; demand-supply balancing.

1. INTRODUCTION
Currently, the global energy sector is undergoing a transition from fossil fuels to renewable energy sources, to combat climate change caused by pollution and to provide more affordable and accessible energy for all [1]. Renewable energy sources (e.g. solar, wind, hydropower) are increasingly being integrated into power grids, offering cleaner and more sustainable alternatives to the traditional ones. Despite the great opportunities brought by renewable energy, its intermittent nature, influenced by weather conditions, introduces uncertainty in production representing a significant challenge for the stability of the grid [2]. At the same time, energy demand fluctuates, and storage solutions are limited. Coordinating energy demand, generation and storage becomes even more complicated in the current context in which there is a strong global trend towards transportation electrification, driven by environmental concerns and government policies. Electric vehicles (EVs) require a huge amount of energy to charge contributing to a significant load demand, negatively impacting the performance and reliability of power grids [3]. Moreover, decision making processes handle large amounts of data to determine when energy should be consumed, or when an energy consumer with storage could contribute back to the grid to help manage demand peaks. Centralizing these processes in a cloud-based environment is often impractical due to potential bottlenecks caused by limited network bandwidth and large amount of data that needs to be processed. This can be avoided by using edge-fog-cloud architectures and lightweight coordination algorithms operating on a wide range of IoT devices.

In this context, we consider that there is good potential for managing the renewable energy peaks by coordinating a set of EVs as a decentralized energy storage. In this way, EVs can mitigate the uncertainty of renewable energy generation by optimizing the scheduling of discharge and charge operations while contributing to the stability of the power grid [4]. However, the coordination of EVs charging and discharging according to renewable energy generation is a complex optimization problem involving continuous variables (e.g. the state of charge of EV batteries, renewable energy production), discrete variables (e.g. the on/off status of charging stations) and many constraints (e.g. constraints related to the scheduled time for charging/discharging, or related to the distance to the charging station) [5]. Additional complexity arises from the need to balance the variable supply of energy from renewable sources, which is stochastic and exposed to uncertainties, with the fluctuating demand of electricity, making the problem NP-hard [6]. The challenging multifaceted optimization problem can be effectively addressed using bio-inspired meta-heuristics. State of the art solutions used for solving this kind of problem include heuristic and metaheuristic algorithms (e.g. genetic algorithms, simulated annealing), and machine learning techniques such as reinforcement learning [7]. Most of the existing solutions consider objectives related to the minimization of the travel distances for EV users, reducing the infrastructure costs, and ensuring efficient energy distribution [8]. However, balancing the variable supply of renewable with the fluctuating energy demand using a fleet of EVs still requires investigation.

In this paper, we propose an innovative lightweight strategy for coordinating EVs charging and discharging to align with the availability of local renewable energy. We aim to ensure the optimal utilization of energy resources and balance the demand with the generation and a positive and satisfactory experience for the EVs' owners by considering aspects related to their comfort. Our coordination method is using the Whale Optimization algorithm (WOA) [9] which is inspired by the hunting behavior of humpback whales that uses an ingenious method to catch their prey, namely the bubble-net feeding method. We have defined the EVs charging/discharging schedule as a matrix that models the assignment of EVs per charging station and the amount of energy charged. A population individual in WOA is represented by such a scheduling matrix instance. In the coordination process, we have considered constraints related to the charging station capacities, EV battery, and driver preferences. The population of individuals is updated in each iteration using three main phases: search for prey, shrinking encircling, spiral updating position. The search for prey corresponds to the exploitation of the EVs optimization space, while the shrinking of the encirclement and the spiral update position together correspond to the exploration of the space. A fitness function evaluates how well the EVs schedule balances the renewable energy production and consumption and penalizes individuals who violate the defined constraints. WOA was designed for continuous variables, however our EVs coordination method works with discrete variables and integers for updating the individuals in each phase. To handle integer values, we rounded the charging and discharging energy values in each cell of the EVs scheduling matrix to the nearest integer after specific mathematical operations. Additionally, element-wise mathematical operations are performed on the energy values. The paper also analyzes deployment solutions of the WOA algorithm in a centralized cloud environment and in an edge-fog-cloud setup.

The paper is structured as follows. Section II presents state of the art approaches in the area. Section III defines the WOA solution for coordinating the EVs charging and discharging operations. Section IV presents evaluation results and discusses deployment solutions for the WOA algorithm. Sections V presents conclusions.

