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Optimised Allocation of Distributed Generation and Electric Vehicles Integration in Microgrids: A Multi-Criteria Approach

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ABSTRACT

This paper presents the allocation and planning of renewable distributed generations such as wind turbines and photovoltaic systems, and non-renewable generators such as fuel cells in the microgrids that incorporate electric vehicle parking lots while considering financial, operational and voltage stability goals. The proposal is modelled in the form of a bi-objective optimisation problem. One of the objective functions minimises the distributed generators' planning cost and the microgrid's operational cost, while the other function maximises the microgrid's voltage stability index. The optimisation problem is solved, satisfying technical constraints of power flow, network operational, and voltage stability limits while incorporating the models of the electric vehicles parking lots and distributed resources. The ε-constraint-based Pareto optimisation solution is used to determine a single-objective formulation in the next step. Then, a fuzzy decision-making tool derives a compromise solution. Finally, the Crow Search algorithm finds a trustable optimal solution to the problem. The performance of the proposal is validated on a standard microgrid network using numerical analyses and shows that the proposal can effectively determine the optimal economic conditions.

1 | Introduction

In addition to environmental benefits, compared to traditional natural fossil resources, distributed generation units (DGs) have various benefits from the perspective of customer's, electricity distribution network operators, and commercial power plants [1–3]. Due to their high capital costs, their number is still low in power systems but gradually increasing thanks to governmental subsidies. Microgrids are suitable platforms to proliferate the presence of different types of small-scale DGs in the form of various technologies such as photovoltaics systems (PVs), wind turbines (WTs), and fuel cells (FCs). To maximise the capabilities of these resources for improving the network indices, their proper and optimal placement in the microgrid is a critical challenge to be addressed [4]. In addition, not only should the placement of DGs not adversely affect the microgrid's operational conditions, but it should also result in a reduced cost of energy for customers and more desirable technical indices [5].

Planning of DGs has been widely addressed in the literature. Reference [6] introduces a multi-objective method to obtain the optimal location and capacity of multiple DGs considering various load models. Specifying the penetration level of DGs while considering voltage constraints is investigated in

[7, 8]. Recently, evolutionary and non-gradient based optimisation techniques such as genetic algorithm, ant colony and particle swarm optimisation have been adopted to solve such problems [9–11]. Some studies have focused on demonstrating that DG placement can improve various operational conditions, e.g., [12] shows that DGs improve the problem of voltage drop, while [13] shows the improvement of the harmonics. Reference [14] presents a review of the methods used in designing multi-objective approaches for the placement of DGs and discusses the issues, future perspectives, and recent progress. In [15], DGs' optimal sizing and placement are formulated as a constraint, and a non-separable and multi-objective optimisation is proposed using the conventional dual method. In this method, harmonic distortion is also included in the objective functions. On the other hand, [16, 17] reduce the cost of DGs along with voltage drop and network line losses. To enhance the reliability and operating indicators of distribution networks, [18] suggests a hybrid planning approach that combines DG planning with distribution automation that incorporates automated voltage-var control in addition to automatically dealing with the faults. In [19], a complete-information dynamic game-based bi-level synchronised planning of DGs and soft open points is suggested to balance the needs of DG investors, network operators, and end-users while allowing for dynamic power adjustments between feeders. Reference [20] introduces an integrated and centralised objective function for DG planning in a regulated electricity system to determine the best mix of the power plant and DG growth for reducing decision-period costs associated with generating expansion, maintenance, fuel, emissions, distribution losses, and predicted energy not provided. DG placement, along with optimal placement, sizing, and management of battery energy storage systems is presented in [21] in the form of a mixed-integer non-linear programming model. Reference [22] takes on a crucial task- exploring the optimal placement of renewable distributed generators such as solar photovoltaics, wind turbines and electric vehicles (EVs) into the radial distribution system. This is a strategic move aimed at minimising power loss and improving the voltage profile and stability index. In [23], a combined approach based on voltage stability index and the Marine predators algorithm is proposed to solve the problem of DGs, shunt capacitors and EVs allocation in the distribution system. Reference [24] proposes an effective approach to solve renewable distributed generators and EV parking lots (EVPL) allocation problems in the distribution system to reduce power loss and enhance voltage profile.

The above literature review demonstrates that the majority of research works have focused on the economic aspects. Yet, a wide variety of technical measures need to be addressed in microgrids. In addition, there are different types of DG, but most studies have considered one or two of them when planning DGs. Therefore, in this study, the optimal allocation of FCs, PVs and WTs is focused on considering not only the economic goals but also voltage stability and operational conditions. The proposal consists of two objective functions of: (1) minimising the overall costs of planning DGs and the operating cost of MG; (2) maximising voltage stability index subject to constraints of optimal power flow, the planning-operation model of distributed generation, and EVPL the model. The ε-constraint-based Pareto optimisation method is used to formulate a single-objective, integrated problem. Then, a fuzzy decision-making approach is adopted to extract a compromise solution. Finally, the Crow search algorithm (CSA) is used to determine a reliable optimal solution.

In summary, the main innovations and contributions of this work to the research field can be summarised as:

- Developing a comprehensive multi-objective optimisation framework for simultaneously planning various types of DGs (FCs, PVs, and WTs) within a microgrid incorporating EVPL.
- Formulating a novel integrated model that concurrently accounts for economic, operational, and voltage stability measures, providing a holistic approach to DG and microgrid planning,
- Deploying a CSA to extract a reliable optimal solution for the above problem.

The remainder of the paper is organised as follows: The proposal is introduced in Section 2 and its simplification and solution are discussed in detail. Then, Section 4 evaluates the performance of the proposal and reports the findings of various study cases. Section 4 discusses the superiority of the proposal using a numerical case study against three other approaches. Finally, the key findings of the research are summarised and highlighted in the last Section.

2 | The Proposal

This section introduces the formulated problem in the form of a multi-objective problem and then elaborates on how this multi-objective problem is transformed into a single-objective problem and how it is solved later.

2.1 | Formulated Problem

The proposal is to define the optimal placement of FCs, PVs and WTs with an aim to realise the minimum planning cost and maximum voltage stability index while satisfying the microgrid's optimal power flow, voltage stability and DGs' planning-operational constraints. Therefore, this model is formulated as:

$$\begin{aligned} \min \quad & f_1 = Cost = \sum_{n\in\Omega_n} C_n^{W} w_n + \sum_{n\in\Omega_n} C_n^{PV} pv_n \\ & + \sum_{n\in\Omega_n} C_n^{FC} fc_n + \sum_{t\in\varphi_t} 365 \times \lambda_t \times P_{ref,t}^{G} \\ \min \quad & f_2 = SI = -\sum_{t\in\Omega_t} WSI_{wb,t} \end{aligned} \tag{1}$$

