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A Multi-Objective Planning Strategy for Electric Vehicle Charging Stations towards Low Carbon-Oriented Modern Power Systems

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Abstract: This paper proposes a multi-objective planning framework for electric vehicle (EV) charging stations in emerging power networks that move towards green transportation electrification. Four cases are investigated to study the impacts of EV integration on environmental and economic requirements. In order to facilitate the installation of EV charging stations, the proposed model is formulated to combine the planning models of renewable energy systems, energy storage systems (ESSs), thyristor-controlled series compensators, and transmission lines into the EV-based planning problem. The first objective function aims to maximize EVs' penetration by increasing the networks' capacity to supply charging stations throughout the day, whereas the second objective, on the other hand, emphasizes lowering the carbon dioxide emissions from fossil fuel-based generation units in order to benefit the environment. The third objective is to meet the financial requirements by lowering the initial investment and operating costs of the installed devices. The proposed model is written as a multi-objective optimization problem that is solved using the multi-objective version of the Gazelle optimization algorithm (MGOA). The efficiency of the MGOA was tested by solving a set of four benchmark test functions and the proposed problem. The obtained results demonstrated the MGOA's superiority in solving multi-objective optimization problems when compared to some well-known optimization algorithms in terms of robustness and solution quality. The MGOA's robustness was between 20% and 30% and outperformed other algorithms by 5%. The MGO was successful in outperforming the other algorithms in providing a better solution. The Egyptian West Delta Network simulations revealed a 250 MWh increase in the energy supplied to EVs when energy storage was not used. However, storage systems were necessary for shifting EV charging periods away from high solar radiation scenarios. The use of ESS increased greenhouse gas emissions. When ESS was installed with a capacity of 1116.4 MWh, the carbon emissions increased by approximately 208.29 million metric tons. ESS's role in improving the EV's hosting capacity grows as more renewables are added to the network. ESS's role in improving the EV's hosting capacity rises as more renewables are added to the network.

Keywords: electric vehicles; energy storage systems; transmission lines planning; renewable energy sources; multi-objective Gazelle optimization algorithm; smart grid

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1. Introduction

Carbon dioxide emissions have risen steadily over the past decades. Energy-related CO_2 emissions were approximately 35 billion metric tons in 2020 and are expected to exceed 40 billion metric tons by 2050 [1]. Globally, governments worldwide have adopted many policies to tackle this issue and generally deal with the problems of climate change. One of these policies is the electrification of the transportation sector. It is planned that by the year 2050, electric vehicles (EVs) will contribute to reducing CO_2 emissions and represent 31% of overall passenger vehicles [1].

The massive use of EVs adversely impacts the power network's inertia, reliability, and frequency regulation capability and is exacerbated if renewable sources are heavily installed. However, these issues can be turned into a solution to many power grid issues if EV penetration is well planned. EVs can provide power grid ancillary services, including peak clipping, load shifting, and frequency management [2]. Many planning strategies for integrating and optimizing EVs in power networks have been proposed in the literature. Static and multi stages-based planning frameworks are commonly presented to model the problem. For example, Abdi-Siab et al. [3] developed a bi-level optimization strategy for the expansion of distribution systems in the presence of plug-in EVs. The upper level aimed to calculate the annual investment, prospective production, and maintenance costs. At the same time, the lower level was concerned with minimizing the cost of the energy purchased from the main grid and optimizing the daily schedule. The results showed that the smart charging strategy led to a lower investment cost and demonstrated the superiority of the proposed solving strategy compared to the strategies that adopted a separate optimization problem. A carbon-oriented planning model that combines the planning of natural gas systems, fast-charging stations for EVs, PV plants, fuel cells, and carbon capture and storage units was proposed by Wu et al. [4]. Moreover, the suggested model was recruited to consider the future scenarios' anticipated adaptation costs and the initial planning costs. The simulations showed that carbon emissions could greatly affect the planning results. When the carbon emission cap was lowered, the planning costs went up, and more infrastructure was installed. Quijano et al. [5] presented a new strategy for improving the hosting capacity of modern distribution networks in the presence of plug-in EVs. The strategy sought to identify the maximum penetration of wind plants, considering the forecast basis, the dynamic operation of EVs, voltage regulation units, and the distributed generators (DGs) penetration. The suggested approach was formulated as a two-stage linear optimization problem. The first stage maximizes the capacity of the installed distributed generation units, while the second minimizes energy losses. The obtained results demonstrated that, by controlling the dispatched power to the EV aggregators, the hosting capacity of the DGs was significantly increased compared to the uncontrolled case.

Commonly, the planning models of the diverse projects that have used transformer taps, energy storage systems (ESSs), transmission lines, and voltage regulators are incorporated into the EV planning problem to facilitate the installation of EV stations. For instance, Mehrjerdi et al. [6] provided a model to determine the nominal level of facilities required, such as fast, intermediate, and slow speed chargers, and to calculate the capacity of EV charging stations. Further, the model was extended to determine the size and operational scheduling of ESSs optimally. The line reinforcement strategy was also employed to strengthen the grid. The results showed an increase in the rated power of fast-speed chargers compared to the intermediate and slow ones. Furthermore, the reduction of line reinforcement resulted in an increase in the battery power installed. Fachrizal et al. [7] introduced an integrated model that facilitated the combination of PV units and EVs and provided an assessment tool to evaluate the hosting capacity of LV distribution networks. To this end, four scenarios were executed, and the system performance was analyzed. The results found that EV smart charging significantly improved the hosting capacity of EVs in residential areas, while PV curtailment significantly increased the hosting capacity of PVs. The authors in [8] also presented a framework to optimally determine the size of the PV units and EVs for charging stations, taking into account load-matching indices. The suggested approach used the self-consumption-sufficiency balance as a new score based on a principle similar to the F1 score in machine learning, which combines a classifier's precision and recall into a single metric by taking their harmonic mean. The high value of the suggested score referred to the fact that the system was close to a self-sufficient state and could not export or curtail a large amount of local generation. The results showed that a self-sufficient state could be achieved with a more extensive combination of PV modules and EVs.

Considering EVs' uncertainty, EVs' behavior is stochastic, and its modeling is critical [9]. A precise formulation for the dynamic operation of EVs is required for their secure integration into the power networks. Stochastic and robust-based methods are commonly used to formulate EV-related uncertainties. A long-term expansion planning model for microgrids was investigated by Mehrjerdi et al. [10]. The objective was to expand the capacity of generation sources, such as the micro-turbine, PV modules, wind station, and ESS, where the EV charging stations appeared as load centers or dispatchable units. The short- and long-term uncertainties were considered. The findings revealed that considering the short-term operation of the dispatchable units reduced the calculated cost to 28% and contributed to minimizing the cost of the long-term plan. Manríquez et al. [11] analyzed the effects of the massive use of EVs on the Chilean national electric network expansion for the year 2030. Data from representative days was used to formulate uncertainties and model the hourly dynamics of the network. Further, the demand for EVs was investigated by considering five scenarios that differed in the number of EVs and the charging strategies employed. The results demonstrated that smart charging resulted in a 2.4% increase in solar power-based generation units and a 2.5% decrease in conventional generating units. Baringo et al. [12] proposed an adaptive, robust optimization framework for expanding the distribution system while accounting for short-term variability and long-term uncertainties. The expansion model was formulated and extended to involve planning renewable energy sources (RESs), ESSs, and EV charging stations. On some representative days inspired by different dynamic operational conditions, short-term uncertainties in load behavior, RESs, EVs, and electricity prices were modeled. Long-term uncertainties were also investigated by considering the uncertainties associated with future peak loads, the electricity future outlook on the transmission network, and the number of EVs. The simulations proved the superiority of the proposed robust approach in terms of computational performance compared to the stochastic approach.

The overall increase in EV usage may deteriorate the power system's reliability and security if it is not appropriately considered and no counteractions are taken [13]. Several studies were carried out to handle this issue. The planning problem of power systems and EVs' charging infrastructure was addressed by Yao et al. [14] to improve power network resilience when subjected to extreme weather conditions. The *N-k* reliability criterion was considered to enhance the security of the systems. The simulation results demonstrated the EVs' ability to improve power network resilience by reducing the amount of load shedding required. Further, a reliability-constrained methodology that considered demand response programs was proposed by Kamruzzaman et al. [13] to maximize EV penetration in modern power systems. The proposed method was carried out by considering the demand response measurements and EVs' load profiles and employing the Monte Carlo simulation to assess some well-known reliability indices. The results revealed that the proposed method could significantly address the negative impacts of EVs and thus maximize EV penetration.

Generally, EV planning is complex, especially if the multi-objective frameworks are formulated to manage several components. Recently, several efficient metaheuristic algorithms have been broadly developed and used to solve EV planning problems. A multi-objective nonlinear planning model was developed by Fan et al. [15]. The aim was to reduce investment costs and maximize charging stations' utilization. The suggested model was solved via a multi-objective Tchebysheff decomposition-based evolutionary algorithm. The results demonstrated the efficiency of the applied methodology in obtaining high-quality solutions. The multi-objective particle swarm optimizer was used by Sadeghi et al. [16] to optimally identify the size of the microgrid's resources, such as PV, wind, and EVs. The problem was formulated to minimize the lifecycle cost of the network, which included the initial, maintenance, and replacement costs, and reduce the probability of power supply loss. An algorithm that relied on the greedy randomized adaptive search and tabu search algorithms was developed by Da Silva et al. [17] to estimate the nominal level of DGs and EVs that can be hosted in distribution networks. The results demonstrated the capability of the proposed algorithm to obtain high-quality solutions and reach high-quality solutions in a few iterations. A bi-level approach based on metaheuristics was developed by Ali et al. [18] to optimally allocate PV and wind power units considering EV parking lots in microgrids. The multi-objective anti-lion optimizer was used to formulate the proposed solving strategy. Ali et al. [19] introduced a two-layer metaheuristic algorithm based on the grey wolf optimizer to improve the hosting capacity of PV-powered plants while dealing with constraints. In addition to maximizing the PV hosting capacity, the proposed model was formulated to harmonize the use of transformers, VAr resources, and EVs. The inner level was concerned with optimizing the charging and discharging power of EVs, transformer taps, and VAr resources, while the outer level focused on maximizing PV penetration.