2. RELATED WORK

In general, WOA has been successfully applied to a wide range of optimization problems (i.e., continuous single-objective problems, binary problems, etc.) in various domains [10]. Selecting the optimal locations for charging stations is crucial in developing efficient and reliable infrastructure for EVs. Properly positioned charging stations ensure convenient access for EVs' owners, reduce congestion, and enhance the overall efficiency of the charging network. Cheng et al. propose an Improved WOA (IWOA) to solve the problem of poor accuracy and stability in optimizing the locating and sizing of nonconvex and nonlinear electric vehicle (EV) charging stations (CSs) [11]. The authors consider the true path of the traffic network structure in the planning and use IWOA to solve the proposed model. IWOA introduces the convergence factor, differential evolution, and the concept of antibody concentration (to increase the local search ability) into the WOA algorithm. The quality of the initial solution is significantly better, and, as the population diversity increases, WOA can escape the local maximum. Li et al. use a modified WOA for selecting the location of CSs [12]. To generate the initial population, they use a Circle chaotic map, and a Tent chaotic map to generate pseudorandom numbers that results in a better distribution of the initial search space and a better algorithm convergence speed. A reverse learning mechanism is introduced with a significant impact on expanding the screening range and improving the convergence speed. This strategy helps to balance and improve the global search ability and local development ability of the algorithm. Mehroliya et al. use WOA in optimal planning of CSs, distributed generators (DGs), and shunt capacitors (SCs) along with electrical network reconfiguration [13]. The multi-objective problem of allocating EV CSs, along with DGs and capacitors aims to improve the voltage stability and minimize active and reactive power losses in the radial distribution system. Rizwan et al. [14] use WOA to determine location and size for DGs and CSs in a radial distribution system for the voltage profile improvement and reduction of power loss.

With regards to balancing the energy demand with energy consumption using EVs coordination, Hai et al. describe an approach for optimal operation of a microgrid with several distributed energy resources and EVs aiming to obtain minimum operational costs [15]. It incorporates the vehicle to grid (V2G) concept to reduce the cost of the network by using energy from plugin-EVs. They develop a novel optimization algorithm, hybrid WOA and pattern search (HWOA–PS), which addresses the global search space issue of WOA, and evaluate the efficacy of the suggested random structure on a grid-tied microgrid. Paul et al. propose an optimal hydro-thermal scheduling technique for EVs to obtain a maximum utilization of renewable energy sources for economic power generation with less emission [16]. They use a new approach for V2G with a wind–solar based HTS system for improving grid reliability and resilience based on a chaotic-quasi-opposition-based WOA. The statistical analysis for economic load scheduling and economic emission scheduling show the superiority in performance and robustness of CQWOA algorithm over other algorithms on the same experimental platform. Shaheen et al. develop an intelligent and cost-effective V2G strategy that benefits both EV users and the power grid [17]. The goal is to optimize the timing of EV charging and discharging activities when vehicles are parked, to reduce daily charging costs for EV owners, and help manage energy demand on the electric grid side. Four metaheuristic algorithms are used to find the most effective approach (Particle Swarm Optimization, Differential Evolution, WOA, Grey Wolf Optimization) WOA emerging as the most efficient and reliable method for optimizing EV charging and discharging schedule activities. [18] aims at minimizing the detrimental effect of EV charging station load on the electrical network. To achieve their goal, they compare eight techniques: modified teaching-learner-based optimization, JAYA, modified JAYA, ant–lion optimization, WOA, grasshopper optimization technique, modified WOA, and hybrid whale particle swarm optimization (HWPSOA). The objective is to optimize the voltage stability, reliability, and power loss (VRP) index of the distribution network (DN) under two different cases of operations such as after placing EVCSs alone and in the presence of both EVCSs and renewable energy sources. The proposed objective function is tested on an IEEE 33 bus-modified DN composed of solar PV, wind as the prime sources and fuel cells as the supplementary source. The numerical findings show that the HWPSOA yields better-quality solutions. Nandini et al. introduce a novel demand response and energy storage program tailored for multi-energy microgrids (MEM) [19]. Their research presents a comprehensive stochastic framework for MEM that accounts for uncertainties in energy prices and demands and that addresses the simultaneous utilization of multiple energy carriers, including cooling, heating, hydrogen storage, and compressed air. It proposes a new whale and wavelet transform-based optimization algorithm, which overcomes the limitations of conventional optimization methods. By considering uncertainties and interactions among diverse energy carriers, the program optimizes energy management efficiently. Adetunji et al. study the optimal coordinated charging of EVs in a centralized charging model using the cost minimization, load variance minimization and power loss minimization as objective functions [20]. An EV is modelled considering the hourly demand, driving/waiting time, battery capacity and energy demand. The distributed network operator monitors the grid and aims to minimize power losses. WOA yielded best performance for the problem.