Subject to:

$$P_{n,t}^{G} + P_{n,t}^{W} + P_{n,t}^{PV} + P_{n,t}^{FC} + \sum_{j\in\Omega_n} A_{n,j} P_{n,j,t}^{L} = P_{n,t}^{D} + P_{n,t}^{EV} \qquad \forall n,t \tag{2}$$

$$Q_{n,t}^{G} + \sum_{j\in\Omega_n} A_{n,j} Q_{n,j,t}^{L} = Q_{n,t}^{D} \qquad \forall n,t \tag{3}$$

$$P_{n,j,t}^{L} = g_{n,j}\left(V_{n,t}\right)^2 - V_{n,t}V_{j,t}\left\{g_{n,j}\cos(\theta_{n,t} - \theta_{j,t})\right.$$

$$+ b_{n,j} \sin(\theta_{n,t} - \theta_{j,t})\} \quad \forall n, j, t \tag{4}$$

$$Q^L_{n,j,t} = -b_{n,j}\left(V_{n,t}\right)^2 + V_{n,t}V_{j,t}\left\{b_{n,j}\cos(\theta_{n,t} - \theta_{j,t})\right.$$
$$\left. - g_{n,j}\sin(\theta_{n,t} - \theta_{j,t})\right\} \quad \forall n, j, t \tag{5}$$

$$\theta_{n,t} = 0 \quad \forall n = ref, t \tag{6}$$

$$\left(P^L_{n,j,t}\right)^2 + \left(Q^L_{n,j,t}\right)^2 \le \left(SL^{\max}_{n,j}\right)^2 \quad \forall n, j, t \tag{7}$$

$$V^{\min}_n \le V_{n,t} \le V^{\max}_n \quad \forall n, t \tag{8}$$

$$\left(P^G_{n,t}\right)^2 + \left(Q^G_{n,t}\right)^2 \le \left(SG^{\max}_n\right)^2 \quad \forall n, t \tag{9}$$

$$\begin{aligned} WSI_{wb,t} &= \left(V_{wb-1,t}\right)^4 - 4\left(V_{wb-1,t}\right)^2\left\{R_{wb-1,wb}\left(P^D_{wb,t} + P^{EV}_{wb,t} - P^W_{wb,t} - P^{PV}_{wb,t} - P^{FC}_{wb,t}\right) + X_{wb-1,wb}Q^D_{wb,t}\right\} \\ &\quad - 4\left\{\left(X_{wb-1,wb}\left(P^D_{wb,t} + P^{EV}_{wb,t} - P^W_{wb,t} - P^{PV}_{wb,t} - P^{FC}_{wb,t}\right) - R_{wb-1,wb}Q^D_{wb,t}\right)^2\right\} \end{aligned} \tag{10}$$

$$WSI_{wb,t} \ge WSI^{\min}_{wb} \tag{11}$$

$$P^W_{n,t} \le S^{w,\max}_{n,t} w_n \quad \forall n, t \tag{12}$$

$$P^{PV}_{n,t} \le S^{pv,\max}_{n,t} pv_n \quad \forall n, t \tag{13}$$

$$P^{FC}_{n,t} \le S^{fc,\max}_n fc_n \quad \forall n, t \tag{14}$$

$$0 \le P^{EV}_{n,t} \le CR_{n,t} \quad \forall n, t \tag{15}$$

$$\sum_{t \in \Omega_t} \eta^{EV} P^{EV}_{n,t} = EC_n \quad \forall n \tag{16}$$

Equation (1) introduces two objective functions: one attempting to minimise the annual capital cost of DGs along with the annual cost of the microgrid's energy fed from the upstream grid, while the other attempts to minimise the microgrid's voltage stability margin index. The voltage stability index varies between zero (denoting voltage collapse) and one (denoting voltage stability), considering the worst stability index (WSI) [25].

Equation (2)-(6) show, respectively, the balance of active and reactive power, line active power, line reactive power and the voltage angle of the reference bus, which are repeated for each scenario [26, 27]. It is to be noted that P^G and Q^G are the distribution substation powers located in the reference bus (*ref*). Therefore, the mentioned terms in the rest of the buses will be 0 because other buses are free of distribution substations. Also, according to the IEEE1547 standard, the main task of DG is assumed as energy generation [18], and thus, its ancillary services, such as reactive power injection, are not considered in the proposal.

The constraints of the microgrid's indices, such as line power limits, bus voltage, and distribution substation capacity, are given by Equations (7) to (9), respectively [28–31]. Specifically, Equations (7) and (9) represent the thermal limits of lines and substations, while Equation (8) relates to the allowable voltage limits, addressing both overloading and underloading conditions (i.e., injecting more power than is permitted) [32–35]. Additionally, the WSI is given by Equation (10) and must satisfy the constraint defined in Equation (11). Furthermore, Equations (12) to (14) represent the constraints on power generation for wind turbines (WT) [36–38], photovoltaic systems (PV) [39–41], and fuel cells (FC). The binary decision variable "w" in these constraints indicates whether the construction of DG units (PV or FC) is cost-effective and beneficial for improving voltage stability and microgrid indices. If "w" equals one, the DG is installed and operational, whereas if "w" equals zero, it is not included in the solution.

The EVPL model is employed in Equation (2) and the charge rate limit [42–45] of EVs in EVPL is given by Equation (15), while the energy consumption model of EVPL is presented in Equation (16). The number of EVs per operation hour varies. Therefore, the charging rate is assumed to be time dependent. *CR* at each time is equal to the charge rate of all EVs that are connected to the network and *EC* is equal to the energy consumption of all EVs in the operation horizon [46–49].

2.2 | Integrated Problem Model

The transformation from the multi-objective problem of Equation (1) to a single-objective model can be realised using the Pareto optimisation. The ε-constraint-based Pareto optimisation [50] has been utilised in this paper, in which the objective function of the single-objective problem equals one of the objective functions of the multi-objective problem, while the rest of the functions appear as constraints of the single-objective problem. These objective functions as a constraint enter the single objective problem, and its maximum value is ε. In this case, the proposed problem can be transformed into an integrated problem in the form of:

$$\min \quad f_1 = Cost \tag{17}$$

subject to constraints (2)-(16) and:

$$f_2 = SI \le \varepsilon \tag{18}$$

Based on the above problem, the investment cost (*Cost*) and the voltage stability index (*SI*) are considered the objective function and constraint, respectively. Based on Equations (17) to (18), f_2 is limited by ε and changes from f_2^{min} to f_2^{max}. Therefore, by changing ε, the modified single-objective optimisation problem can be solved to obtain an optimal point. In solving the optimisation problem, inequality constraints must be respected to ensure feasible solutions. To handle these constraints, a penalty function is introduced. The penalty function penalises any violation of the inequality constraints, ensuring that the optimisation process focuses on feasible solutions. This function is integrated into the objective function and is expressed by $\mu \times \max(0, a-b)$; where $a \le b$ is the constraint, and $\mu \ge 0$ is the Lagrangian multiplier.

Finally, the set of all solutions found for ε values (from f_2^{min} to f_2^{max}) is called the Pareto front, from which the best solution should be obtained. To this end, a fuzzy decision-making approach has been adopted that determines the interaction point among various functions, i.e., it extracts a point from Pareto front points, defined as the compromise point. A fuzzy membership function in the range of [0, 1] is dedicated to individual solutions in the Pareto front. Different methods can be used to present the membership function, but the most convenient and conventional method is incorporating linear fuzzy membership function in the form of

$$\hat{f} = \begin{cases} 1 & f \leq f^{\min} \\ \dfrac{f - f^{\max}}{f^{\min} - f^{\max}} & f^{\min} \leq f \leq f^{\max} \\ 0 & f \geq f^{\max} \end{cases} \tag{19}$$

Then, a min-max method can be used to determine the best compromise solution as follows [50]:

1. Calculating membership functions for various objective functions from Equation (19)
2. Calculating the minimum membership values amongst the objective functions. To put it simpler, in this section, $\min(\hat{f}_1, \hat{f}_2)$ for two objective functions f_1 and f_2 in the proposed problem are calculated.
3. The maximum value from the membership values calculated in step 2 is determined. It should be noted that the solution corresponding to this step will be equal to the compromise point between the objective functions.