Aside from metaheuristics, mathematical methods have been steadily employed to solve EV-based optimization problems. What impedes the mathematical methods is that their efficiency dramatically deteriorates when they are applied to solve large-scale nonlinear problems. Many heuristic and decomposition approaches were developed in the literature to simplify the problem. In addition, diverse linearization strategies were employed to linearize nonlinear formulations. For example, Zhang et al. [20] proposed a two-stage optimization model to identify the nominal hosting capacity levels for PV units incorporating soft open points and EVs in distribution networks. The model was converted to mixed-integer second-order cone programming using a convex relaxation strategy. The column-and-constraint generation-based solving algorithm was developed to solve the problem. The suggested solving methodology achieved an acceptable relaxation gap of 0.0573%. The authors in [21] developed a heuristic approach to calculate to what extent domestic EVs can penetrate low-voltage networks, considering different scenarios for heat pump penetration. A new zonal methodology was also employed for EV optimization. The problem was formulated as a linear optimization problem and solved using the CPLEX solver within OATS optimization software.

Based on the above discussion, a hosting capacity model that combines the planning models of many infrastructures as well as provides system operators with a comprehensive view of the impacts of EV integration into emerging networks is rarely presented. Furthermore, testing and developing new solution algorithms is essential to expanding the toolbox of methods. In order to address these issues, this study presents a multi-objective planning framework for increasing the hosting capacity of EVs in power systems while maintaining the environmental requirements for realistic emerging networks. The planning model is extended to combine the planning models of PV plants, ESSs, thyristor-controlled series compensators (TCSCs), and transmission lines to improve the installation of EV charging stations. The main contributions of this paper are summarized as follows:

- This paper investigates a planning model for emerging networks to enable the increase in the use of EVs.
- A multi-objective planning approach for EV charging stations, ESSs, PV plants, TCSCs, and transmission lines is formulated. It makes it easier to determine the maximum number of EVs that can be integrated into the main grid over a day.
- Four scenarios are suggested to identify the environmental impacts of the uncounted penetration of EVs into the grid.
- The multi-objective version of the Gazelle optimization algorithm was developed to solve the proposed problem. It is an extension of the single-objective Gazelle optimization algorithm (GOA), which was first developed by Agushaka et al. [22] in 2022.
- The proposed planning model and adopted solving algorithm were tested using the realistic Egyptian West Delta Network (WDN).

The remainder of the paper is organized as follows. The problem is formulated in Section 2. The multi-objective Gazelle optimization algorithm is presented in Section 3. The simulation results are presented and discussed in Section 4. The conclusions and direction of future works are summarized in Section 5.

2. Mathematical Model

2.1. Objective Functions

The proposed problem has three objectives that are formulated as follows: The first objective (F_1) aims to maximize EVs' penetration, as demonstrated in (1). The target is to calculate to what extent the systems can host EVs, considering the worst-case scenario. This work considers EV charging scenarios (i.e., the grid-to-vehicle scenario) but ignores smart vehicles' ability to support the grid during peak hours or in contingencies (i.e., the vehicle-to-grid scenario).

$$F_1 = max\left(\sum_{h\in H}\sum_{i\in B} P_{EV}^{i,h}\right) \tag{1}$$

The EVs' hoped-for environmental benefits cannot be achieved if fossil fuel-based power plants mainly provide their charging power. Therefore, the second objective (F_2) plans to reduce the carbon dioxide emitted from fossil fuel-based generation units, as shown in (2). The objective is to control the use of EVs such that they do not lead to high carbon emissions from the generation units needed to cover this penetration. The total carbon emitted from the generation units (Car_{CO2}) is estimated by (3), where γ is expressed in ton/MWh.

$$F_2 = min(Car_{CO2}) \tag{2}$$

$$Car_{CO2} = \sum_{h\in H}\sum_{i\in B} \gamma\, P_{Th}^{i,h} \tag{3}$$

The third objective (F_3) focuses on minimizing the investment and operation costs of the devices installed, as described in (4). The first term in (4) covers the cost of the transmission lines and TCSCs required to facilitate the integration of EV charging stations into networks, as calculated in (5). While the second and third terms describe, as explained by (6) and (7), the investment and operating costs of generation stations and ESSs. Accounting for the cost of ESSs is an essential step in developing energy-saving planning strategies, which can help promote the use of ESSs in many applications [23].

$$F_3 = min\left(C^T + C^G + C^{ESS}\right) \tag{4}$$

$$C^T = \sum_{h\in H}\sum_{\substack{i,j\in B\\ i\neq j}} \frac{\lambda(1+\lambda)^y}{(1+\lambda)^y - 1}\left(\alpha_L^{ij}\left(L_{ij}^h - L_{ij}^{h-1}\right) + \alpha_{TCSC}^{i,j}\left(S_{ij}^{TCSC,h} - S_{ij}^{TCSC,h-1}\right)\right) \tag{5}$$

$$\begin{aligned} C^G = \sum_{h\in H}\sum_{i\in B} \tfrac{\lambda(1+\lambda)^y}{(1+\lambda)^y-1}\big(&\alpha_{g\_cap}^i(P_{Th}^{i,h} - P_{Th}^{i,h-1}) + \alpha_{ren\_cap}^i(P_{PV}^{i,h} - P_{PV}^{i,h-1}) \\ &+365\ \alpha_{g\_op}^i P_{Th}^{i,h} + 365\ \alpha_{ren\_op}^i P_{PV}^{i,h}\big) \end{aligned} \tag{6}$$

$$C^{ESS} = \sum_{h\in H}\sum_{i\in B} \alpha_{ESS\_cap}^h + \alpha_{ESS\_rep}^h + \alpha_{ESS\_el}^h + \alpha_{ESS\_op}^h \tag{7}$$

where $\frac{\lambda(1+\lambda)^y}{(1+\lambda)^y-1}$ is the capital recovery factor. λ and y denote the interest rate and the planning period, respectively. α_L^{ij} and $\alpha_{TCSC}^{i,j}$ are the investment cost of transmission circuits and TCSCs installed at the route *i-j*. $\alpha_{g\_cap}^i$ and $\alpha_{g\_op}^i$ are the capital and operating costs of the thermal generation unit installed at node *i*. $\alpha_{ren\_cap}^i$ and $\alpha_{ren\_op}^i$ are the capital and operating costs of the renewable units built at node *i*. $\alpha_{ESS\_cap}^h$, $\alpha_{ESS\_rep}^h$, $\alpha_{ESS\_el}^h$, and $\alpha_{ESS\_op}^h$ are the capital, replacement, end-life, and operating costs of ESSs. They are calculated as illustrated in [24].

2.2. Operational and Project Constraints

The intensive use of RESs and EVs drives power grids closer to their stability limits, making instability more likely. To safely host EVs and RESs, it is important to use a simple and accurate planning model that considers the power flow reliability and stability constraints [25,26]. The DC power flow is used in this work to formulate the constraints as explained by (8)–(21) [24,27]. Constraint (8) describes the active power flow balance formulation. It maintains the balance between the injected and absorbed nodes' powers. The total power injected into any bus should equal the active power absorbed into the same bus. Equation (9) ensures that the power flow through new and existing transmission lines and TCSCs in each scenario should not exceed the maximum thermal limits. The constraint shown in (10) controls the nodes' voltage angles within the permissible limits.

$$P_{Th}^{i,h} + P_{PV}^{i,h} - P_{d,i}^{h} - P_{ch,i}^{h} + P_{dch,i}^{h} = \sum_{\substack{i,j \in N \\ i \neq j}} P_{ij}^{h} \tag{8}$$

$$-P_{ij}^{max} \leq \frac{L_{ij}{}^{h}\left(\theta_i^s - \theta_j^s\right)}{X_L^{ij}\left(1 - \lambda_{TCSC}^{ij,h}\right)} \leq P_{ij}^{max} \tag{9}$$

$$\theta_i^{min} \leq \theta_i^h \leq \theta_i^{max} \tag{10}$$

Equations (11) and (12) govern the active power generated from PV and fossil fuel-based generation stations. The power dispatched from any generation unit should not violate the designed rating values. Additionally, ESSs are constrained by (13) and (14) to maintain charging and discharging powers less than or equal to their maximum values. The ESSs' storage capacity installed should be lower than nominal levels, as illustrated by (15).

$$P_{PV\_min}^{i} \leq P_{PV}^{i,h} \leq P_{PV\_max}^{i,h} \tag{11}$$

$$P_{Th\_min}^{i} \leq P_{Th}^{i,h} \leq P_{Th\_max}^{i} \tag{12}$$

$$0 \leq P_{dch}^{i,h} \leq P_{dch\_max}^{i,h} \tag{13}$$

$$0 \leq P_{ch}^{i,h} \leq P_{ch\_\mathrm{max}}^{i,h} \tag{14}$$

$$0 \leq E_{ESS,i}^{h} \leq E_{ESS,i}^{max} \tag{15}$$

Each storage system's maximum charging and discharging power is calculated by (16) and (17). The state of charge (SOC) of the ESS is determined by (18).

$$0 \leq P_{dch}^{i,h} \leq min\left(P_{ESS\_max}, \frac{SOC_{ESS}^{i,h} - E_{ESS\_\mathrm{max}}^{i}}{\Delta t}\right) \tag{16}$$

$$0 \leq P_{ch}^{i,h} \leq min\left(P_{ESS\_max}, \frac{E_{ESS\_\mathrm{max}}^{i} - SOC_{ESS}^{i,h}}{\Delta t}\right) \tag{17}$$

$$SOC_{ESS,i}^{h} = SOC_{ESS,i}^{h-1} + \eta_{ESS}^{ch} P_{ch,i}^{h} - \frac{P_{dch,i}^{h}}{\eta_{bat}^{dch}} \tag{18}$$

Equations (19) and (20) guarantee that the number of transmission lines and ESSs does not exceed the maximum number. They imply that projects can be built at any time to be ready for use. Equation (21) governs the size of the TCSCs installed between routes.

$$L_{ij}^{h-1} \leq L_{ij}{}^{h} \leq L_{ij}^{max} \tag{19}$$

$$N_{ESS}^{i,h-1} \leq N_{ESS}^{i,h} \leq N_{ESS\_max}^{i} \tag{20}$$

$$\lambda_{TCSC\_min}^{ij} \leq \lambda_{TCSC}^{ij,h} \leq \lambda_{TCSC\_max}^{ij} \tag{21}$$

This study adopts a scenario-based approach to formulate the model uncertainties. Realistic data for solar radiation and load consumption are used to simulate the stochastic behavior of the PV units and loads. The successive scenarios strategy is used to estimate the capacity of the ESS required accurately and the EV levels that can penetrate across all scenarios, where the problem is solved in each scenario by taking the previous scenario's ESS behavior into account to define the maximum permissible charging and discharging powers that the ESS can support regarding the grid and accommodate its function.