3. WOA FOR EVS SCHEDULING

3.1 Problem Definition

The proposed method aims to optimally schedule EVs for: (i) charging during periods of surplus renewable energy, helping to stabilize the grid by addressing the energy peaks, and (ii) discharging during periods of renewable energy deficit, which is unable to meet demand, supplementing the shortfall of energy. Thus, given a set of EVs and a set of CSs deployed in a bounded area, the objective is to create a charging/discharging schedule $S(EV, CS, T)$ for an interval T such that:

$$E_{renewable}(T) - E_{demand}(T) \pm E_S(T) \cong 0 \quad (1)$$

where $E_{renewable}$ is the amount of renewable energy available at time T, E_{demand} is the energy demand at time T, while E_S is the energy charged/discharged by the scheduled EVs at time T. The schedule is modeled as an individual in WOA defined as a matrix of $2m * n$ dimension where m is the number of CSs with two plugs each, and n is the number of discrete time slots of the scheduling interval T:

$$S(EV, CS, T) = \begin{bmatrix} s_{1,1} & \cdots & s_{1,T} \\ \vdots & \ddots & \vdots \\ s_{2m,1} & \cdots & s_{2m,T} \end{bmatrix} \quad (2)$$

where $s_{i,j} > 0$ represents the amount of energy the EV scheduled at the i^{th} plug during the j^{th} time slot should charge or discharge. The matrix will have elements with zero as value in the cells corresponding to the times when no EVs are assigned to the CSs.

The energy demand profile associated with the EVs schedule S is determined considering each discrete time slot t_j:

$$E_S(T) = [E(t_1), \ldots E(t_j) \ldots E(t_T)] \quad (3)$$

$$E(t_j) = \sum_{i=1}^{2m}(s_{i,j}) \quad (4)$$

We consider constraints related to the CSs capacities, EV battery constraint and driver preferences, as follows:

- An EV should be planned to be discharged in the slot t_j with an amount of energy $s_{i,j}$ that will not make it go under the minimum limit imposed by the driver or battery specification:

$$SoC_{min} \le SoC_{current} + \frac{s_{i,j}*100}{c_{max}} \quad (5)$$

  where SoC_{min} is the battery's minimum state of charge, $SoC_{current}$ is the battery's current state of charge, c_{max} is the battery's maximum capacity and $s_{i,j}$ is the amount of energy with which the EV is scheduled to be discharged.

- The amount of energy $s_{i,j}$ with which an EV is scheduled to be charged cannot be greater than the EV's charging capacity per discrete time slot ($B_{capcity}$):

$$s_{i,j} \le B_{capcity} \quad (6)$$

- The amount of energy with which the EV is scheduled to be charged/discharged $s_{i,j}$cannot be greater than the charging station capacity ($cs_{i,capacity}$) per considered time slot:

$$s_{i,j} \le cs_{i,capacity} \quad (7)$$

- For an energy charging operation, the amount of energy at a certain time t_i should not exceed the surplus of renewable energy, $E_{renewable}^{surplus}$:

$$E(t_j) \le E_{renewable}^{surplus}(t_i) \quad (8)$$

- The driver can express some preferences related to the maximum distance in kilometers to the CS.
- The driver can express some preferences related to the time slot intervals in which the charging or discharging may be scheduled using a binary vector P:

$$P(ev_n) = [p_{n,j}] \quad (9)$$

where $p_{n,j} = 1$ encodes that the time slot j is preferred by the driver of the EV with id n and 0 otherwise.