2.3 | Solving the Problem

Because the presented problem is a mixed-integer non-linear problem, this work uses CSA to solve it. This novel algorithm, developed in 2016 [51], has a short computation time and produces reliable results with a low standard deviation. Algorithm 1 shows the steps of the CSA.

As the penalty function [52], where it equals μ.max (0, a—b) for restrictions $a \leq b$. $\mu \geq 0$ is the Lagrangian multiplier, and the inequality constraints are integrated into the objective function to address the stated issues. The CSA then calculates the best possible values for the decision variables wt, pv, fc, P^W, P^{PV}, P^{EV} and P^{FC} given the set of {0, 1}, {0, 1}, {0, 1}, and the constraints (12)–(15) and μ. The following phase involves solving the power flow model using the forward-backwards approach [53], with the remaining variables being calculated using equality constraints. In the end, the objective function and the penalty function are merged to establish a fitness function, which depends on the values of the individual variables.

ALGORITHM 1 | Crow search algorithm (CSA).

1) Establishing the parameters that may be altered, including the total number of birds in the flock (N), the maximum number of iterations ($iter_{max}$), the awareness probability (AP), and the duration of the flight (fl).
2) Get the initial location via random and the crows' memory.
3) Assessing the objective function depending on the date of step 2.
4) Update the crows' positions

```
for iteration = 1: iter_max
  for i = 1: N
    Choose one of the crows randomly (such as j)
    Determine the random value (0,1) for j-th crow, i.e. r_j.
    if r_j ≥ AP
      position (i, iteration + 1) = position(i, iteration)
      + r_j × fl × {memory(i, iteration)—position(i,
      iteration)}
      Evaluate the feasibility of all crows' positions.
    else
      position (i, iteration + 1) = a random value for a
      position between the minimum and maximum.
    end
  end
  Calculate the value of the objective function using
  the current position.
  Update the crows' memory.
  if fitness (position(i, iteration + 1)) surpasses
    fitness (position(i, iteration))
  memory (i, iteration + 1) = position (i, iteration + 1)
  else
    memory (i, iteration + 1) = memory (i, iteration)
  end
end
```

3 | Performance Evaluation

In general, the proposed scheme has no limitations for implementation on different data of networks, resources, and EVs. To evaluate the performance of the proposal, it is applied to a test microgrid system with an IEEE standard 33-bus radial distribution network, and a single-line diagram as shown in Figure 1. This MG has 32 lines and 32 load points, with the network lines and load values given in [53]. The base voltage and power are assumed to be 12.66 kV and 1 MW, and the voltage fluctuations are in the range of 0.95-1.05 pu [54–56]. The demand in the rest of the period equals the multiplication of peak load and load coefficient curve [57–61]. This curve is given in Figure 2 [3]. WT, PV and FC are the assumed three types of DGs used here, with specifications as stated in Table 1. The produced power by WT and PVs are assumed to be dependent on wind speed and solar irradiation [62–66], and thus, their output power generation curve is time dependent, with the daily curve given in Figure 2 [8]. Therefore, terms $S^{w,max}$ and $S^{pv,max}$ vary with time and are obtained by the multiplication of these curves and the rated DGs'

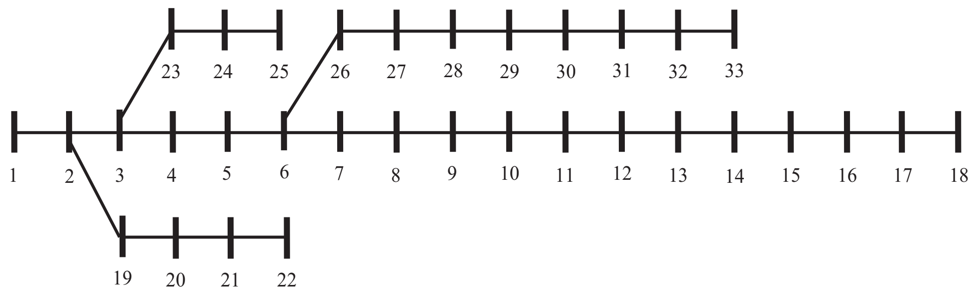

FIGURE 1 | Considered IEEE 33-bus distribution system [35] as the network for the testbed microgrid in this study.

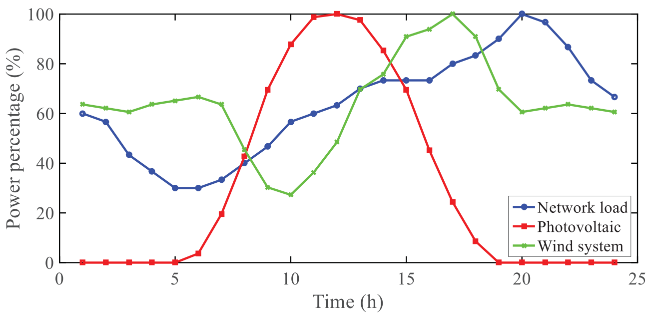

FIGURE 2 | Assumed daily curve of load factor and power generation rate of PV and WT [3, 67–69] in this study.

TABLE 1 | Assumed specifications of DGs in this study.

DG	Capacity (MW)	Investment cost ($/MW/year)
WT	0.5	23,200
PV	0.5	29,000
FC	0.5	22,000

capacities. The output of the FC is assumed to be constant with respect to time, therefore, $S^{fc,max}$ is constant. According to [25], the minimum allowed WSI is 0.8. Also, the number of population (N) and replication ($iter_{max}$) for CSA are assumed respectively as 80 and 3000, while the other parameters of CSA, such as awareness probability (AP) and the duration of the flight (fl) are considered respectively as 0.1 and 2, according to [51]. The reported parameter values for CSA were obtained by trial and error such that the best solution was obtained in a reasonable computational time. For example, N was initially assumed to be 50, then its value was increased by increments of 5. For values greater than 80, the results were almost the same, but the computational time increased. Therefore, N was set to 80. The energy transaction prices in the intervals of [1:00-7:00], [8:00-16:00, 23:00-24:00] and [17:00-22:00] are assumed respectively to be 16, 24 and $30/MWh [3]. The data of EVs, including EVs number in each bus and time, total number of EVs in each EVPL, charge rate, EV efficiency, EVs type and energy consumption of EVs, are taken from [3, 25]. The proposal is realised in MATLAB 2015b, and then different case studies were developed to evaluate its performance, as discussed below.

TABLE 2 | Optimal site and size of DGs for case study-1.