3. Optimization Algorithm

3.1. Gazelle Optimization Algorithm

The GOA is a population-based optimizer. It was first developed by Agushaka et al. [22] in 2022. The GOA simulates the capability of the gazelles to survive in environments where a predator dominates. Gazelles are considered one of the most common prey items for predators. Similar to any population-based algorithm, the mechanism of the GOA's operation is described in two phases—exploitation and exploration. The next phase to be conducted is identified based on a randomly generated number. If it is less than 0.5, the exploitation phase is executed; otherwise, the exploration phase is carried out. The operating mechanism of the GOA is explained in Figure 1.

The exploitation phase mimics gazelles' behavior when they graze peacefully or their behavior when the predator stalks them. In this phase, the Brownian motion, characterized by uniform and controlled steps, effectively covers the domain's neighborhood areas. The exploitation phase can be modeled as follows:

$$X^{t+1} = X^t + S \times R \times R_B \times \left(X^t_{elite} - R_B \times X^t\right) \tag{22}$$

where X^t and X^{t+1} are the gazelles' current and next positions, respectively. X^t_{elite} is a matrix in which the top gazelle vector is replicated N times. S is the gazelles' grazing speed. R_B and R are vectors that, respectively, represent random numbers for Brownian motion and random numbers in [0,1]. The exploration phase simulates the behavior of gazelles when they suddenly spot the predators and the behavior of the predators when they chase the gazelles. The population is divided into two equal groups. The first group represents gazelles, and the second group represents predators. The behavior of gazelles can be derived as follows:

$$X^{t+1} = X^t + S^{top} \times \mu \times CF \times R_B \times \left(X^t_{elite} - R_L \times X^t\right) \tag{23}$$

where S^{top} is the maximum speed that gazelles can reach, and R_L is a vector of random numbers calculated using the Lévy distribution [22]. The behavior of the predators can be formulated by:

$$X^{t+1} = X^t + S^{top} \times \mu \times R \times R_L \times \left(X^t_{elite} - R_L \times X^t\right) \tag{24}$$

where CF regulates the predators' movement, it varies at each iteration and is calculated by:

$$CF = \left(1 - \frac{t}{T}\right)^{2\frac{t}{T}} \tag{25}$$

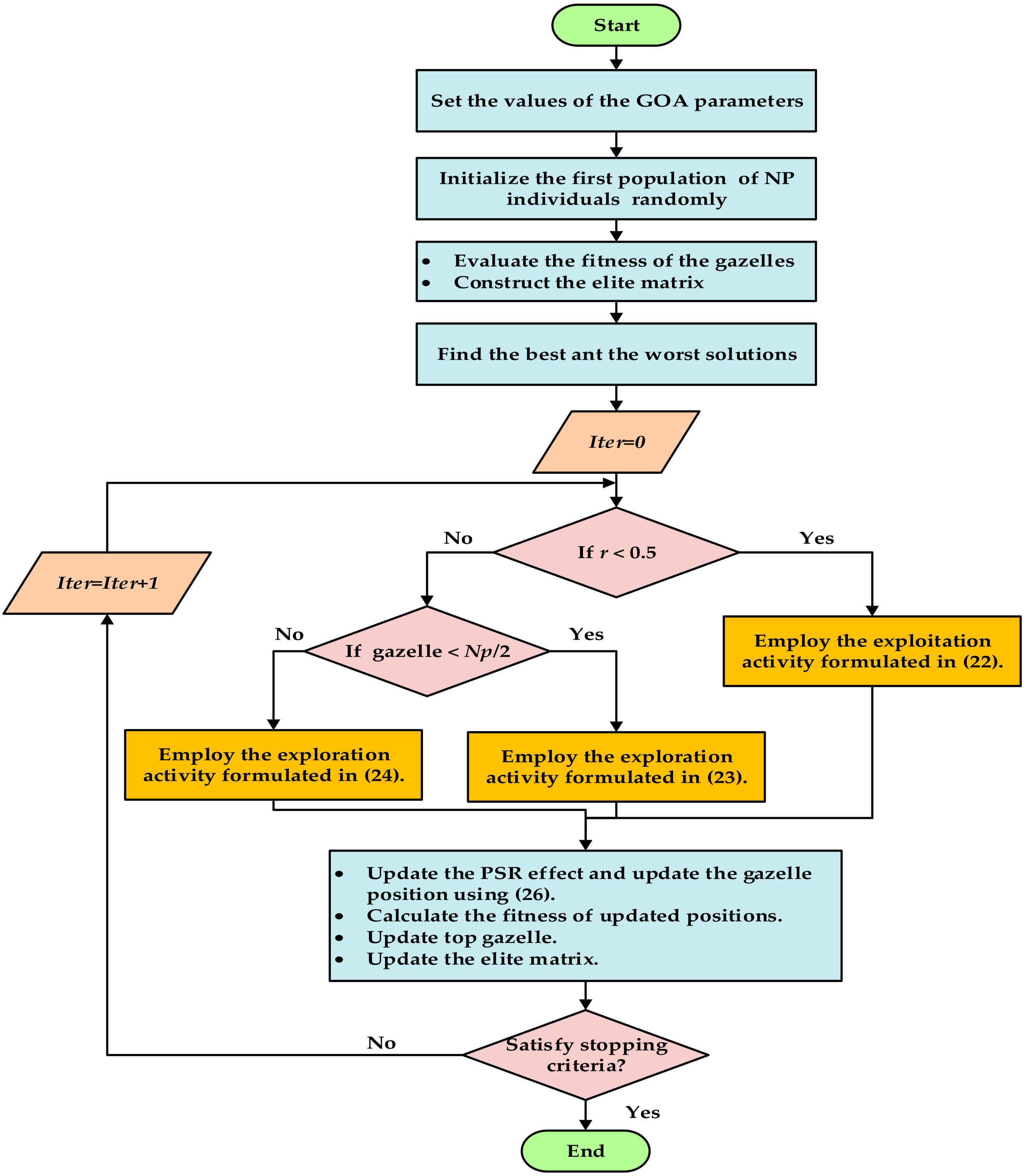


Figure 1. Flowchart of the single-objective version of the GOA [22].

In order to avoid trapping at local optima, the algorithm uses the effect of the predator success rates (*PSR*) to improve the quality of the solutions obtained as follows:

$$X^{t+1} = \begin{cases} X^t + CF \times (LB - R \times (UB - LB)) \times U, \; if \; r \leq PSR \\ X^t + (PSR(1-r) + r) \times \left(X^{r1} - X^{r2}\right), \; if \; r > PSR \end{cases} \quad (26)$$

where r_1 and r_2 are random indices of two individuals in the population. U equals 0 or 1 based on the value of r. More details about the GOA can be found in [22].

3.2. Multi-Objective Gazelle Optimization Algorithm

The current version of the GOA is not able to deal with multi-objective optimization problems. The current version only stores a single solution as the best solution. It is not able to save many solutions as the best solutions for multi-objective problems. The priori and posteriori approaches are commonly used for solving multi-objective problems [28]. Each approach has its advantages and disadvantages. In the priori approach, the multi-objective functions are converted to a single-objective function by aggregating the objectives using a set of weights that is decided based on the significance of each objective. After that, a single-objective solver can be implemented to detect the optimal solution. The posteriori method can maintain the multi-objective problem formulation, and the Pareto optimal solution can be found in a single run [18,28]. Further, its accuracy does not depend on the weights set by experts. The Pareto optimal method preserves a set of dominant solutions that can strike a balance between objectives. This work uses the Pareto optimal approach to formulate the GOA multi-objective version (MGOA). The MGOA can be summarized in Algorithm 1 as follows:

1. The population is first initialized by:

$$X = rand \times (UB - LB) + LB \tag{27}$$

2. After that, in each iteration, the gazelles' position is updated using (22)–(26).
3. A dominating formula is derived for two or more objectives, as follows. The solution X_1 dominates the solution X_2 on if

$$\forall_o \in \{1, 2, \ldots \ldots k\} : f_o(X_1) \leq f_o(X_1) \tag{28}$$

$$\exists_o \in \{1, 2, \ldots \ldots k\} : f_o(X_1) < f_o(X_1) \tag{29}$$

4. In each iteration, the non-dominated solutions are stored in a repository similar to the archives in the multi-objective particle swarm optimizer (MPSO) [29] and the multi-objective salp swarm algorithm (MSSA) [28].
5. The discovered target space is tabulated.
6. Individuals' optimal memory location is updated.
7. The members of the current population that have been dominated are added to the repository, thereby increasing its size.
8. The repository's collected members are re-checked, and the members dominated are eliminated. This level reduces the repository's population.
9. If the number of individuals exceeds the repository's maximum capacity, a portion of the population is eliminated, and the tabulation process is restarted.
10. If the termination criterion is not met, the algorithm returns to the second step and repeats the remaining steps; otherwise, the optimization process terminates.