The fitness function consists of two components one that evaluates how well the EVs schedule balances the renewable energy production and consumption (see relation 1) and one component that penalizes individuals who violate the driver's specific preferences and defined constraints:

$$f(S(EV, CS, T)) = w_1 * EnergyComponent(S) + w_2 * Pref(S(EV, CS, T)) \quad (10)$$

where, *EnergyComponent* is defined using relation 1, w_1, $w_2 \in [0,1]$, $w_1 + w_2 = 1$ are weights that specify the degree of importance given to each of the two components.

To penalize individuals if the preferences of the drivers are not met, we use the following relation:

$$Pref(S(EV, CS, T)) = \sum_{i=1}^{k} \max(0, penalty_i) \quad (11)$$

where $penalty_i$ is the penalty given for violating a specific preference and k is the total number of preferences.

3.2 Heuristic Coordination

We considered that the EVs scheduling matrix is a whale individual in WOA. To generate the initial population of whale individuals we have used a random approach considering the defined constraints and we have reallocated the EVs to CSs, so that most of the preferences specified by the drivers are satisfied. The WOA phases (search for prey, shrinking encircling, spiral updating position mechanism) have been adapted to our EVs scheduling problem.

In the *prey search phase*, each individual updates its position based on its current position, the position of an individual randomly selected from the population, and two coefficient vectors $\vec{A}, \vec{D}$:

$$S(EV, CS, t+1) = INT(S_{rand}(EV, CS, t) - \vec{A} * \vec{D} + 0.5) \quad (12)$$

$$\vec{D} = \vec{C} * S_{rand}(EV, CS, t) - S(EV, CS, t) \quad (13)$$

INT is a function that takes the integer part from the long variable, $S(EV, CS, t+1)$ is the EV scheduling matrix at time $t+1$, $S_{rand}(EV, CS, t)$ is an EVs scheduling matrix randomly selected from the population, $\vec{A}$ and $\vec{C}$ are coefficient vector defined as:

$$\vec{A} = 2 * a * \vec{r} - a \quad (14)$$

$$\vec{C} = 2 * \vec{r} \quad (15)$$

where $\vec{r}$ is a random vector in the (0, 1] range and a is a value that decreases from 2 to 0 linearly through the iterations and is computed using the following formula:

$$a = 2 - \frac{2*it}{it_{max}} \quad (16)$$

where: it-current iteration; it_{max} - maximum number of iterations.

In the *shrinking encircling phase*, every individual updates their position relative to the best individual. In this way all individuals are heading to promising regions in the search space. In our approach, this is performed using the following formula:

$$S(EV, CS, t+1) = INT(S_{best}(EV, CS, t) - \vec{A} * \vec{D} + 0.5) \quad (17)$$

$$\vec{D} = \vec{C} * S_{best}(EV, CS, t) - S(EV, CS, t) \qquad (18)$$

where $S_{best}(EV, CS, t)$ is the best EVs scheduling matrix identified.

In the *spiral updating position* phase, each individual's position is updated using the helix-shaped movement mechanism:

$$S(EV, CS, t+1) = INT(\vec{D'} * e^{b*l} * \cos(2 * \pi * l) + S_{best}(EV, CS) + 0.5)(t) \qquad (19)$$

$$\vec{D'} = S_{best}(EV, CS, t) - S(EV, CS, t) \qquad (20)$$

where l is a random number in [-1, 1], $e \approx 2.71$ is the Euler's constant, b is a constant for defining the shape of logarithmic spiral.

The original algorithm equation was designed for continuous space, but we're working with discrete space and integers. To work with integer energy values, we rounded them in each cell of the EV planning matrices to the nearest integer after performing specific mathematical operations in the 3 algorithm steps. Additionally, an EV might be assigned to different CSs at various times in different candidate solutions, or there may be fewer EVs than available slots, leaving some matrix positions empty. Thus, we perform element-wise mathematical operations on energy values, regardless the specific EV. The energy value of the EV allocated to CS_i at time t_i in the current solution will be updated based on the energy value of the EV assigned to CS_i at time t_i from the best solution or from a randomly selected solution in the current population (depending on the phase in the algorithm), even if it's not the same EV.

Our algorithm takes as inputs the EVs, CSs, target energy profile, WOA relevant parameters and the scheduling interval T.