DG type	Buses	Size (MW) in each location
FC	16, 28	0.5, 0.5
WT	18, 25	0.38, 0.5
PV	33	0.30

3.1 | Evaluating the Results of Different Objective Functions

Several case studies were evaluated, three of which are introduced and discussed below:

- Case study-1: Finding the least total investment and energy costs
- Case study-2: Maximising the voltage stability index
- Case study-3: Finding the least total investment and energy costs while maximising voltage stability index

3.1.1 | Case Study-1

Let us assume that the proposed problem has a single-objective structure, which finds the minimum total investment and energy costs. Therefore, Equations (1) to (14) model the problem, but f_2 function is removed from Equation (1). Moreover, Equation (2) to Equation (6) express power distribution equations, and since the microgrid has a radial structure, the backwards-forward load flow technique [13] is used to solve the power flow problem. Table 2 lists the planning results of this case and shows that the DGs are generally placed in the buses at the end of the feeder because of the larger voltage drop (i.e., less than 0.95 pu) at feeder end nodes [7]. Therefore, DG is placed in these buses to enhance the voltage of all buses above 0.95 pu

Figure 3 shows the microgrid's operation indices before and after DG placement in case study-1 and illustrates the voltage profile at peak period (20:00, as shown in Figure 2), the daily curve of the substation apparent power, and the daily curve of the microgrid power loss. As seen from this figure, the microgrid operational indices are improved largely with the optimal placement of DGs. Based on Figure 3a, the least voltage is 0.97 pu but 0.91 pu before the DG placement, denoting that it has been improved by

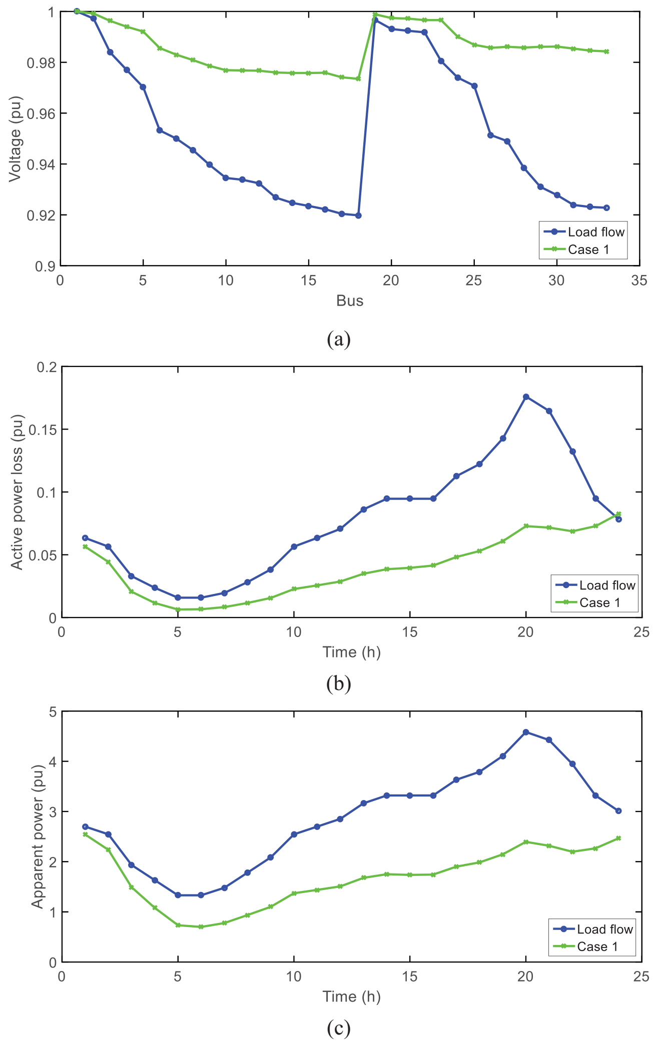

FIGURE 3 | MG performance indices, a) MG voltage profile at 20:00, daily curve of active MG losses, c) daily curve of distribution substation apparent power.

6.6%. Also, as per Figure 3b, the microgrid line losses reduce by the optimal placement of DGs. For example, the highest power loss before DG placement is 0.18 pu, while it reduces to 0.13 pu after DG placement in case study-1, denoting a decrease of 27.8%. Based on Figure 3c, with optimal planning of DGs, the power demand from the upstream network has decreased. The maximum amount of apparent power before DG placement is 4.6 pu, which reduces to 2.5 pu after DG placement in case study-1, denoting a decrease of 46.7%.

TABLE 3 | Optimal site and size of DGs for case study-2.

DG type	Buses	Size (MW) in each location
FC	16, 28, 30	0.5, 0.5, 0.5
WT	15, 18, 25	0.38, 0.5, 0.5
PV	17, 33	0.30, 0.35

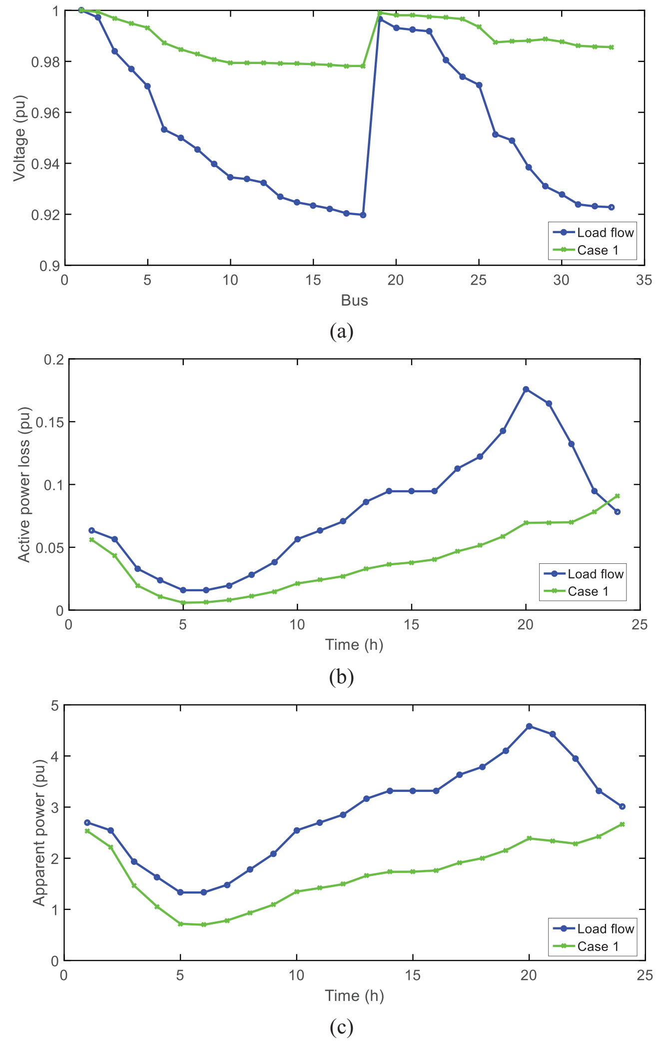

FIGURE 4 | Operation indices in the second case, a) voltage profile at 20:00, daily curve of active losses, c) daily curve of apparent power of the distribution substation.

3.1.2 | Case Study-2

Here, function f_2 is the objective function, so in Equations (1)-(14), and f_1 is removed from Equation (1). The results of optimal placement and capacity of DGs are listed in Table 3. It can be seen that this study has the same results as case study-1 and the DGs are placed again in the buses at the end of the feeder. But in this case study, a larger number of DGs are selected than in case study-1 because the voltage stability should be optimal. This index improves when the power demand from the upstream network decreases, therefore, more DGs are installed. The microgrid operation indices before and after case study-2 are depicted by Figure 4. The lowest voltage is 0.975 pu after DG placement, so it improves by 7.2%. The power loss is also 0.12 pu at the peak load hour, so it decreases by 33.3% by DG placement. Finally, the apparent power at 20:00 is 2.2 pu, so it decreases by 51.2% by the DG placement. The reason for the higher percentage improvement of the operation indices in case study-2 compared to case study-1 is the larger number of DGs in this case.

TABLE 4 | Evaluation of different variables of the proposed problem for rate of increase = 0.