Algorithm 1: Pseudo-code of MGOA.

Define the problem's dimension, population size (N_p), upper (UB) and lower (LB) bounds of the decision-making variables.
Set the stop criteria (T).
Set MGOA parameters.
Initialize the population (X) by (27).
Compute the cost functions, and check the problem constraints.
Assign a high penalty value to solutions that violate the constraints.
Define the top gazelle.
Construct the elite matrix.
While $(t \leq T)$
  For $i = 1$: N_p
    If $r < 0.5$
    Update the positions of the gazelles using MGOA's exploitation equation (22).
    Else
  If $i < N_p/2$
    Update the positions of the gazelles using MGOA's exploration equation (23).
  Else
    Update the positions of the gazelles using MGOA's exploration equation (24).
  End If
  End if
    Update The PSR effect and update the positions of the gazelles using (26).
  End for
      Calculate the fitness of the objective functions.
      Check the problem constraints and add a high penalty cost to the solution that violates the constraints.
      Define the non-dominant solution.
      Update the MGOA's archive.
      Update the top gazelle and the elite matrix.
End While

4. Results and Discussion

The proposed planning model and solution algorithm were applied to the Egyptian West Delta network. It is a sub-transmission network in Egypt. It has 52 buses, 8 generation units, and 55 transmission routes, each with two circuits. By 2030, it is planned to install a new generation unit at bus 53, as depicted in Figure 2, to supply loads of 2195.8 MW. The transmission and generation data are presented in [30]. This study arbitrarily suggested that the candidate locations for EV charging stations, PV systems, and ESSs were buses 10, 20, 40, and 50. Figure 3 [31,32] describes the stochastic behaviors of the PV units and load centers.

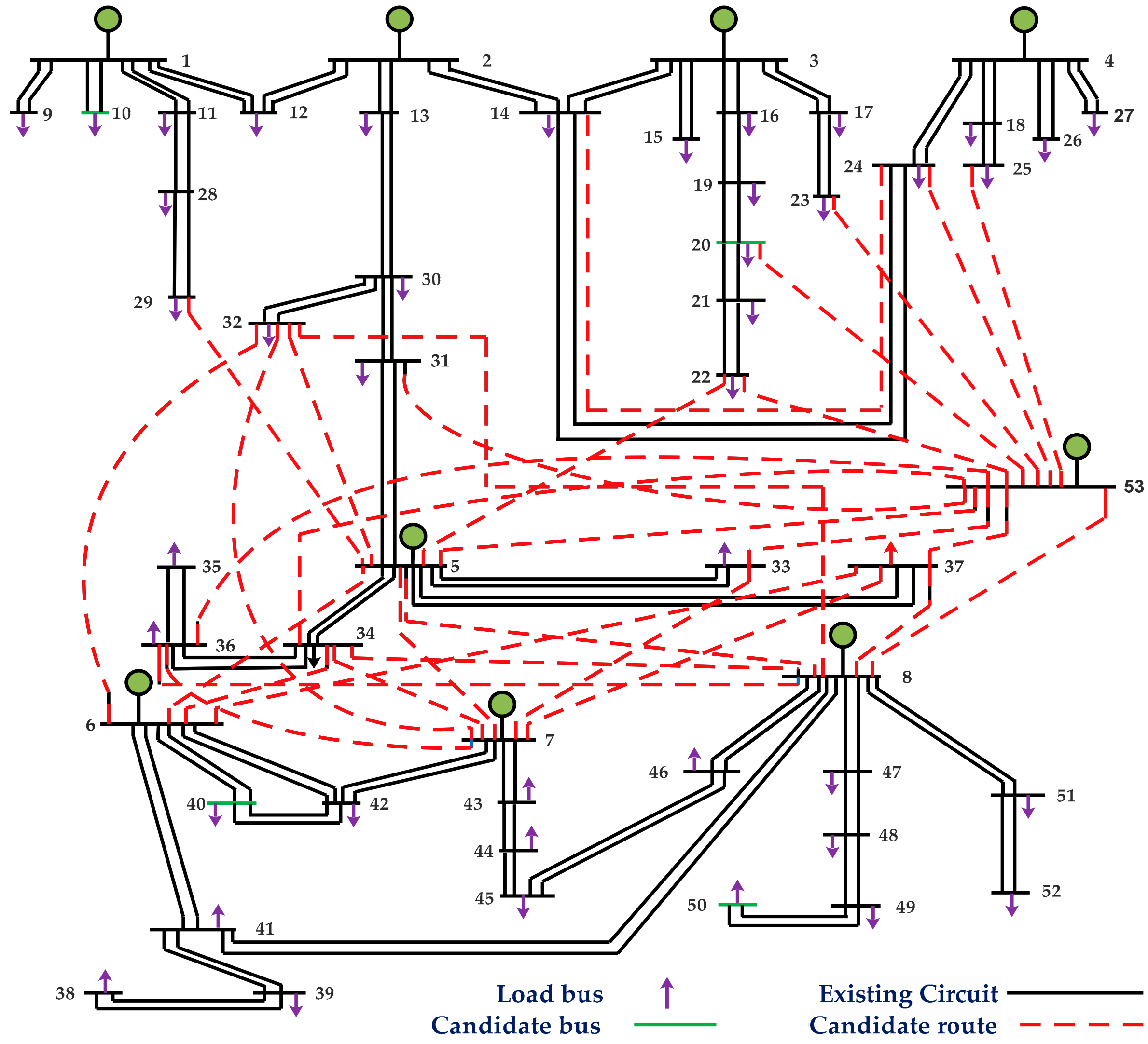


Figure 2. Initial configuration of WDN, adopted from [30].

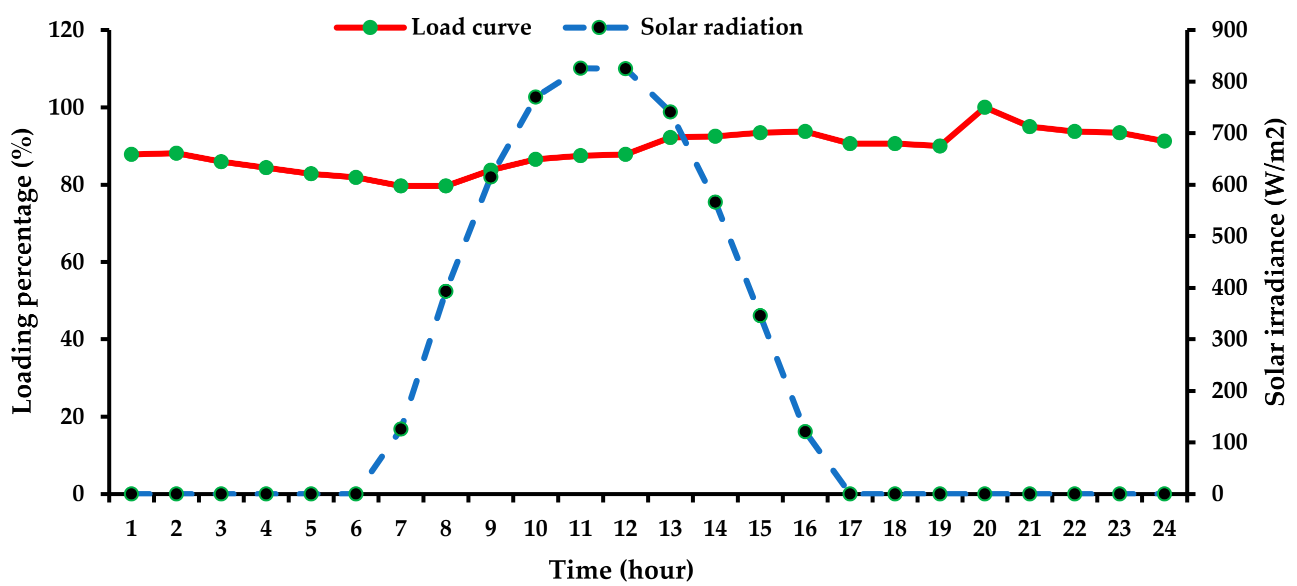


Figure 3. Solar irradiance profile and load behavior during the day.

The sodium-sulfur battery was used in this work. Its technical and economic characteristics were defined in [33]. The investment and operating costs of power plants were given in [34]. The combined cycle-generating unit was selected.

Four planning cases were executed to study the environmental and economic impacts of the integration of EV charging stations into emerging networks. The four cases are:

- Case #1: The WDN was planned to consider the environmental requirements as a priority, increasing EV penetration, and the financial requirements as second and third priorities, respectively. The ESSs were forced to charge in scenarios of high solar irradiance.
- Case #2: As in Case #1, the environmental requirements were the priority, but ESSs were not used.
- Case #3: The WDN was planned to consider the increasing EV penetration as a priority, then the environmental and economic requirements as second and third priorities, respectively. The ESSs were also forced to charge in scenarios of high solar irradiance.
- Case #4: The WDN was planned with EV penetration as a priority, like Case #3. However, the ESSs were not planned in this case.

4.1. Testing the Performance of MGOA

The efficacy of the MGOA was experimentally tested by solving a set of four benchmark-challenging test functions, named ZDT, developed by Zitzler et al. [35], in addition to the multi-objective planning problem investigated in this work. The mathematical models of the ZDT functions are given in [36].

The performance of the MGOA was compared to the multi-objective salp swarm algorithm (MSSA) [28] and the multi-objective particle swarm optimizer (MPSO) [29]. The MSSA and MOPSO are well-known algorithms in the literature for solving multi-objective optimization problems. It is worth stating that the population size is set to 200 for the ZDT functions and 40 for the planning problem. The maximum number of iterations applied in this work is 1000 for solving the ZDT functions and 500 for solving the proposed problem. The results are obtained through 30 independent runs for the ZDT functions and 20 for the proposed planning problem.

