Optimal setting of PV and battery energy storage in radial distribution systems using multi-objective criteria with fuzzy logic decision-making

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Abstract
Minimising the total power losses and enhancing the voltage profile is achieved using a proposed multi-objective chaotic salp swarm algorithm with fuzzy logic decision-making. The proposed multi-objective chaotic salp swarm algorithm is utilised to determine the optimal size and location of photovoltaic in radial distribution system to minimise the total power losses, total voltage deviation, and maximise the voltage stability index. In addition, the proposed multi-objective chaotic salp swarm algorithm is used to find suitable scheduling for battery energy storage charge/discharge during 24 h considering the intermittent nature of photovoltaic power generation. The proposed algorithm is tested on standard and practical radial distribution systems (IEEE 33-bus and 94-bus Portuguese systems). The performance of the proposed algorithm is validated by comparing its results with those obtained by other competitive optimisation techniques. The obtained results prove the ability of the proposed algorithm to achieve an efficient setting for photovoltaics and battery energy storages and determine their optimal allocations in order to minimise the power losses and enhance the voltage profile with satisfying all operating constraints.

1 | INTRODUCTION

In the last few years, the growing interest in decreasing the effects of CO\textsubscript{2} emissions has led the power systems community to think of exploiting clean renewable energy resources \cite{1}. A part of the renewable energy resources is usually referred to as distribution generators (DGs) which are small generating units connected directly to distribution systems at strategic points to increase the reliability of customer’s power delivery \cite{2}. Consequently, the integration of DGs changes the radial distribution systems (RDSs) from their passive structures with one direction power flow into active distribution systems (ADS) with multi-directional power flows. However, the future large-scale penetration of DGs will bring both positive and negative consequences, depending on different points of view. The main negative consequences include the power flows, the voltage levels, and the power losses \cite{3}. In consequence, analysis of these resources and their impacts on electric utilities are crucially required.

Regarding the voltage level, distribution network operators’ (DNOs) concern to preserve the distribution system voltage level within limits. However, the existence of DGs in the RDS in the absence of load demand increases the generation and reverses power flow along the line in which voltage rise becomes critical. Hence, many control schemes have been investigated for voltage control in ADS \cite{4–7}. In order to guarantee the optimal operation of RDSs, voltage control should be carried out with the integration of DGs \cite{8}. Many optimisation techniques have been applied to determine the optimal locations and sizes of the DGs. The challenge of recognising the optimal allocations for DGs in RDS has concerned considerable research efforts \cite{9, 10}. Two different methodologies have been developed, the first one is based on analytical optimisation tools and the second is based on metaheuristic optimisation techniques. The optimal size and allocation for single DG have been implemented to minimise power losses and enhance voltage profiles \cite{11–13}. Artificial intelligence-based optimisation methods have been used to determine the optimal placement for multiple DGs.
[14, 15]. On the other hand, analytical approaches have been presented [15, 16].

In fact, many research works focused on sizing the DG units at the peak load demand; however, there are many factors which have been ignored in the previous research works, namely when dealing with DG units that use renewable energy resources, such as wind power and photovoltaic (PV), one must consider the availability of the primary energy resource conditions and the load time-varying. Thereby, power losses and voltage level issues become a matter of concern in case of low or high DGs power penetration and light or heavy load demand. A few research works have considered the time variation of the load demand and the uncertainty of the DG power generation [17–20].

To avoid the fluctuation in the power system caused by the non-dispatchable DGs unit such as PV, a power curtailment and battery energy storage (BES) has been utilised [21, 22]. However, using BES is considered more efficient than the power curtailment where the energy can be stored during light load or high renewable penetration and can be withdrawn during the peak load period to decrease the total energy losses and enhance the voltage profile. Nevertheless, to increase the benefits of the BES in the distribution system it is important to determine its optimal size and location. Numerous algorithms for determining the optimal size and location of BES have been presented in [23–25]. Hence, the optimal setting and scheduling of the PV and BES to simultaneously minimise the total energy loss and enhance the voltage profile in RDSs can be considered a multi-objective optimisation problem [20, 26].