Objective function	Case study-1	Case study-2
Planning cost ($/year)—$f_1$	345,260	633,840
Voltage stability index—f_2	23.7821	23.8493

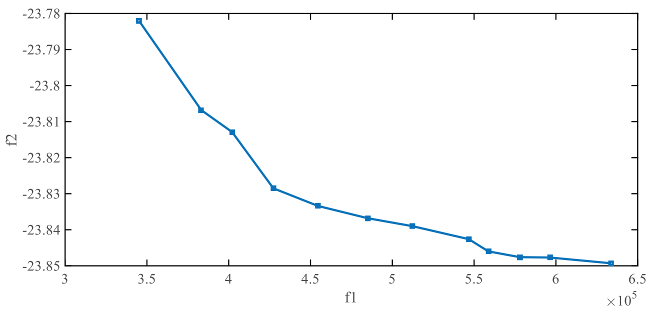

FIGURE 5 | Pareto front of the proposed model for case study-3 for rate of increase = 0.

3.1.3 | Case Study-3

To reach the compromise solution, the minimum and maximum values of f_1 and f_2 need to be acquired simultaneously. Table 4 lists the minimum and maximum functions derived from the first and second cases and shows that the minimum and maximum planning costs (f_1) are identical to the overall cost of investment and energy (i.e., 345,260 and 633,840$/year, respectively). These values are equal to the voltage stability index (f_1) 23.7821 and 23.8493, respectively. So, the ranges of f_1 and f_2 changes are 288580 and 0.0672$/year, respectively. Figure 5 depicts the Pareto front of the proposal for this case study and shows that the changes in the two programming cost functions and the voltage stability index are not in the same direction. So, if f_2 decreases, the planning cost increases. Comparing Tables 2 and 3 shows that more resources are needed to boost the voltage stability index, thus increasing the planning cost. Table 5 lists the results after the fuzzy decision-making approach is used to determine the compromise point and shows that the value of the mentioned objective functions at the compromise point is close to its optimal value, as such, the voltage stability index is 34.2% away from its optimal (maximum) value. Also, the planning cost is 32.4% away from its optimal (minimum) value. Table 5 reports the sensitivity of the voltage security index and planning cost for different energy prices, loads, construction costs and capacities of DGs. According to this table, the increasing load and construction cost of DGs lead to a high increase in planning cost, while the increase in the other parameters results in a slight increase in the planning cost. The increase in load, construction cost of DGs and capacity of DGs decreases the voltage security index, each with different impact levels. The increase in load highly reduces the voltage security indexs while the increase in the construction cost of DGs has a slighter impact. The energy price increase also has a very small effect on the voltage security index. Table 6 shows the planning results of DG at the compromise point. Similar to Table 2 and 3,

TABLE 5 | Sensitivity analysis and compromise point of the proposed problem for different levels of load, energy price, DG capacity and cost.

Parameter	Rate of increase (%)	Voltage stability index	Planning cost ($/year)
Load	0	23.8470	438,730
	10	23.2571	475,330
	20	22.7061	511,410
Energy price	0	23.8470	438,730
	10	23.8470	440,211
	20	23.8470	442,022
DG capacity	0	23.8470	438,730
	10	23.8720	441,030
	20	23.8910	444,100
DG investment cost	0	23.8470	438,730
	10	23.8119	469,120
	20	23.7803	505,010

TABLE 6 | Optimal site and size of DGs for the third case for rate of increase = 0.

DG type	Buses	Size (MW) in each location
FC	16, 28, 30	0.5, 0.5, 0.5
WT	18, 25	0.5, 0.5
PV	33	0.35

TABLE 7 | Evaluation of different variables of the proposed problem in different cases for rate of increase = 0.

Variable	Case study-1	Case study-2	Case study-3
Planning cost ($/year)	345260	633840	438730
Voltage stability index	23.7821	23.8493	23.8470
Energy loss (pu)	1.116	1.023	1.062
Maximum voltage deviation	0.0254	0.024	0.0245

DGs are installed in the buses at the end of the feeder, but in this case, their number is between the numbers given by case study-1 and 2. Table 7 also reports the values of different parameters for different case studies, where the highest value of operating indices is in case study-1, and the least value is in case study-2. But the opposite is valid for the DGs' planning cost. As such, case study-3 is a compromise between the previous two cases.

TABLE 8 | Comparative analysis results.

Algorithm	CSA of the proposal	Grey Wolf optimisation	Krill Herd optimisation	Particle swarm optimisation
Computation time (s)	216	291	378	463
Mean value of planning cost ($/year)	438,730	442,370	446,710	455,511
Mean value of voltage stability index	23.8470	23.8390	23.8311	23.8208
Standard deviation of planning cost (%)	0.94	1.12	1.74	2.98
Standard deviation of voltage stability index (%)	0.97	1.15	1.78	3.04

Based on Equations (2) and (12)-(14), while the nominal capacity (maximum power) produced by the resources is fixed, their produced active power can change over time. However, since the operating cost of these resources is lower than the operating cost of the network, they generally inject a power equal to their maximum capacity into the network. Also, in this study, the cost of energy exchange between the distribution network and the upstream network is considered. In this paper, based on Equation (1), it is assumed that the distribution network receives energy from the upstream network at a certain price at each operating hour.

4 | Comparative Analysis

To evaluate the superiority of the proposal, its performance is compared against three solvers of Krill Herd Optimisation [70], Particle Swarm Optimisation [52], Grey Wolf Optimisation [71] and CSA. The size of the population and the maximum iteration of convergence for these solvers are, respectively, 80 and 3000. The remaining parameters of the algorithms are extracted from [51, 52, 70, 71]. To compute statistical measures such as mean and standard deviation of the optimal solution, each solver is re-run 30 times for the same numerical problem of case study-3. The convergence results of these algorithms are reported in Table 8. As seen from this table, the CSA solver used in the proposal finds the most optimal point with a shorter period than the other solvers. Additionally, the standard deviation of objective functions in the CSA solver is lower than in other solvers; thus, the dispersion in the ultimate solution is the least.

5 | Conclusion

A multi-objective is formulated to determine the optimal sitting and sizing of FCs, PVs and WTs within microgrids to reduce energy costs and increase system stability. The first objective function minimises the planning cost (sum of investment and energy costs), and the second function maximises the voltage stability index while satisfying the technical and operational constraints of the network, EVPL and DGs. An ε-constraint-based Pareto optimisation is developed to convert the formulated problem into a single-objective problem, which is then solved using the CSA solver. The interaction point between two objective functions was derived by fuzzy decision-making. Through numerical analyses, the study demonstrated that the proposal improves the voltage profile of the microgrid and reduces its maximum voltage deviation, power loss, and the energy transaction with the upstream network by optimising the placement and capacity of DGs and optimal operation of the EVPL. The study verified that the increase in investment cost corresponds to the improvement of the microgrid's voltage stability index. The studies also showed that the used CSA solver can effectively obtain the optimal solution at the least computation time compared to three other evolutionary algorithms. Additionally, numerical analyses over the considered sample test system demonstrated that the proposal determines the best compromise point between the two contradicting cost and technical objective functions.

The key limitation of the proposal is assuming an AC microgrid in the studies of this paper. However, considering global transportation and electrification trends, DC or hybrid AC/DC microgrids are also emerging, which need more detailed analysis. In addition, since the proposed plan considers the presence of renewable resources with uncertain generations, the need for stochastic or robust modelling of the proposed plan can be evaluated. Furthermore, the formulated objective problem for DGs' proper siting can be expanded to also enhance the network's reliability and resiliency. These can be future research topics in line with this research.