Algorithm 1: Optimal EVs scheduling using WOA

Inputs: L_{EV}- electric vehicles, L_{CS} - charging stations, $E_{target}(T)$ energy profile to be matched
Outputs: S_{best} (L_{EV}, L_{CS}) – the optimal scheduling of EVs at CSs
Begin
1. *Pop* = ∅, *Fitness*= ∅, $\vec{A}$ = ∅, $\vec{C}$ = ∅, *iter* = 0
2. *Pop* = **Generate** (L_{EV}, L_{CS}, *popSize*, *T*)
3. S_{opt} (L_{EV}, L_{CS}) = **Select-Best** (*Pop*, **Fitness** (*Pop*))
4. **while** (*it* <= it_{max})
5. **for each** *S* (*EV*, *CS*) **in** *Pop* **do**
6. *l* = **Random**(-1, 1), *p* = **Random** (0, 1),$\vec{r}$ = **RandomV** (0,1)
7. *a* = **Compute** (*it*, it_{max}), $\vec{A}$ = **Update** ($\vec{r}$, *a*), $\vec{C}$ = **Update**($\vec{r}$)
8. **if** (*p* < 0.5) **then**
9. **if** (|A| < 1) **then**
10. *S*(L_{EV}, L_{CS}) = **Update** (*S*(L_{EV}, L_{CS}), $\vec{A}$, $\vec{C}$, S_{best} (L_{EV}, L_{CS}))
11. **else**
12. S_{rand}(*EV*, *CS*) = **SelectRandom**(*Pop*)
13. *S* (*EV*, *CS*) = **Update** (*S* (*EV*, *CS*), $\vec{A}$, $\vec{C}$, S_{rand} (*EV*, *CS*))
14. **endif**
15. *S* (*EV*, *CS*) = **Update** (*S*(*EV*, *CS*), S_{opt} (*EV*, *CS*), *l*, *b*)
16. **endif**
17. **endfor**
18. *Population* = **AdjustIndividual**(*Pop*)
19. S_{best} (EV, CS) = **Update-Best** (*Pop*, **Fitness** (*Pop*))
20. *it* =*it*+1
21. **endwhile**
22. **return** S_{best} (EV, CS)

End

In the initialization phase (line 2), the initial population of individuals (i.e., EV scheduling matrix) is generated by considering the list of EVs, the list of CSs, the time interval for each scheduling and the dimension of the population. Then the best individual in the population is identified based on fitness values (line 3). In the iterative phase (lines 4-21), in each iteration, the algorithm updates the population of individuals by applying the strategies described above (lines 8-16). Then, for every individual in the population, the algorithm checks if it is inside the search space (line 18). If it is not, it is amended. In our approach we considered that an individual is inside the search space if it respects the constraints. The final step of the iterative phase is the best individual' update according to the fitness values of the individuals that are part of the updated population (line 19). The algorithm returns the best individual, which in our case is the best scheduling of EVs for charging/discharging at CSs.

4. Evaluation Results

This section presents the experimental setup and evaluation results discussing also the algorithm deployment in an edge-fog-cloud setup.

4.1 Experimental Results

To evaluate the proposed approach, we have used a dataset comprising information of 80 EVs of the following types: (a) Renault ZOE with a battery capacity of 22 kWh and maximum charge power of 22 kW (RZ22); (b) Renault ZOE with a battery capacity of 41 kWh and a maximum charge power of 22 kW (RZ41); (c) Nissan LEAF with a battery capacity of 24 kWh and a maximum charge power of 7 kW (NL24); (d) Hyundai KONA with a battery capacity of 64 kWh and a maximum charge power of 11 kW (HK64). Additionally, we have used four CSs, each equipped with two Type 2 charging plugs with the charging capacity ranging from minimum 2.8 kWh to the maximum of 25.8 kWh.

Table 1. The evaluation scenarios

Scenario	#EVs & stations	#EVs per type	SoC
1: Charge	80(4)	RZ22: 19; RZ41: 17 NL24: 26; HK64: 18	10% - 35%
2: Discharge	80(4)	RZ22: 19; RZ41: 23 NL24: 18; HK64: 20	75% - 100%

We have fine-tuned the WOA parameters as following: value of 1 for *b*, population size between 50 and 200 and for maximum number of iterations values between 5 and 45.

We considered the evaluation scenarios summarized in Table 1. Scenario 1 considers renewable energy peaks in the local grid that need to be locally consumed by scheduling the charging of EVs (Figure 1).