Two different types of multi-objective methods have been utilised in RDSs to deal with the DGs allocation. The first one uses the weighting sum for separate objective functions, in this case, the multi-objective problem is converted to a single objective problem. However, the main problem in this method is the choice of weighting factor values. The second popular multi-objective optimisation method uses a trade-off among the functions. Pareto dominance concept can be used to classify the solutions as dominated or non-dominated solutions, according to the objective functions, then the best solution can be chosen from the non-dominated solutions by the decision-maker [10]. Several algorithms have been implemented to solve the multi-objective problems such as; Pareto archived evolution strategy (PAES), non-dominated sorting genetic algorithm (NSGA-II), strength Pareto evolutionary algorithm (SPEA), improved version SPEAII, and multi-objective particle swarm optimisation (MOPSO) [27].

Metaheuristic optimisation techniques have been widely employed to perform multi-objective optimisation to optimally place DGs in RDSs in numerous researches works. Minimising the power loss and enhancing the voltage profile have been accomplished by utilising improved multi-objective harmony search in [28]. Three objective functions namely power loss, voltage deviation (VD), and voltage stability index (VSI) are optimised using quasi-oppositional teaching–learning based on penalty factor in [29]. In [30], a multi-objective shuffled bat algorithm is proposed to study the influence of DGs with different load models.

However, there are some problems associated with using the heuristic optimisation technique due to the random initialisation of the search agents such as low convergence rate and falling in a local solution. Recently, the chaotic theory is widely used to improve the performance of metaheuristic optimisation algorithms. In this regard, a generated chaotic variable can be utilised instead of using random initial variables especially for the algorithms most sensitive to the initial values [31]. The performance of GA, HS, ABC, FA, KHA, BOA, and GWO is fully improved with using different chaotic maps [32].

Regarding the above discussion, the main contributions can be summarised as follows:

- Proposing a multi-objective chaotic salp swarm algorithm (MCSSA) with developed fuzzy logic decision-making.
- Applying the proposed MCSSA to determine the optimal allocation of PV units in RDS to minimise the total losses, voltage deviation, and maximise VSI, simultaneously.
- Suitable scheduling for BES charge/discharge during 24 h is proposed to consider the intermittent nature of PV power generation.
- The effectiveness of the proposed technique is tested on standard and practical RDSs (IEEE 33-bus and 94-bus Portuguese systems) with different operating scenarios.

Section 2 presents the problem formulation including the main objective functions. Section 3 presents the PV with uncertainty power generation. Section 4 describes the BES charging/discharging models. Section 5 presents the modelling of the PV and BES systems. Section 6 explains the proposed MCSSA with the fuzzy decision. In Section 7, the optimal allocation of the PV using the proposed MCSSA is presented. Numerical results based on the test systems are presented in Section 8. Finally, the conclusions are presented in Section 9.

## 2 | PROBLEM FORMULATION

This section introduces the main objective functions, which are used for optimal placement of PV and optimal charging/discharging of BES in RDS.

### 2.1 | Objective functions

The main purpose of allocating PV and BES in the RDS is to minimise power losses, VD, and maximise the VSI. The mathematical formulation for the three objective functions is presented in the following subsections:
2.1.1 Minimisation of total active power

One of the most important targets of installation of PV and BES into RDS is to reduce the power loses, $P_{\text{loss}}$.

$$f_1 = \min (P_{\text{loss}})$$ (1)

The total power losses $P_{\text{loss}}$ in distribution network is calculated using the branch current loss formula as [33]:

$$P_{\text{loss}} = \sum_{\zeta=1}^{N_{\text{br}d}} |I_{\zeta}|^2 R_{\zeta}$$ (2)

where, $\zeta$ is the branch number, $N_{\text{br}d}$ is the total number of branches, $|I_{\zeta}|$ is the absolute value of the current passing through the branch, and $R_{\zeta}$ is the branch resistance.