Nomenclature

n	Bus index
j	Bus index
ref	Reference bus
Ω_n	Set of buses
Ω_t	Set of time
$wb\text{-}1$	The bus to which the *wb* bus is connected
wb	The bus with worse voltage stability
t	Time index

Variables

f_1	Objective function related to the total annual investment and energy costs in $
f_2	Objective function related to voltage stability
Cost	Total annual investment and energy costs in $
SI	Voltage stability
P^{EV}	Active power of EVs in per-unit (pu)
P^{G}	Active power of distribution substation in pu
P^{L}	Distribution line active power (pu)
P^{W}	Active power of the WT unit (pu)
P^{PV}	Active power of the solar PV unit (pu)
P^{FC}	Active power of the FC (pu)
Q^{G}	Reactive power of distribution substation (pu)
Q^{L}	Reactive power of distribution line (pu)
WSI	Voltage stability margin index
W	Binary variable of wind unit construction
Pv	Binary variable of PV unit construction
Fc	FC binary variable
V	Voltage range (pu)
θ	Voltage angle in radians

Parameters

C^{W}	Annual cost of wind unit construction ($/year)
C^{PV}	Cost of PV unit construction ($/year)
C^{FC}	Cost of FC construction ($/year)
CR	Charge rate of EVs (pu)
EC	Energy consumption of EVs (pu)
A	Auxiliary matrix ($A_{n,j}$ is one in the case buses n and j are connected via a line, otherwise, it is zero)
g, *b*.	Conductivity and susceptance of the line (pu)
P^{D}.	Active load (pu)
Q^{D}	Reactive load (pu)
SL^{max}	Line capacity (pu)
SG^{max}	Distribution substation capacity (pu)
V^{max}.	Maximum voltage magnitude (pu)
V^{min}.	Minimum voltage magnitude (pu)
R	Line resistance (pu)
X.	Line reactance (pu)
$S^{w,max}$.	Maximum active power of WT (pu)
$S^{pv,max}$.	Maximum active power of PV (pu)
$S^{fc,max}$.	Maximum active power of FC (pu)
η^{EV}	Efficiency of EVs

Author Contributions

Mehdi Veisi: conceptualisation, data curation, formal analysis, methodology, software, validation, writing – original draft. **Daniel Sahebi:** data curation, funding acquisition, methodology, resources, validation, visualisation, writing – review and editing. **Mazaher Karimi:** funding acquisition, investigation, methodology, project administration, resources, supervision, visualisation, writing – original draft, writing – review and editing. **Farhad Shahnia:** conceptualisation, formal analysis, investigation, project administration, validation, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interests.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author.

References

1. L. Bagherzadeh, H. Shayeghi, S. Pirouzi, M. Shafie-khah, and J. P. S. Catalão, "Coordinated Flexible Energy and Self-Healing Management According to the Multi-Agent System-Based Restoration Scheme in Active Distribution Network," *IET Renewable Power Generation* 15, no. 8 (2021): 1765–1777.

2. M. Norouzi, J. Aghaei, and S. Pirouzi, "Enhancing Distribution Network Indices Using Electric Spring Under Renewable Generation Permission," in *2019 International Conference on Smart Energy Systems and Technologies (SEST)* (IEEE, 2019), 1–6.

3. H. Kiani, K. Hesami, A. Azarhooshang, S. Pirouzi, and S. Safaee, "Adaptive Robust Operation of the Active Distribution Network Including Renewable and Flexible Sources," *Sustainable Energy, Grids and Networks* 26 (2021): 100476.

4. E. Faraji, A. Abbasi, S. Nejatian, M. Zadehbagheri, and H. Parvin, "Probabilistic Planning of the Active and Reactive Power Sources Constrained to Securable-Reliable Operation in Reconfigurable Smart Distribution Networks," *Electric Power Systems Research* 199 (2021): 107457.

5. A. Shahbazi, J. Aghaei, S. Pirouzi, et al., "Holistic Approach to Resilient Electrical Energy Distribution Network Planning," *International Journal of Electrical Power & Energy Systems* 132 (2021): 107212.

6. A. El-Zonkoly, "Optimal Placement of Multi-Distributed Generation Units Including Different Load Models Using Particle Swarm Optimization," *IET Generation, Transmission and Distribution* 12, no. 3 (2011): 760–771.

7. H. Ayres, W. Freitas, M. De Almeida, and L. Da Silva, "Method for Determining the Maximum Allowable Penetration Level of Distributed Generation Without Steady-State Voltage Violations," *IET Generation, Transmission and Distribution* 14, no. 5 (2014): 495–508.

8. P. Chen, R. Salcedo, Q. Zhu, et al., "Analysis of Voltage Profile Problems Due to the Penetration of Distributed Generation in Low-Voltage Secondary Distribution Networks," *IEEE Transactions on Power Delivery* 8, no. 1 (2012): 2020–2028.

9. R. Singh and S. Goswami, "A Genetic Algorithm Based Approach for Optimal Allocation of Distributed Generations in Power Systems for Voltage Sensitive Loads," *ARPN Journal of Engineering and Applied Sciences* 25 (2009): 78–87.

10. F. Abu-Mouti and M. El-Hawary, "Optimal Distributed Generation Allocation and Sizing in Distribution Systems via Artificial Bee Colony Algorithm," *IEEE Transactions on Power Delivery* 17, no. 11 (2011): 2090–2101.

11. A. Aref, M. Davoudi, A. Seifi, I. Ganjkhany, and M. Davoudi, "Particle Swarm Optimization Based Method for Optimal Placement and Estimation of DG Capacity in Distribution Networks," *International Journal of Science & Technology* 31 (2012): 486–491.

12. O. Ipinnimo, S. Chowdhury, and J. Mitra, "Intelligent Voltage Dip Detection in Power Networks With Distributed Generation (DG)," in *North American Power Symposium (NAPS)* (IEEE, 2012), 1–6.

13. A. Abdolabadi and H. R. Najafi, "A New Islanding Scheme Based On Multi-Objective Optimization for Distribution Systems Implemented With DGs," in *Electrical Engineering (ICEE), 2017 Iranian Conference on* (IEEE, 2017), 1278–1283.

14. A. Alarcon-Rodriguez, G. Ault, and S. Galloway, "Multi-Objective Planning of Distributed Energy Resources: A Review of the State-of-the-Art," *Renewable Sustainable Energy Rev* 14 (2010): 1353–1366.

15. O. Erdinc, A. Tascikaraoglu, N. G. Paterakis, I. Dursun, M. C. Sinim, and J. P. S. Catala, "Comprehensive Optimization Model for Sizing and Siting of DG Units, EV Charging Stations and Energy Storage Systems," *IEEE Transactions on Smart Grid* 12, no. 2 (2017): 1–12.

16. S. Biswas, S. Goswami, and A. Chatterjee, "Optimum Distributed Generation Placement With Voltage Sag Effect Minimization," *Energy Conversion and Management* 12 (2012): 163–174.

17. S. Biswas and S. Goswami, "Genetic Algorithm Based Optimal Placement of Distributed Generation Reducing Loss and Improving Voltage Sag Performance," in *Proceedings of the International Conference on Advances in Electrical & Electronics*, The Institute of Doctors Engineers and Scientists (IDES), (2010), 49–51.

18. S. Pirouzi, M. Zaghian, J. Aghaei, et al., "Hybrid Planning of Distributed Generation and Distribution Automation to Improve Reliability and Operation Indices," *International Journal of Electrical Power & Energy Systems* 135 (2022): 107540.

19. Y. He, H. Wu, R. Bi, et al., "Coordinated Planning of Distributed Generation and Soft Open Points in Active Distribution Network Based on Complete Information Dynamic Game," *International Journal of Electrical Power & Energy Systems* 138 (2022): 107953.