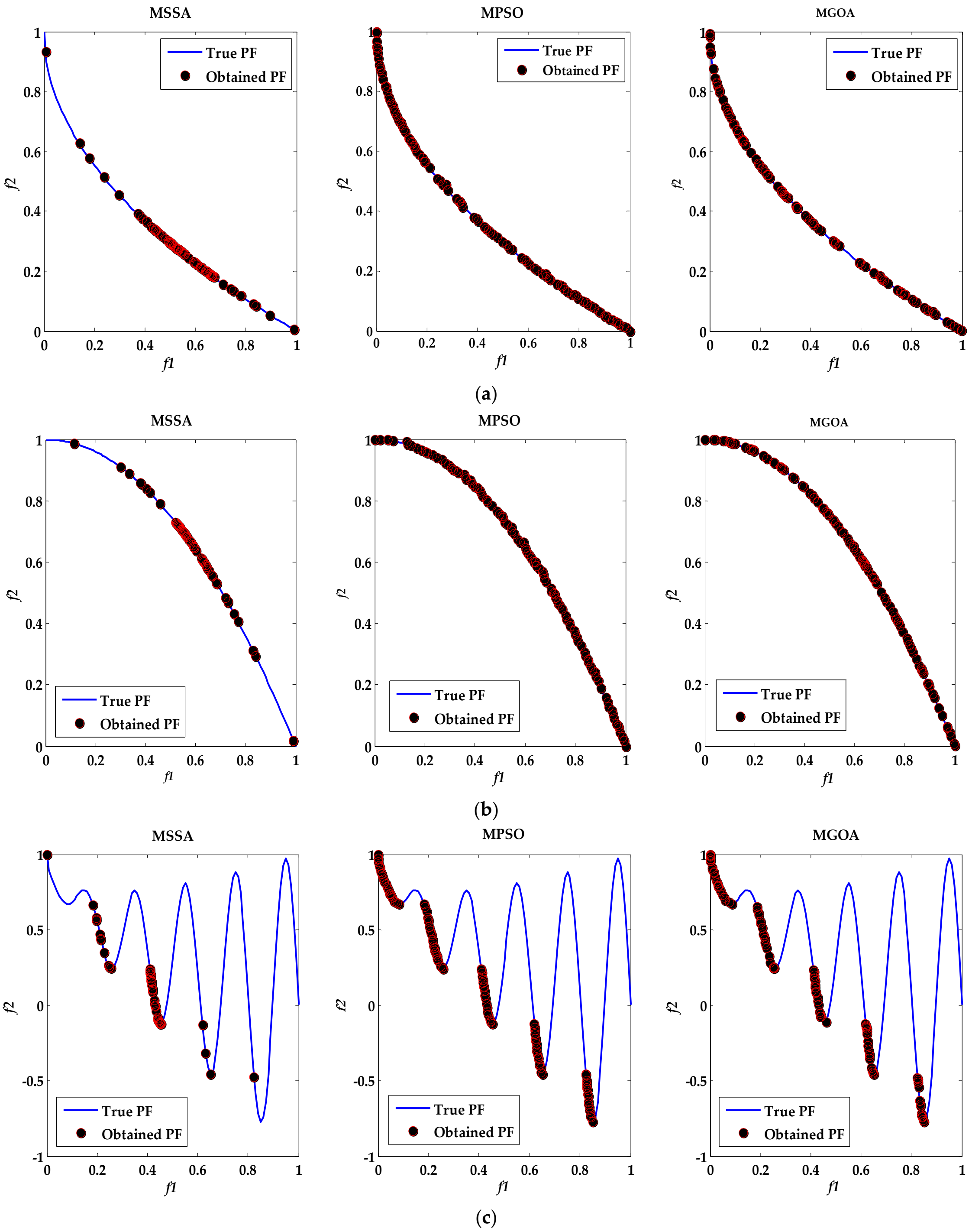
4.1.1. ZDT Test Problems

Table 1 shows that the MGOA performed better than the MSSA and MPSO on most ZDT functions. All algorithms were compared using the inverted generational distance metric (IGD) as a performance indicator. The MGOA was superior in terms of the average (*Ave*), standard deviation (*Std*), median, and best and worst solutions.

Table 1. Results of MGOA, MSSA, and MPSO for solving the ZDT test functions (using IGD).

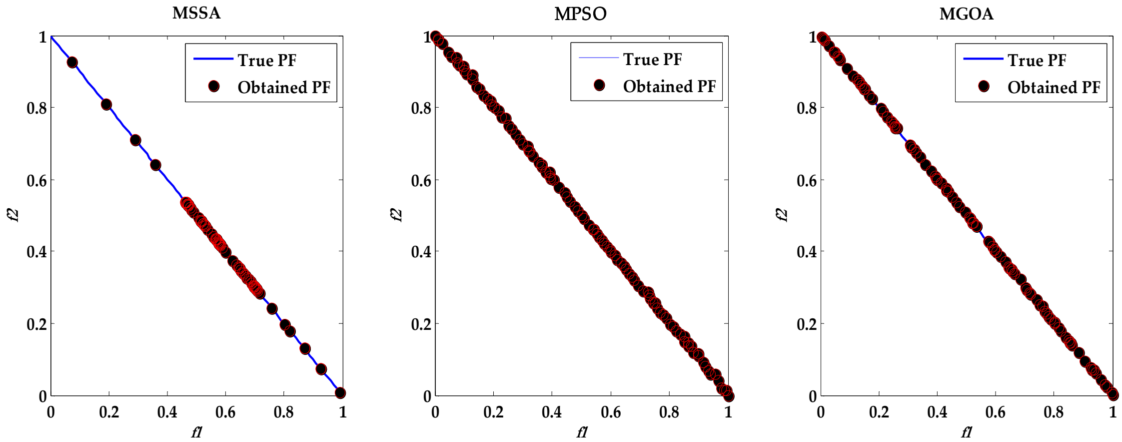
Function	Algorithm	Ave.	Std.	Median	Best	Worst
ZDT1	MGOA	0.00237	0.00060811	0.001714	0.002078	0.0031
	MSSA [28]	0.00286	0.000841427	0.0025	0.0023	0.0043
	MPSO [28]	0.00422	0.003103	0.0037	0.0015	0.0101
ZDT2	MGOA	0.00117576	0.000057544	0.00107459	0.0010384	0.0014706
	MSSA [28]	0.0037	0.00130958	0.0044	0.0015	0.0047
	MPSO [28]	0.00156	0.000174	0.0017	0.0013	0.0017
ZDT3	MGOA	0.02403	0.0007621	0.0250	0.0234	0.0298
	MSSA [28]	0.02986	0.000898888	0.0296	0.0291	0.0314
	MPSO [28]	0.03782	0.006297	0.0362	0.0308	0.0497
ZDT1 (Linear front)	MGOA	0.0024589	0.0004557	0.004532	0.001905	0.0027835
	MSSA [28]	0.0033	0.000731437	0.0034	0.0025	0.0041
	MPSO [28]	0.00922	0.005531	0.0098	0.0012	0.0165

By inspecting the set of Pareto optimal points in Figure 4, it may be determined that the solutions obtained by the MGOA were uniformly distributed and nearly similar to those obtained by the MSSA and MPSO. The results also demonstrated the MGOA's ability to approximate the true front of these functions efficiently. In all functions, the MGOA's coverage was very competitive, and its convergence was very high. Although these functions are diverse in complexity and difficulty, the MGOA succeeded in driving solutions to explore different regions of the true Pareto optimal front and avoid trapping in one region.



(a) (b) (c)

Figure 4. *Cont.*



(**d**)

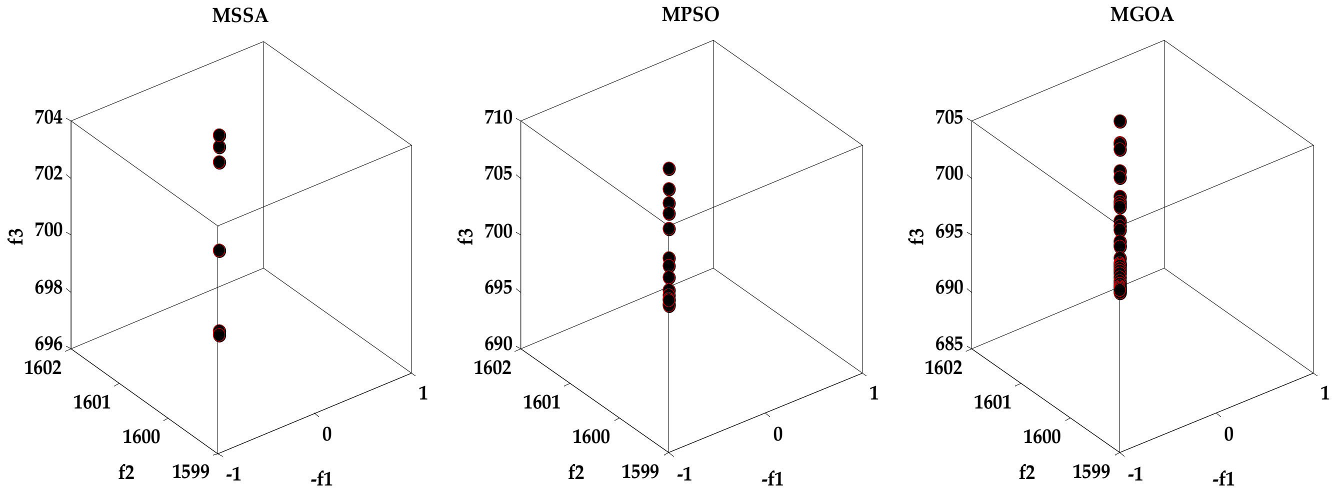
Figure 4. Best Pareto front determined by MGOA, MSSA, and MPSO on: (**a**) ZDT1, (**b**) ZDT2, (**c**) ZDT3, and (**d**) ZDT1 with a linear front.