Hence, minimising the total power losses in the RDS leads to reducing the total energy losses $E_{\text{loss}}$ during 24 h as follows:

$$E_{\text{loss}} = \sum_{t=1}^{24} P_{\text{loss}} (t)$$ (3)

2.1.2 Minimisation total voltage deviation

The total voltage deviation $VD$ indicates the level of the RDS voltage and how is far from the specified value $V_{\text{sep}}$. Hence, $VD$ for the system can be calculated using the voltage magnitude $V_i$ at bus $i$ based on a specified voltage as:

$$\frac{VD}{\text{pu}} = \sum_{i=1}^{n_{\text{bus}}} \left( \frac{V_i - V_{\text{sep}}}{V_{\text{max}} - V_{\text{min}}} \right)^2$$ (4)

where, $V_{\text{sep}}$ is taken 1.00 p.u, $V_{\text{max}}$ and $V_{\text{min}}$ are the maximum and the minimum limits of the RDS, respectively. Therefore, the second objective function is:

$$f_2 = \min (VD)$$ (5)

2.1.3 Maximisation of voltage stability index

The VSI is defined as the ability of the system to keep the voltage within the satisfied range. The main target is to maximise the VSI which owns the lowest VSI in the system [34]:

$$VSI = V_i^4 - 4 (P_j R_{ji} + Q_j X_{ji}) V_i^2 - 4 (P_j X_{ji} - Q_j R_{ji})$$ (6)

where, $i, j$ are the sending and receiving bus; $P_j, Q_j$ are active and reactive power at the receiving bus; and $R_{ji}, X_{ji}$ are the resistance and reactance between buses $i, j$. The third objective function can be expressed as:

$$f_3 = \max (\min (VSI_j))$$ (7)

3 MODELLING OF PV POWER GENERATION

The stochastic behaviour of PV can be modelled using probability distribution functions (PDF) [17]. A collected historical data of solar irradiance at period are utilised to generate a typical day’s frequency distribution of the irradiance. Beta PDF is used to implement PV power generation as follows.

3.1 Solar irradiance model

For each hour $t$ of the typical day, Beta PDF is used to represent the probabilistic nature of solar irradiance $i^t$ (kW/m²) as follows:

$$f_b (i^t) = \begin{cases} \frac{\Gamma (\alpha' + \beta')}{\Gamma \alpha' + \Gamma \beta'} (i^t)^{\alpha' - 1} (1 - i^t)^{\beta' - 1} & 0 \leq i^t \leq 1, \\ 0, & \text{otherwise} \end{cases}$$ (8)

where, $\alpha'$ and $\beta'$ are the Beta PDF parameters which can be calculated using the mean $\mu_i^t$ and the standard deviation $\sigma_i^t$ of the solar irradiance $i$ at time $t$ as:

$$\beta' = (1 - \mu_i^t) \left( \frac{1 + \mu_i^t}{\sigma_i^t} \right)^2$$ (9)

$$\alpha' = \frac{\mu_i^t * \beta'}{(1 - \mu_i^t)}$$ (10)

3.2 PV power generation

To determine the PV output power, the continuous PDF for a specific time hour $t$ is separated into several states. Power generation of PV array is produced by the probability of all possible states for that hour. The hourly average output power $P_{\text{PV}}$ array corresponds to a specific time segment $t$ can be calculated as follows:

$$P_{\text{PV}} = \sum_{i=1}^{n_{\text{bus}}} P_i (i^t) f_b (i^t)$$ (11)

where, $P_i (i^t)$ is the output power of the PV module and it is expressed as [17]:

$$P_{i} (i^t) = N_{\text{in}} \times V_i \times I_c \left( \frac{V_{\text{MPP}} \times I_{\text{MPP}}}{V_o \times I_s} \right)$$ (12)
where, $N_m$ is the number of PV modules, $V_{\text{MPP}}$ and $I_{\text{MPP}}$ the voltage and current at maximum power point, respectively, $V_o$ is the open-circuit voltage and $I_s$ is the short-circuit current, and $V_c$, $I_c$ are the cell voltage and current, respectively, and they can be calculated using the following equations:

$$V_c = V_o - K_v \times T_c$$

$$I_c = \eta_c \left( I_s + K_i (T_c - 25) \right)$$

where, $K_v$, $K_i$ are the voltage and current temperature coefficient (V/0°C), (A/0°C), respectively, $T_c$ is the cell temperature $^0\text{C}$ and it can be determined using the ambient temperature $T_A$ and the nominal operating temperature $T_0$ as:

$$T_c = T_A + \eta_c \left( T_0 - 20 \right)$$

In this work, the solar irradiance data given in [19] for $\mu^I$ and $\sigma^I$ for 3 years and the PV module parameters are adopted to represent the Beta PDF of the solar irradiance as shown in Figure 1(a). It is clear that the mean and standard deviation (SD) of the solar irradiance are weather and time depended which starts form 6:00 AM to 19:00 PM. For this period, 20 states of solar irradiance with step 0.05 (kW/m²) are considered for each hour, and the expected PV powers are calculated as shown in Figure 1(b). Finally, the typical day for the 3 years is generated in p.u as shown in Figure 1(c).

4 | MODELLING OF BATTERY ENERGY STORAGE

As mentioned, BES plays an important role in the integration of the PV system to convert it to a dispatchable energy source. In this regard, the BES unit can work as a charging load or a discharging generator. Hence, The BES charging/discharging energy $E^t_{\text{BES}}$ at bus $i$ in period $t$ can be expressed as [35]:

$$E^t_{\text{BES}} = \begin{cases} 
E^{t-1}_{\text{BES}} - \frac{(P^t_{\text{BES}})_d}{\eta_d} \Delta t, & P^t_{\text{BES}} > 0 \\
E^{t-1}_{\text{BES}} - \eta_c \times (P^t_{\text{BES}})_c * \Delta t, & P^t_{\text{BES}} \leq 0
\end{cases}$$

where, $(P^t_{\text{BES}})_c$ and $(P^t_{\text{BES}})_d$ are the charge and discharge power of the BES, respectively; $\eta_c$ and $\eta_d$ are efficiencies of the charge and discharge, $\Delta t$ is the sampling time. However, the $E^t_{\text{BES}}$ must satisfy the minimum $E^\text{min}_{\text{BES}}$ and maximum $E^\text{max}_{\text{BES}}$ energy limits of the BES unit as follows:

$$E^\text{min}_{\text{BES}} \leq E^t_{\text{BES}} \leq E^\text{max}_{\text{BES}}$$

In this work, the $E^\text{min}_{\text{BES}}$ and $E^\text{max}_{\text{BES}}$ limits are taken to be 20% and 90% of the connected size of the BES unit, respectively.

5 | MODELLING OF PV AND BES POWER

Distinct to the non-dispatchable PV integration, the hourly PV + BES power can be dispatched over the day using the charging/discharging BES power, hence the daily charging $(E^c_{\text{BES}})$ and discharging $(E^d_{\text{BES}})$ energies at bus $i$ are obtained as:

$$(E^c_{\text{BES}})_i = \sum_{t=1}^{24} (P^t_{\text{BES}})_c \times \Delta t$$

$$(E^d_{\text{BES}})_i = \sum_{t=1}^{24} (P^t_{\text{BES}})_d \times \Delta t$$
Therefore, the total output energies $E_{(PV\, +\, BES)}$, of the PV + BES and $E_{PV}$ of the PV generation unit at bus $i$ in case of BES discharging and charging is calculated respectively as:

$$E_{(PV\, +\, BES)} = (E_{BES, d}) + (E_{PV})_G$$ (20)

$$E_{PV} = (E_{BES, c}) + (E_{PV})_G$$ (21)

where $(E_{PV})_G$ is the quantity of PV energy transporting to the grid at bus $i$. The charging and discharging energies of the BES unit at bus $k$ with a roundtrip efficiency ($\eta_B = \eta_d \times \eta_c$) is expressed as:

$$(E_{BES, d}) = \eta_B (E_{BES, c})$$ (22)

Using (20) to (22), the $E_{PV}$, of the PV generation unit can be calculated as:

$$E_{PV, i} = \frac{E_{(PV\, +\, BES), i} - (1 - \eta_B) (E_{PV})_G}{\eta_B}$$ (23)

To find the maximum PV unit output power at bus $i$, a capacity factor for the module unit $C_{PV}$ can be used as follows:

$$P_{PV, i} = C_{PV} E_{PV, i}$$ (24)

where,

$$C_{PV} = \frac{P_{PV, i}}{E_{PV}}$$ (25)

$P_{PV, i}$ is the maximum output of a PV module unit, and $E_{PV, i}$ is the amount of PV generated energy over a 24 h day.