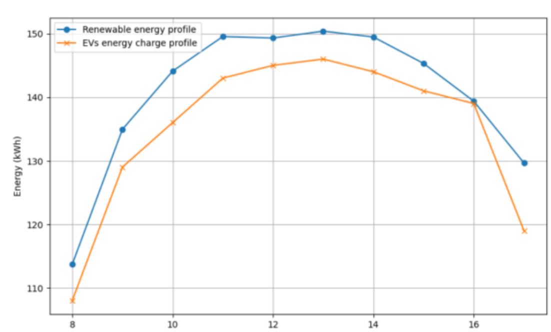

Figure 1: EVs charge scheduling in scenario 1

It can be noticed that in scenario 1, our proposed solution provides a charging schedule which allows EVs to consume the energy surplus. Scenario 2 considers congestion in the local energy grid due to higher demand than energy production. In this case our algorithm schedules the EVs to decrease their overall energy demand and discharge their energy to match the energy requirements of the local grid (see Figure 2).

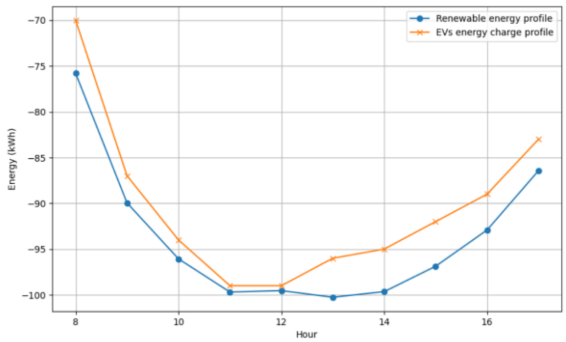

Figure 2: EVs discharge scheduling in scenario 2

Moreover, we can notice that in each scenario, the EVs energy profile resulting from the schedule approximates well the target energy profiles considered.

To assess the similarity degree, we have used the *Pearson coefficient*, obtaining a value of 0.978 for Scenario 1 and 0.987 for Scenario 2. The Pearson coefficient has a value close to 1 which means that the two curves are very similar in the two scenarios.

WOA performance for EVs scheduling was assessed based on the fitness measure. The *fitness* measures the quality of the solution found by WOA and allows us to visually analyze the algorithm's convergence behavior. A converging algorithm will show a decreasing trend in the best fitness over iterations, with diminishing improvements as it progresses. Figures 3 and 4 show the fitness score evaluation for the considered scenarios.

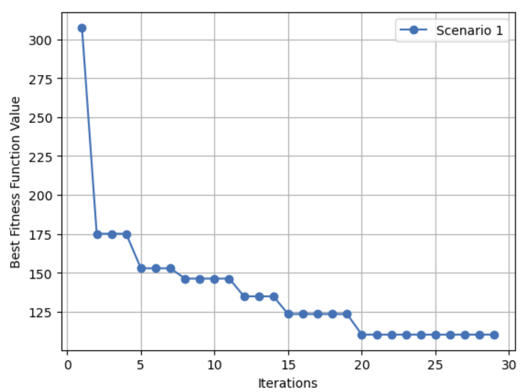

Figure 3: Best fitness value evolution for scenario 1

We notice that the variations of the fitness value are initially more pronounced, but become smoother as the number of iterations increases, eventually stabilizing. This means that the algorithm has achieved convergence, and it obtained a good fitness value, very close to the optimal ones it could achieve. Even if the fitness values of the best solutions identified in each scenario, are not zero, they are good because, the minimum value we can obtain for fitness depends on the number of EVs and the current SoC of each EV.

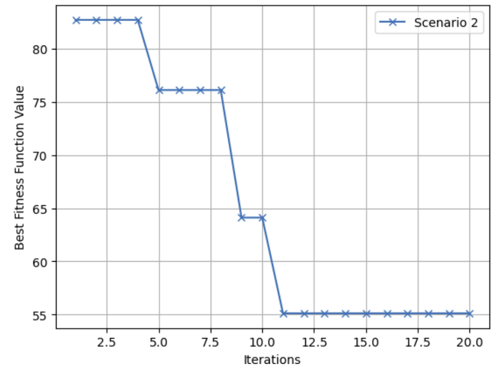

Figure 4: Best fitness value evolution for scenario 2

4.2 Deployment in edge-fog-cloud setup

The proposed solution for EVs coordination can be deployed centralized or due to its lightweight nature closer to the edge.