4.1.2. Proposed Problem

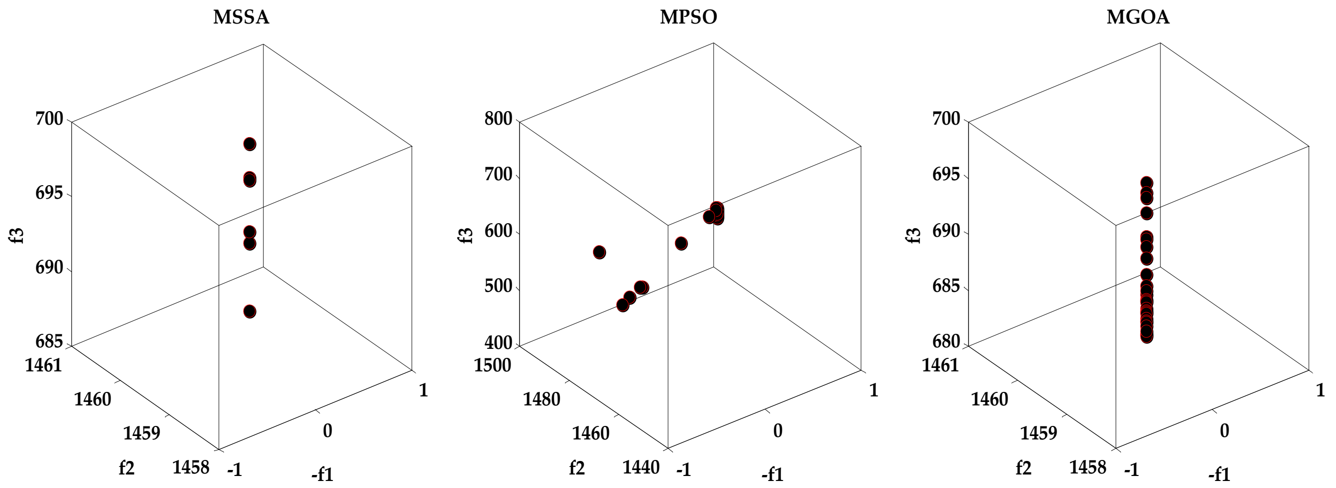
Table 2 summarizes the results obtained by the MGOA, MSSA, and MPSO when employed to solve the problem in Scenario number 7. Figure 5 depicts the dominant solutions (F1, F2, and F3) for Cases #1, #2, #3, and #4. By inspecting the results in Table 2, it can be observed that the MGOA had merits over the MSSA and MPSO in terms of robustness and obtaining high-quality solutions. The robustness of the MGOA ranged between 20 and 30%, while the MSSA and MPSO varied by about 20–25% and 15–25%, respectively.

Table 2. Results of MGOA, MSSA, and MPSO in solving the problem (Scenario number 7).

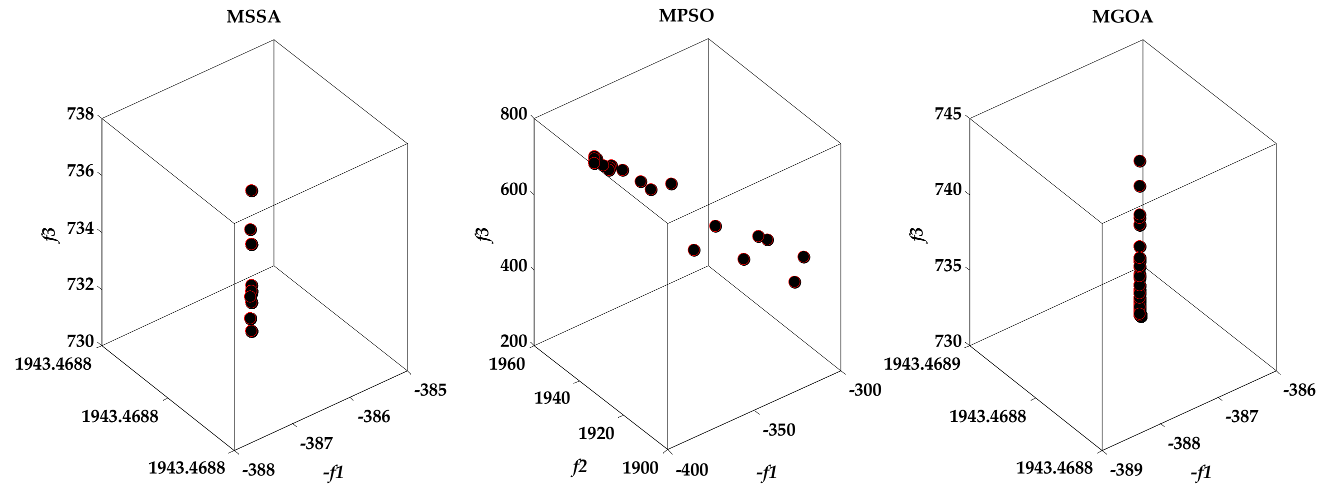
Case Number	Solver	Best Solution			Robustness	Time (s)
		- F1	F2	F3		
Case #1	GOA	0	1600.945	689.645	5	1010.47
	SSA	0	1600.945	696.366	4	641.22
	PSO	0	1600.945	693.550	5	805.03
Case #2	GOA	0	1459.345	682.454	6	1081.47
	SSA	0	1459.345	688.538	6	721.31
	PSO	0	1459.345	683.835	5	826.12
Case #3	GOA	−387.0318	1943.468	731.529	4	1017.55
	SSA	−386.862	1943.468	733.230	4	644.66
	PSO	−387.0318	1943.468	733.194	3	821.87
Case #4	GOA	−547.031	1943.468	736.929	6	1027.31
	SSA	−546.975	1943.468	742.478	5	650.26
	PSO	−547.031	1943.468	740.695	5	845.23



(**a**)

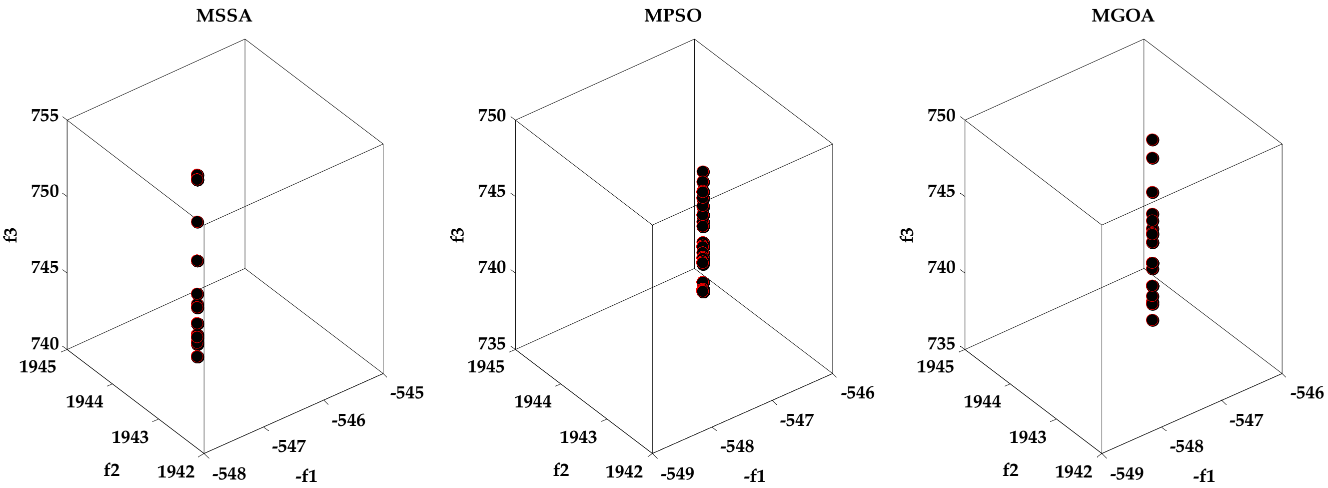


(**b**)



(**c**)

Figure 5. *Cont*.



(**d**)

Figure 5. Best Pareto front determined by MGOA, MSSA, and MPSO on: (**a**) Case #1, (**b**) Case #2, (**c**) Case #3, and (**d**) Case #4.

Moreso, Table 2 indicates that the MSSA consumed less time than the MGOA and MPSO. For example, the MSSA saved about 33.3% and 12.6% of the time required for solving Case # 2 by the MGOA and MPSO, respectively.

4.2. WDN Planning

This sub-section analyzes the impacts of different planning strategies for EV charging stations on environmental requirements and EV penetration size. As mentioned before, the network was planned in the first strategy, considering that achieving the environmental requirements was the priority through minimizing the amount of carbon emitted from fossil fuel-based units. In the second strategy, the network was planned while neglecting ESSs, with plans to discuss the technical effects of ESSs on the emission of CO_2. The WDN was planned in the third strategy, increasing EV penetration as the highest priority while still addressing environmental concerns. Finally, in the fourth strategy, the ESS planning model was ignored in order to estimate how much the use of ESSs affects the size of the EV charging stations installed. Table 3 presents the energy charged by EVs, the amount of carbon emitted, the size of the ESSs installed, and the total planning cost in each case.

Table 3. Results obtained in Cases #1,2,3, and 4.

Item	Case #1	Case #2	Case #3	Case #4
Energy charged by EVs (GWh)	0	0.005964	9.89	10.14
Carbon emission (million metric tons)	37,882.81	37,674.52	46,643.2	46,643.25
Size of ESS (MWh)	1116.4	0	1116.4	0
Total cost (million USD)	1249.7	830.71	1278.9	848.73

Figures 6 and 7 describe the amount of carbon emitted in each case. It may be observed that the general use of EVs led to high carbon emissions from the generation stations to cover this penetration, as shown in Cases #3 and #4. The network could technically accommodate the estimated size of vehicles between 9.89 and 10.14 GWh, as described in Figures 8 and 9. This size caused an increase of approximately 23% in CO_2 emitted compared to Case #1, as described in Figure 7.