20. H. Abushamah, M. Haghifam, and T. Bolandi, "A Novel Approach for Distributed Generation Expansion Planning Considering Its Added Value Compared With Centralized Generation Expansion," *Sustainable Energy, Grids and Networks* 25 (2021): 100417.

21. A. Valencia, R. Hincapie, and R. Gallego, "Optimal Location, Selection, and Operation of Battery Energy Storage Systems and Renewable Distributed Generation in Medium–Low Voltage Distribution Networks," *Journal of Energy Storage* 34 (2021): 102158.

22. R. Zangmo, S. K. Sudabattula, S. Mishra, et al., "Optimal Placement of Renewable Distributed Generators and Electric Vehicles Using Multi-Population Evolution Whale Optimization Algorithm," *Scientific Reports* 14, no. 1 (2024): 28447.

23. N. Dharavat, S. K. Sudabattula, and V. Suresh, "Optimal Integration of Distributed Generators (DGs) Shunt Capacitors (SCs) and Electric Vehicles (EVs) in a Distribution System (DS) Using Marine Predator Algorithm," *International Journal of Renewable Energy Research (IJRER)* 12 (2022): 1805–1818.

24. N. Dharavat, S. K. Sudabattula, S. Velamuri, et al., "Optimal Allocation of Renewable Distributed Generators and Electric Vehicles in a Distribution System Using the Political Optimization Algorithm," *Energies* 15, no. 18 (2022): 6698.

25. S. Pirouzi and J. Aghaei, "Mathematical Modeling of Electric Vehicles Contributions in Voltage Security of Smart Distribution Networks," *Simulation* 95, no. 5 (2019): 429–439.

26. Y. Su, J. Teh, and C. Chen, "Optimal Dispatching for AC/DC Hybrid Distribution Systems With Electric Vehicles: Application of Cloud-Edge-Device Cooperation," *IEEE Transactions on Intelligent Transportation Systems* 23 (2023): 1–12.

27. Y. Su, J. Teh, and W. Liu, "Hierarchical and Distributed Energy Management Framework for AC/DC Hybrid Distribution Systems With Massive Dispatchable Resources," *Electric Power Systems Research* 225 (2023): 109856.

28. W. Jiang, X. Wang, H. Huang, D. Zhang, and N. Ghadimi, "Optimal Economic Scheduling of Microgrids Considering Renewable Energy Sources Based on Energy Hub Model Using Demand Response and Improved Water Wave Optimization Algorithm," *Journal of Energy Storage* 55 (2022): 105311.

29. M. Dehghani, M. Ghiasi, T. Niknam, et al., "Blockchain-Based Securing of Data Exchange in a Power Transmission System Considering Congestion Management and Social Welfare," *Sustainability* 13, no. 1 (2020): 90.

30. L. Chen, H. Huang, P. Tang, D. Yao, H. Yang, and N. Ghadimi, "Optimal Modeling of Combined Cooling, Heating, and Power Systems Using Developed African Vulture Optimization: A Case Study in Watersport Complex," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* 44, no. 2 (2022): 4296–4317.

31. Z. Yuan, W. Wang, H. Wang, and N. Ghadimi, "Probabilistic Decomposition-Based Security Constrained Transmission Expansion Planning Incorporating Distributed Series Reactor," *IET Generation, Transmission & Distribution* 14, no. 17 (2020): 3478–3487.

32. D. Yu and N. Ghadimi, "Reliability Constraint Stochastic UC by Considering the Correlation of Random Variables With Copula Theory," *IET Renewable Power Generation* 13, no. 14 (2019): 2587–2593.

33. M. Eslami, H. A. Moghadam, H. Zayandehroodi, and N. Ghadimi, "A New Formulation to Reduce the Number of Variables and Constraints to Expedite SCUC in Bulky Power Systems," *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences* 89 (2019): 311–321.

34. H. Chahkandi Nejad, S. Tavakoli, N. Ghadimi, S. Korjani, S. Nojavan, and H. Pashaei-Didani, "Reliability Based Optimal Allocation of Distributed Generations in Transmission Systems Under Demand Response Program," *Electric Power Systems Research* 176 (2019): 105952.

35. M. Ghiasi, Z. Wang, M. Mehrandezh, H. H. Alhelou, and N. Ghadimi, "Enhancing Power Grid Stability: Design and Integration of a Fast Bus Tripping System in Protection Relays." in *IEEE Transactions on Consumer Electronics*, https://doi.org/10.1109/TCE.2024.3519389.

36. Y. Cao, Q. Wang, J. Du, S. Nojavan, K. Jermsittiparsert, and N. Ghadimi, "Optimal Operation of CCHP and Renewable Generation-Based Energy Hub Considering Environmental Perspective: An Epsilon Constraint and Fuzzy Methods," *Sustainable Energy, Grids and Networks* 20 (2019): 100274.

37. O. Abedinia, M. Zareinejad, M. H. Doranehgard, G. Fathi, and N. Ghadimi, "Optimal Offering and Bidding Strategies of Renewable Energy Based Large Consumer Using a Novel Hybrid Robust-Stochastic Approach," *Journal of Cleaner Production* 215 (2019): 878–889.

38. H. Leng, X. Li, J. Zhu, H. Tang, Z. Zhang, and N. Ghadimi, "A New Wind Power Prediction Method Based On Ridgelet Transforms, Hybrid Feature Selection and Closed-Loop Forecasting," *Advanced Engineering Informatics* 36 (2018): 20–30.

39. Q. Meng, T. Liu, C. Su, H. Niu, Z. Hou, and N. Ghadimi, "A Single-Phase Transformer-Less Grid-Tied Inverter Based on Switched Capacitor for PV Application," *Journal of Control, Automation and Electrical Systems* 31 (2020): 257–270.

40. M. Mir, M. Shafieezadeh, M. A. Heidari, and N. Ghadimi, "Application of Hybrid Forecast Engine Based Intelligent Algorithm and Feature Selection for Wind Signal Prediction," *Evolving Systems* 11, no. 4 (2020): 559–573.

41. M. Mehrpooya, N. Ghadimi, M. Marefati, and S. A. Ghorbanian, "Numerical Investigation of a New Combined Energy System Includes Parabolic Dish Solar Collector, Stirling Engine and Thermoelectric Device," *International Journal of Energy Research* 45, no. 11 (2021): 16436–16455.

42. N. Ghadimi, M. Sedaghat, K. K. Azar, B. Arandian, G. Fathi, and M. Ghadamyari, "An Innovative Technique for Optimization and Sensitivity Analysis of a PV/DG/BESS Based on Converged Henry Gas Solubility Optimizer: A Case Study," *IET Generation, Transmission & Distribution* 17, no. 21 (2023): 4735–4749.

43. G. Bo, P. Cheng, K. Dezhi, et al., "Optimum Structure of a Combined Wind/Photovoltaic/Fuel Cell-Based on Amended Dragon Fly Optimization Algorithm: A Case Study," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* 44, no. 3 (2022): 7109–7131.

44. J. Liu, C. Chen, Z. Liu, K. Jermsittiparsert, and N. Ghadimi, “An IGDT-Based Risk-Involved Optimal Bidding Strategy for Hydrogen Storage-Based Intelligent Parking Lot of Electric Vehicles,” *Journal of Energy Storage* 27 (2020): 101057.

45. W. Cai, R. Mohammaditab, G. Fathi, K. Wakil, A. G. Ebadi, and N. Ghadimi, “Optimal Bidding and Offering Strategies of Compressed Air Energy Storage: A Hybrid Robust-Stochastic Approach,” *Renewable Energy* 143 (2019): 1–8.