Based on the normalised values shown in Figure 1. The capacity factor is $C_{PV} = 0.1063$.

Consequently, the $P_{PV, i}$ can be calculated using the following equation:

$$P_{PV, i} = C_{PV} \left( \frac{E_{(PV\, +\, BES, i)} - (1 - \eta_B) (E_{PV})_G}{\eta_B} \right)$$ (26)

%6 | MULTI-OBJECTIVE ALGORITHM AND FUZZY DECISION FORMULATION

In this section, the proposed MCSSA with the developed fuzzy decision-making is introduced to optimally allocate the PV + BES power generation system.

6.1 | Overview of the salp swarm algorithm

Salp swarm algorithm (SSA) has been presented in [36], it is a swarm-based technique which simulates salp chain behaviour in searching for their food. The mathematical formulation of the SSA is divided into two populations. The first population is the leader which locate on the front of the chain where the other are the followers. The updating equation for the leader position solutions is expressed as follows:

$$X^l_i = \begin{cases} F_i + r_1 \left[ 2r_2 (U^l - L^l) + L^l \right], & r_3 < 0.5 \\ F_i - r_1 \left[ 2r_2 (U^l - L^l) + L^l \right], & r_3 \geq 0.5 \end{cases}$$ (27)

where, $X^l_i$ is the current leader position of the $i$ dimension and $F_i$ is the target (food) position of the $i$ dimension. $r_1, r_2$, and $r_3$ are random values used to keep the populations within the search space, $U^l, L^l$ are the upper and lower limits. $r_1$ is used to ensure the balance between exploration and exploitation phases as:

$$r_1 = 2e^{-\left( \frac{k}{K_{max}} \right)^2}$$ (28)

where, $K_{max}$ is the maximum iteration number and $k$ is the current iteration, $r_2$ is adopted movement parameter and $r_3$ is a random switching parameter.

The position of followers can be adopted with the iteration as follows:

$$X^f_i = \frac{1}{2} \left( X^f_i + X^{f-1}_i \right)$$ (29)

where, $j \geq 2$ and $X^f_i$ gives $j$ Salp position in $i$ dimension.

To implement the MSSA, two structures called a repository and food selection are used. The repository is responsible for arranging the non-dominated solutions obtained so far and the food selection used to guide the SSA agents to update their position directly to the destination. The overall MSSA process is shown in Figure 2.

6.2 | Multi-objective chaotic salp swarm algorithm

Chaos maps are presented as a solution to predict the unsteady actions by utilising a set of chaotic equations called chaotic maps. Recently, many chaotic maps are employed in optimisation algorithms to improve their convergence characteristics. In this work, 10 chaotic maps exhibited in Table 1 are incorporated into the MSSA to update its parameter $r_2$ instead of using random probability as follows:

$$r_2 = y_{k+1}$$ (30)

where, $y_{k+1}$ is the selected chaos map as presented in Table 1. However, it should be mentioned that the behaviour of any chaotic map depends on the initial value $y_1$, hence it is important to set a suitable initial value. In this work, the initial value is chosen at $y_1 = 0.7$ for all chaotic maps as used in [32, 37].
6.3 Fuzzy decision-making

For a multi-objective problem, it is necessary to choose the best solution among the non-dominated Pareto solutions. In this work, developed fuzzy decision-making is used to achieve the best compromise solution. The advantage of using the developed fuzzy decision-making is to permit the planner to give a priority to an objective function over the other through the fuzzy rules.