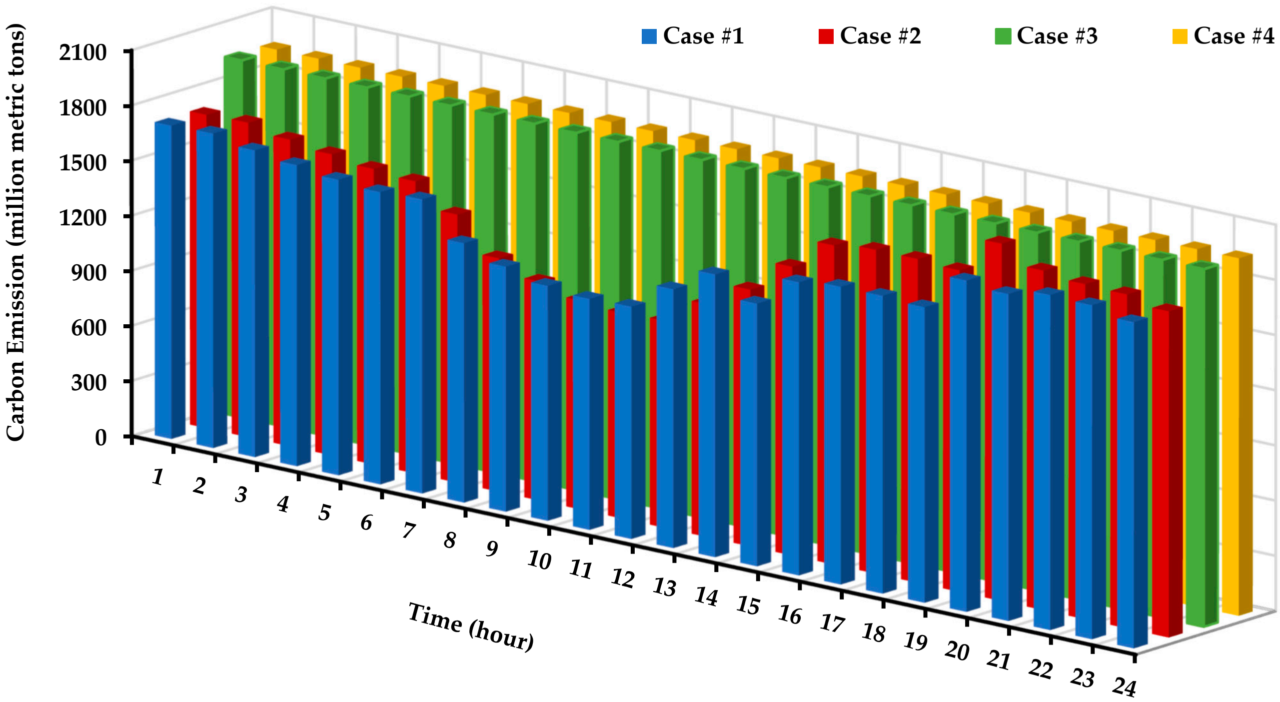


Figure 6. Carbon emissions in each case during the day.

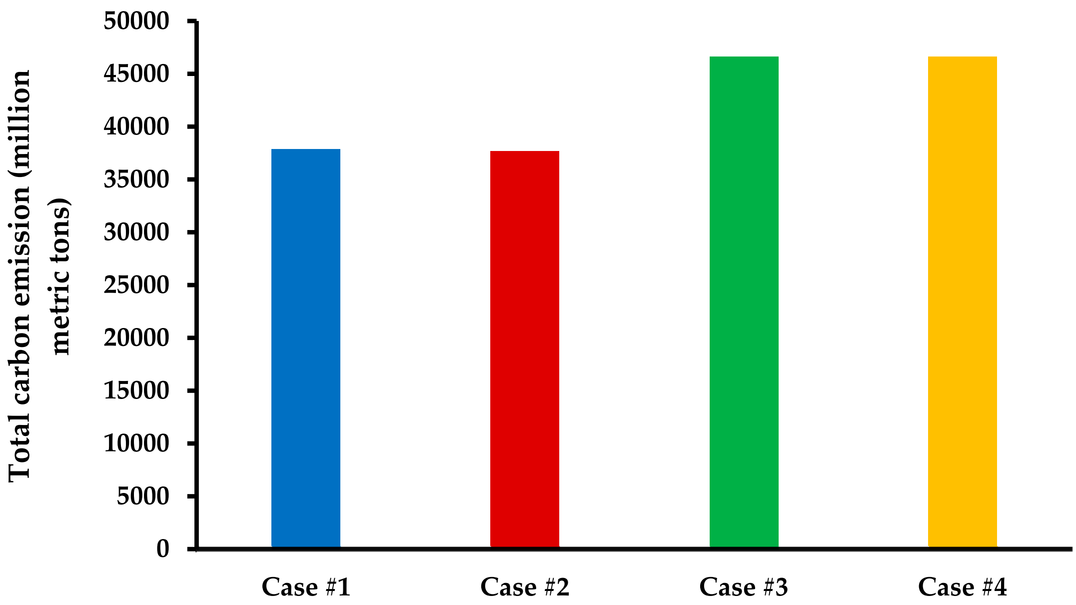


Figure 7. Comparison of total carbon emitted emissions in each case.

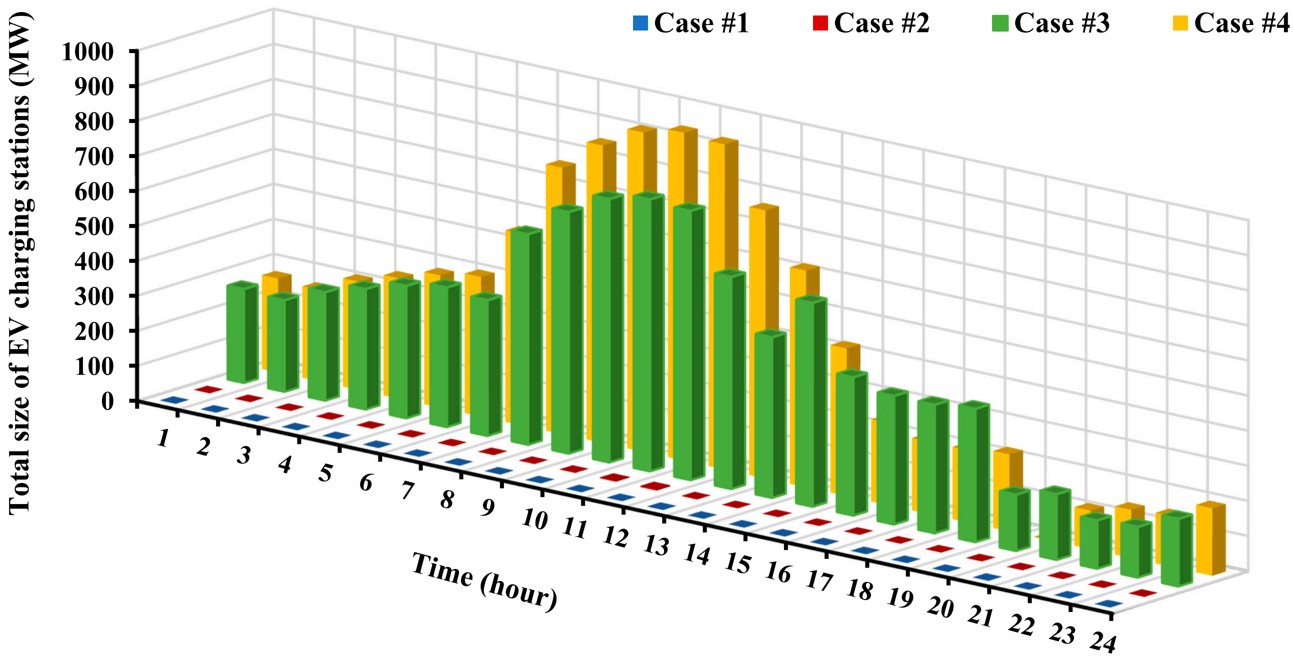


Figure 8. EV hosting capacity in each case during the day.

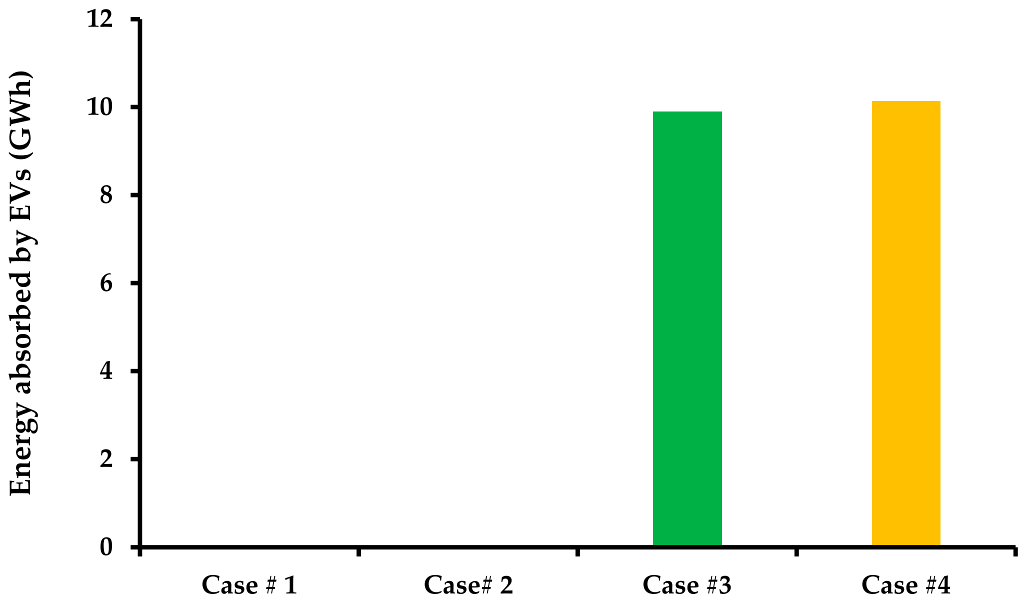


Figure 9. Comparison of the total EV hosted in each case.