In the centralized approach, the WOA algorithm runs as a cloud service, coordinating EVs daily at a large scale. EVs, regardless their geographical location, transmit daily updates to the cloud (e.g., current SoC, location). Simultaneously, the cloud service predicts the next day's renewable energy generation using historical data and real-time weather information collected from external services. Using this data, the cloud service runs the WOA algorithm to coordinate the EVs charging and discharging across all target regions, providing drivers with the specific times and charging station locations. The large amount of data generates a large search space that WOA must search for the optimal EVs coordination, potentially leading to bottlenecks. Bottlenecks can also be caused by communication technologies connecting EVs, drivers and renewable energy sources to the cloud, due to limited network bandwidth making difficult the transmission of large volumes of data to and from the cloud.

To address the limitations of a centralized system, a decentralized edge-fog-cloud architecture can be implemented (see Figure 5).

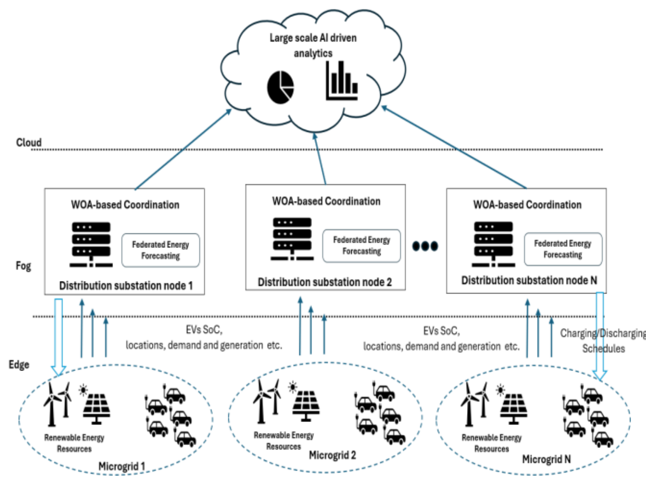

Figure 5: WOA algorithm deployment in edge-fog-cloud

In this setup, the following tasks can be offloaded from the cloud environment to fog nodes: EVs data collection and processing, renewable energy generation prediction, execution of the WOA algorithm, and communication of coordination decisions. More specifically, the WOA algorithm can be deployed at multiple fog nodes, being executed in a decentralized way at the level of distributed substations. An instance of WOA is associated to one microgrid management, analyzing data and deciding on local EVs schedules. In this case, the EVs send their current SoC and location directly to the closest fog node minimizing latency and data network congestion. Additionally, the prediction of energy demand and generation can be federalized as well as the decision making. Given the close location of the fog nodes to the EVs, the decision time will be decreased, moving the coordination process closer to the real time. Moreover, the fog nodes can push the coordination decisions and prediction models to the cloud for leveraging on cross microgrids knowledge and data further improving the optimization process. This decentralized approach, significantly reduces the amount of data sent to the cloud, since the workload is distributed among multiple fog nodes that handle smaller, localized operations.

Finally, the lightweight nature of the WOA based coordination makes it adaptable, allowing it to operate efficiently directly on EVs or even on low-resource devices, such as IoT smart meters deployed at microgrid level. Moreover, due to decentralization and microgrid partitioning, a larger number of EVs can be coordinated.

5. Conclusions

This paper has proposed a lightweight WOA algorithm for balancing energy production and consumption. We demonstrate its use for the optimal coordination of EVs in their charging and discharging processes maximizing the usage of renewable energy and compensating for the renewable energy deficit. When a peak of renewable energy is registered, EVs are scheduled for charging, while in case of renewable energy deficit, EVs are scheduled for discharging. Both charging and discharging processes consider constraints such as EVs' battery capacity, charging stations' capacity, distance and time constraints of EVs owners. We evaluated the algorithm on a charge and a discharge scenario considering 4 types of EVs with different configurations. Experimental results are promising, indicating the algorithm manages to coordinate the EVs such that the resulting energy profile closely matches the renewable energy profile, while the considered constraints are mostly met. Moreover, the fitness value evolution shows good convergence rate, ensuring that our solution can operate efficiently on EVs or even on low-resource devices such as IoT smart meters in microgrids.

6. ACKNOWLEDGMENTS

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