The fuzzy output can be obtained through three stages, fuzzification, if–then rules, and defuzzification. The input and output are replaced by a different membership function (MF) based on its value. Hence, the value of the objective function $F_i$ of individual $u$ can be normalised as follows:

$$u_i = \frac{F_{i}^{\text{max}} - F_i}{F_{i}^{\text{max}} - F_{i}^{\text{min}}}$$  

where $F_i^{\text{min}}$ and $F_i^{\text{max}}$ are the minimum and maximum values of the $i$th objective function. Figure 3 shows the three normalised objective functions are represented using fuzzy memberships.

The output of the fuzzy is a weighting value calculated using 27 rules as presented in Table 2 where the weighting is represented with the decision-maker, since they are intended to describe the DM’s preferences. Table 2 shows the symmetry between the two objectives function.

Table 1 shows the priorities of the objectives function over the other through the fuzzy rules described in Table 2 must be validated with the decision-maker, since they are intended to describe the DM’s preferences. Table 2 shows the symmetry between the two objectives function.

To interpret the rules in Table 2, a simple example can be performed as follows: If the normalised value of $P_{\text{loss/VD}}$, and $\text{VSI}$ have arbitrary values 0.9, 0.5, and 0.2, respectively, then based on the memberships illustrated in Figure 3, the fuzzy input is $H$, $M$, and $L$, respectively, which represents rule 22. The output weighting of the fuzzy is 0.5049 which represents M as in Figure 2(d).

6.4 Spacing metric (SP metric)

To assess the deviation scale of nearby trajectories in the Pareto front, a spacing metric is used and calculated as [3]:

$$\text{SP} = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\tilde{a} - d_i)^2}$$  

$$d_i = \min \left( \sum_{k=1}^{n} |f_k^{i} - f_k^{i+1}| \right)$$
where, $j = 1, 2, \ldots, n$, $m$ is the number of objective functions and $\bar{d}$ is the mean of all $d_i$. The SP-metric value indicates the adjacent solutions in the Pareto set. Hence, if the SP value is close to zero, this means the non-dominated solutions are equally distributed.

### 7 OPTIMAL PV ALLOCATION USING MCSSA

The optimal allocation (location and size) of the PV into RDS using the MCSSA can be achieved using the following steps.

**Step 1:** Read the system data (line data and load data) and define the objective function.

**Step 2:** Set the control variables (PV location $X_{loc}$ and size $X_{size}$) of MCSSA which include (variables number $n$, population number $m$, number of iterations $K_{max}$, lower $L$, and upper $U$ limits of the control variables).

**Step 3:** Start the population of MCSSA randomly within the limits as follows:

\[
X_{loc}(i, j) = \text{rand}(0, 1) \times (U_{loc}(i, j) - L_{loc}(i, j)) + L_{loc}(i, j)
\]

\[
X_{size}(i, j) = \text{rand}(0, 1) \times (U_{size}(i, j) - L_{size}(i, j)) + L_{size}(i, j)
\]

**Step 4:** Run the power flow to calculate the objective functions for each search agent.

**Step 5:** Formulate a repository for the non-dominant solutions and food selection.

**Step 6:** Update the parameters $r_1$, $r_2$, and $r_3$ using the chaotic map, then, update the agent's position.

**Step 7:** Check the repository, if it is full, apply the grid mechanism to remove the current repository agent and insert the new solution.

**Step 8:** Perform food selection.

**Step 9:** If $k < K_{max}$, repeat Step 2, otherwise go to the next step.

**Step 10:** Return the stored final non-dominated solutions in the archive.
RESULT AND DISCUSSION

In this section, the IEEE 33-bus and 94-bus Portuguese RDSs are used to illustrate the feasibility and efficiency of the optimal setting and scheduling of integration PV and BESs in RDSs to minimise the total power and energy losses as well to keep the voltage within acceptable limits (0.95–1.05). In this work, three scenarios are carried out for each test system as follows:

- **Scenario 1**: the proposed MCSSA3 with fuzzy decision-making is utilised to optimally allocate multiple PV units at rated loading condition to minimise the $P_{loss}$, $V_D$, and maximise the $VSI$.
- **Scenario 2**: the uncertainty PV power generation model is employed with time-varying load demand to present the impact of the intermittent nature of PV on the energy losses and voltage profile of the distribution systems.
- **Scenario 3**: a sequential proposed MCSSA is used to optimally schedule the PV + BES power generation for minimising the total energy losses and enhancing the voltage profile using the three objective functions.