In Case #1, the total amount of carbon was about 37,882.81 million metric tons and decreased to 37,674.52 million metric tons when ESSs were not planned and did not share in the power consumed by PV units. This decrease totaled about 208.29 million metric tons. This implies that, in Case #1, the ESS partially relied on fossil fuel power plants to obtain the required power for charging, which harmed the environmental conditions for which they were primarily designed. The energy dispatched from the PV units was insufficient to cover the energy required by the ESSs and loads. Load centers consume all the energy dispatched by the PV units. It can be stated that the ESS's role grows as more RES is added to the network. It is worth remarking that EVs were not allowed for integration into the network when environmental concerns were considered the priority, as illustrated in Figures 8 and 9. Adding electric vehicles would have caused an extra burden on the network. The fossil fuel power plants would have to increase their generation to compensate for this. The PV unit's output was insufficient to cover the energy required by the loads and EVs.

The results also showed that in Case #1 and Case #2, the scenarios in which carbon emissions declined were correlated with periods when solar radiation was as high as that observed in the scenario numbers 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, and 17 (see Figure 6). The mix of several renewable energy sources, which have different production profiles during the day, may positively influence low carbon emissions over the day.

When EV use was considered the priority (see Cases #3 and #4), EV penetration during the day was about 9.89 and 10.14 GWh, respectively, as depicted in Figure 9. The results also showed that the penetrating ability of EVs can be increased during periods of high solar radiation, as noticed in hours 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, and 17 (see Figure 8). In Case #3, the ESSs participated in shifting the EV charging periods away from high solar radiation scenarios by storing energy during these hours and discharging it during other hours as needed. The findings also revealed an increase in carbon emissions due to an increase in the EV hosting capacity. An increase of about 8760.4 million metric tons was calculated in Case #3 compared to Case #1. As a result, any increase in EV hosting capacity should be accompanied by an increase in RES to avoid reliance on fossil fuels to compensate for this increase.

Figure 10 depicts the planning cost for each case. The planning costs in each case were about USD 1249.7, 830.71, 1278.9, and 848.73 million, respectively. It can be noticed that the ESS planning cost constituted a large portion of the planning cost, as illustrated in Cases #2 and 4. A reduction of about 33.5% in the planning cost was observed due to the non-use of ESSs.

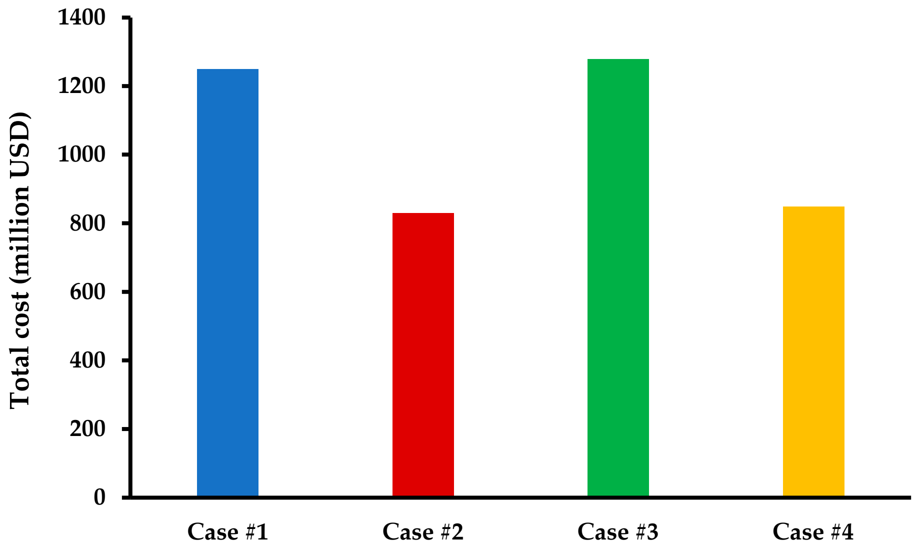


Figure 10. Comparison of the total planning cost in each case.

5. Conclusions

The integration of EVs into power networks commonly affects the network's reliability and operation. Furthermore, if widely adopted, the uncounted use of EVs may negatively impact the environmental requirements and result in high carbon emissions from power plants to cover this penetration. In this work, a planning strategy that safely increases the use of EVs while considering the environmental and technical requirements was developed. The proposed strategy was formulated as an optimization problem with the three objectives of improving the EV host's capacity, reducing carbon dioxide emissions, and decreasing the investment and operating costs of the devices installed. The planning models of RESs, ESSs, TCSCs, and transmission lines were combined into the EV charging station planning model to optimally facilitate EVs' integration from an environmental and technical point of view. The problem was a challenging multi-objective optimization problem. In order to solve it, the multi-objective version of the GOA was derived. Four case studies were carried out on the Egyptian West Delta Network to demonstrate the efficiency of the suggested model. In the first case, achieving the environmental requirements was the first priority, regardless of the EV penetration levels. In the second case, the network was planned while neglecting the ESSs, with plans to discuss the technical effects of the ESSs on the emission of CO_2. The Egyptian West Delta Network was planned in the third case, while increasing EV penetration was the highest priority. Finally, in the fourth case, the ESS planning model was ignored in order to estimate how much the use of ESSs affects the size of the EV charging stations installed. The main findings of this work can be summarized as follows:

- The MGOA was superior in comparison with the MSSA and MPSO in most of the ZDT functions investigated.
- The MGOA outperformed the MSSA and MPSO in terms of robustness and obtaining high-quality solutions when applied to solve the proposed problem. The robustness of the MGOA was about 20–30%, while the MSSA and MPSO were about 20–25% and 15–25%, respectively.
- The MSSA was faster than the MGOA and MPSO in solving the proposed problem. Approximately 12.6–36.7% of the time executed was saved by the MSSA.
- The results demonstrated that the scenarios in which carbon emissions declined were correlated with periods when solar radiation was high.
- According to the case studies, the simulations indicated a 23.2–23.8% increase in carbon emissions due to the widespread use of EVs.
- The total amount of carbon emitted decreased by about 208.29 million metric tons when the ESSs were not planned and did not share in the power consumed by the PV units. The ESS's role rises as more RESs are added to the network.

One point that was out of the scope of this study was the investigation of the impact of reliability constraints, such as the *N*-1 security and short-circuit current requirements, on the penetration of EV charging stations. Moreover, further work is needed to consider the ESSs' degradation in grid-connected operation and their effects on the hosting capacity levels of EVs and RES. The EV's behavior is stochastic; therefore, more analysis is required to investigate their consequences on networks' steady-state and transient stability.

Author Contributions: H.Y.A., M.M.R. and S.H.E.A.A. designed the problem under study; Z.M.A. and M.M.R. performed the simulations and obtained the results; H.Y.A. and Z.M.A. analyzed the obtained results; M.M.R. and S.H.E.A.A. wrote the paper, which was further reviewed by H.Y.A. and Z.M.A. All authors have read and agreed to the published version of the manuscript.

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Nomenclature

DGs	Distributed generators
ESS	Energy storage system
EV	Electric vehicle
GOA	Gazelle optimization algorithm
MGOA	Multi-objective Gazelle optimization algorithm
MPSO	Multi-objective particle swarm optimizer
MSSA	Multi-objective salp swarm algorithm
NaS	Sodium-sulfur battery
PV	Photovoltaic
SOC	State of charge
RESs	Renewable and sustainable energy sources
TCSC	Thyristor-controlled series compensator
WDN	Egyptian West Delta Network
Data and Indices	
$h \in H$	Index and set for scenarios
$i \in B$	Index and set for buses
C^T, C^G, C^{ESS}	Total cost of transmission projects, generation units, and energy storage systems
$L_{ij}^h - L_{ij}^{h-1}$	Total number of circuits exists between buses i and j at scenario h
$N_{ESS}^{i,h}, N_{ESS\_max}^i$	Number of batteries installed at scenario h and maximum number of batteries can be installed at bus i
$P_{EV}^{i,h}$	Estimated EV power at scenario h and bus i
$P_{Th}^{i,h}, P_{PV}^{i,h}$	Output active power in MW of the thermal unit and PV unit, respectively at scenario h and bus i
$P_{d,i}^h$	Active power consumed by the load at bus i (MW)
$P_{ch,i}^h, P_{dch,i}^h$	Charging and discharging active power of batteries at bus i (MW)
$P^{bat,r}$	Rated power of the selected ESS
P_{ij}^h	Active power flow in a route between bus i and j (MVA)
P_{ij}^{max}	Maximum rated of power flow in a route between bus i and j (MW)
$SOC_{ESS,i}^h$	SOC of ESS at bus i and scenario h
θ_i^h	Voltage angle at bus i (p.u)
y	Planning period
$\eta_{bat}^{ch}, \eta_{bat}^{dch}$	Charging and discharging efficiencies of ESS
$\alpha_L^{ij}, \alpha_{TCSC}^{i,j}$	Cost of circuits and TCSC device installed between bus i and bus j
$\alpha_{ren\_cap}^i, \alpha_{ren\_op}^i$	Capital and operating costs of RES installed at bus i
$\alpha_{g\_cap}^i, \alpha_{g\_op}^i$	Capital and operating costs of a fossil fuel-based generation unit installed at bus i
$\alpha_{ESS_{cap}}^h, \alpha_{ESS_{rep}}^h, \alpha_{ESS_{el}}^h, \alpha_{ESS\_op}^h$	Capital cost, replacement cost, end-life cost, and the operating cost of ESSs at bus i
β_{ij}	Susceptance of the route between bus i and j
λ	Interest rate

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