46. K. M. Tan, J. Y. Yong, V. K. Ramachandaramurthy, M. Mansor, J. Teh, and J. M. Guerrero, “Factors Influencing Global Transportation Electrification: Comparative Analysis of Electric and Internal Combustion Engine Vehicles,” *Renewable and Sustainable Energy Reviews* 184 (2023): 113582.

47. T. Song, J. Teh, and B. Alharbi, “Reliability Impact of Dynamic Thermal Line Rating and Electric Vehicles on Wind Power Integrated Networks,” *Energy* 313 (2024): 133945.

48. T. Song and J. Teh, “Coordinated Integration of Wind Energy in Microgrids: A Dual Strategy Approach Leveraging Dynamic Thermal Line Rating and Electric Vehicle Scheduling,” *Sustainable Energy, Grids and Networks* 38 (2024): 101299.

49. L. Yang, J. Teh, and C. M. Lai, “Assessing Power Grid Vulnerability to Extreme Weather: The Impact of Electric Vehicles and Energy Storage Systems,” *Journal of Energy Storage* 112 (2025): 115534.

50. S. Mohseni-Bonab, A. Rabiee, and B. Mohammadi-Ivatloo, “Voltage Stability Constrained Multi-Objective Optimal Reactive Power Dispatch under Load and Wind Power Uncertainties: A Stochastic Approach,” *Renewable Energy* 85 (2016): 598–609.

51. A. Askarzadeh, “A Novel Metaheuristic Method for Solving Constrained Engineering Optimization Problems: Crow Search Algorithm,” *Computers and Structures* 169 (2016): 1–12.

52. W. K. A. Najy, H. H. Zeineldin, and W. L. Woon, “Optimal Protection Coordination for Microgrids with Grid-Connected and Islanded Capability,” *IEEE Transactions on Industrial Electronics* 60, no. 4 (April 2013): 1668–1677.

53. P. R. Babu, C. P. Rakesh, G. Srikanth, M. N. Kumar, and D. P. Reddy, “A Novel Approach for Solving Distribution Networks,” in *Proceedings of the India Conference (INDICON), 2009Annual IEEE* (IEEE, 2009), 1–5.

54. M. Veisi, F. Adabi, A. Kavousi-Fard, and M. Karimi, “A Framework of Electricity Market Based on Two-Layer Stochastic Power Management for Microgrids,” *IEEE Access* 10 (2022): 41047–41063.

55. A. Baziar, R. Bo, M. D. Ghotbabadi, M. Veisi, and W. Ur Rehman, “Evolutionary Algorithm-Based Adaptive Robust Optimization for AC Security Constrained Unit Commitment Considering Renewable Energy Sources and Shunt FACTS Devices,” *IEEE Access* 9 (2021): 123575–123587.

56. M. Veisi, F. Adabi, A. Kavousi-Fard, and M. Karimi, “A Novel Comprehensive Energy Management Model for Multi-Microgrids Considering Ancillary Services,” *IET Generation, Transmission & Distribution* 16, no. 23 (2022): 4710–4725.

57. R. Wang, E. Akbari, L. Bagherzadeh, and S. Pirouzi, “Stochastic Economic Sizing of Hydrogen Storage-Based Renewable off-Grid System With Smart Charge of Electric Vehicles According to Combined Hydrogen and Power Model,” *Journal of Energy Storage* 108 (2025): 115171.

58. R. B. Navesi, A. F. Naghibi, H. Zafarani, H. Tahami, and S. Pirouzi, “Reliable Operation of Reconfigurable Smart Distribution Network With Real-Time Pricing-Based Demand Response,” *Electric Power Systems Research* 241 (2025): 111341.

59. A. F. Naghibi, E. Akbari, S. Shahmoradi, S. Pirouzi, and A. Shahbazi, “Stochastic Economic Sizing and Placement of Renewable Integrated Energy System With Combined Hydrogen and Power Technology in the Active Distribution Network,” *Scientific Reports* 14, no. 1 (2024): 28354.

60. M. H. Oboudi, H. Hamidpour, M. Zadehbagheri, S. Safaee, and S. Pirouzi, “Reliability-Constrained Transmission Expansion Planning Based on Simultaneous Forecasting Method of Loads and Renewable Generations,” *Electrical Engineering* 107, no. 1 (2025): 1141–1161.

61. M. Yao, Z. Moradi, S. Pirouzi, M. Marzband, and A. Baziar, “Stochastic Economic Operation of Coupling Unit of Flexi-Renewable Virtual Power Plant and Electric Spring in the Smart Distribution Network,” *IEEE Access* 11 (2023).

62. M. Norouzi, J. Aghaei, T. Niknam, M. Alipour, S. Pirouzi, and M. Lehtonen, “Risk-Averse and Flexi-Intelligent Scheduling of Microgrids Based on Hybrid Boltzmann Machines and Cascade Neural Network Forecasting,” *Applied Energy* 348 (2023): 121573.

63. M. Zadehbagheri, M. Dehghan, M. Kiani, and S. Pirouzi, “Resiliency-Constrained Placement and Sizing of Virtual Power Plants in the Distribution Network Considering Extreme Weather Events,” *Electrical Engineering* 107, no. 2 (2024): 2089–2105.

64. S. Pirouzi, M. Zadehbagheri, and S. Behzadpoor, “Optimal Placement of Distributed Generation and Distributed Automation in the Distribution Grid Based On Operation, Reliability, and Economic Objective of Distribution System Operator,” *Electrical Engineering* 106, no. 6 (2024): 7899–7912.

65. E. Akbari, A. Faraji Naghibi, M. Veisi, A. Shahparnia, and S. Pirouzi, “Multi-Objective Economic Operation of Smart Distribution Network With Renewable-Flexible Virtual Power Plants Considering Voltage Security Index,” *Scientific Reports* 14, no. 1 (2024): 19136.

66. J. Zhang, H. Wu, E. Akbari, L. Bagherzadeh, and S. Pirouzi, “Eco-Power Management System With Operation and Voltage Security Objectives of Distribution System Operator Considering Networked Virtual Power Plants With Electric Vehicles Parking Lot and Price-Based Demand Response,” *Computers and Electrical Engineering* 121 (2025): 109895.

67. L. Chang, Z. Wu, and N. Ghadimi, “A New Biomass-Based Hybrid Energy System Integrated With a Flue Gas Condensation Process and Energy Storage Option: An Effort to Mitigate Environmental Hazards,” *Process Safety and Environmental Protection* 177 (2023): 959–975.

68. L. Zhu, F. Zhang, Q. i. Zhang, Y. Chen, M. Khayatnezhad, and N. Ghadimi, “Multi-Criteria Evaluation and Optimization of a Novel Thermodynamic Cycle Based on a Wind Farm, Kalina Cycle and Storage System: An Effort to Improve Efficiency and Sustainability,” *Sustainable Cities and Society* 96 (2023): 104718.

69. O. Abedinia, M. Bagheri, M. S. Naderi, and N. Ghadimi, “A New Combinatory Approach for Wind Power Forecasting,” *IEEE Systems Journal* 14, no. 3 (2020): 4614–4625.

70. R. Rani and D. Ramyachitra, “Krill Herd Optimization Algorithm for Cancer Feature Selection and Random Forest Technique for Classification,” in *IEEE International Conference on Software Engineering and Service Science (ICSESS)* (IEEE, 2017), 109–113.

71. S. Mirjalili, S. Mirjalili, and A. Lewis, “Grey Wolf Optimizer,” *Advances in Engineering Software* 69 (2014): 46–61.