8.1 IEEE 33 bus system

IEEE 33-bus RDS is used to validate the proposed algorithm. The load and line data of the system are extracted from [38], and the single line diagram is shown in Figure 4. The total rated load of the system is 3.715 MW and 2.3 MVAR and the base voltage is 12.66 kV. At the rated demand, the power flow results indicate that the total active power losses is 202.67 kW, the minimum voltage is 0.9131 p.u at bus #18, total $V_D$ is 11.71, and the minimum $VSI$ is 0.6951.

| Method   | Mean | STD  | Method   | Mean | STD  |
|----------|------|------|----------|------|------|
| MSSA     | 30.40| 0.60 | MOPSO    | 34.87| 0.66 |
| MCSSA1   | 29.96| 0.92 | NSGA II  | 70.67| 0.67 |
| MCSSA2   | 30.41| 0.90 | SPEA2    | 41.93| 0.23 |
| MCSSA3   | 28.70| 0.14 | PESA-II  | 38.08| 0.26 |
| MCSSA4   | 30.08| 0.64 | MOEA/D   | 47.28| 3.97 |
| MCSSA5   | 30.77| 0.96 | MOALO    | 38.54| 1.18 |
| MCSSA6   | 30.33| 0.78 | MOGWO    | 45.22| 0.30 |
| MCSSA7   | 30.73| 0.98 |          |      |      |
| MCSSA8   | 30.40| 0.65 |          |      |      |
| MCSSA9   | 30.44| 0.86 |          |      |      |
| MCSSA10  | 30.20| 0.70 |          |      |      |

8.2 Performance analysis for MCSSA

The main objective of this analysis is to prove the effectiveness of the proposed MCSSA, its performance, and its accuracy when incorporating different chaotic maps to MSSA. Furthermore, to determine the most efficient chaotic maps...
TABLE 4  Obtained results of IEEE 33-bus

| Method | DAPSO [40] | IA [15] | LSF [15] | BSOA [41] | MCSSA3 |
|--------|------------|---------|----------|-----------|--------|
| 1 PVDG |            |         |          |           |        |
| (Bus)  | (8) 1212   | (6) 2601| (18) 743 | (8) 1857.5| (7) 2741.46 |
| Size (kW) |           |         |          |           |        |
| P\textsubscript{loss} (kW) | 127.17 | 111.1 | 146.82 | 118.12 | 106.27 |
| LR % | 39.7 | 47.39 | 30.48 | 44.01 | 47.46 |
| V\textsubscript{min} | 0.9349 | 0.9425 | – | 0.9441 | 0.9566 |
| 2 PVDGs |            |         |          |           |        |
| (Bus)  | (13) 1227 | (6) 1800| (18) 720 | (13) 880 | (15) 857.62 |
| Size (kW) |           |         |          |           |        |
| P\textsubscript{loss} (kW) | 95.93 | 91.63 | 100.69 | 89.34 | 89.67 |
| LR % | 54.53 | 56.61 | 52.32 | 57.62 | 55.67 |
| V\textsubscript{min} | 0.9651 | 0.9539 | – | 0.9665 | 0.9742 |
| 3 PVDGs |            |         |          |           |        |
| (Bus)  | (10) 681 | (6) 900 | (18) 720 | (13) 632 | (13) 958.89 |
| Size (kW) |           |         |          |           |        |
| P\textsubscript{loss} (kW) | 92.55 | 81.05 | 85.07 | 89.05 | 74.31 |
| LR % | 56.13 | 61.62 | 59.72 | 57.76 | 63.26 |
| V\textsubscript{min} | 0.9654 | 0.9690 | – | 0.9554 | 0.9758 |

FIGURE 6  Pareto optimal front for the IEEE 33-bus system

among the 10 maps which can be integrated into MSSA. The ten maps are used in the basic MSSA and numbered from MCSSA1 to MCSSA10 corresponding to the selected chaos map as arranged in Table 1. A single DG unit is employed in this analysis to be optimally allocated in the IEEE 33-bus at the rated loading condition to obtain the optimised values for the three objective functions. The comparison among all methods is accomplished using the computation time and SP metric.

Figure 5(a) exhibits the boxplot for all proposed MCSSA methods and the basic MSSA through 30 runs. It can be noted that the MCSSA3 which uses Gauss/mouse chaotic map gives the lowest SP compared with the other proposed algorithms. Nevertheless, MCSSA3 is compared with the well-known multi-objective optimisation techniques mentioned in the literature such as PAES2, NSGA-II, SPEAII, MOPSO, and new metaheuristic techniques such as Multi-Objective Ant Lion Optimiser (MOALO) and Multi-Objective Grey Wolf Optimiser (MOGWO). Also, the proposed MCSSA3 proves its superiority as shown in Figure 5(b). The mean and standard deviation (STD) of the computation time during 30 runs for all techniques are summarised in Table 3. It can be observed that the MCSSA3 has the lowest computation time among all techniques. Consequently, in the next section, the MCSSA3 is used to find the optimal setting and scheduling the PV and BES in RDSs.

FIGURE 7  Daily load variation. (a) Load demand; (b) PV power generation.
*Res, residential; Ind, industrial, and Com, commercial
8.3 | PV allocation in IEEE 33 bus system

8.3.1 | Scenario 1

The optimal sizes and locations of the PVDG units are achieved using the proposed MCSSA3 incorporated with developed fuzzy logic decision-making and compared with other optimisation methods as summarised in Table 4. Figure 6 shows the non-dominated solutions and the best compromise solution obtained by MCSSA3 when installing one, two, and three PVDG units. For 1 PV, the best compromise solution is achieved when the three objective functions $P_{loss}$, $V_D$, and $V_{SI}$ are 106.3 kW, 2.379, and 0.8373, respectively, with a maximum installed PV capacity 2741.46 kW at bus #7.

Compared to the results in the literature as in Table 4, the proposed MCSSA3 gives the best results in reducing the power losses and maintaining the bus voltages within the limits where the loss reduction (LR) reaches 47.46%, 55.67%, and 63.26% with the minimum voltages 0.9566, 0.9742, and 0.9758 p.u for 1 PV, 2 PVs, and 3 PVs, respectively. From the obtained results, it can be observed that the integration of 3 PV units into the IEEE 33-bus system significantly enhances its operational performance. Consequently, the results of the 3 PV units are considered for the two following scenarios.

8.3.2 | Scenario 2

In this scenario, the PV power generation model is applied using the optimal sizes and locations obtained in scenario 1, a time-varying daily load demand that consists of three types of loads, residential, industrial, and commercial, is used as displayed in Figure 7(a) [39]. The impact of the load variation on the IEEE 33-bus voltage profile and the power losses for 24 h is shown in Figure 8(a) and Figure 8(b), respectively. It is clear that the voltage profile is less than the lower limit due to the increase in the load demand. To enhance the voltage profile during the 24 h, three PV units are integrated at buses 13, 24, and 30 with the generated active power presented in Figure 7(b).

Significant improvement occurs in the voltage profiles and LR when the PV power is available between 6:00 to 19:00 h as exhibited in Figure 8(b) and Figure 8(c), respectively. However, a shortage of PV integration and growth in the load demand has occurred after 19:00 h, and this leads to decrease in the voltage profile lower than the limit (0.95 p.u).

8.3.3 | Scenario 3

In this scenario, BESs are installed at the PV locations and the proposed MCSSA is used at each hour to optimally schedule the PV + BES power to reduce the power losses, total $V_D$, and
maximise VSI. By using the PV + BES power, the optimal size for the PV and BES can be accomplished using the PV + BES modelling.

Figure 9(a) shows the obtained $P_{(PV+BES)}^{13}$ at bus #13 during 24 h using the proposed MCSSA3 to minimise the total power losses and enhance the voltage profile as shown in Figure 8(b) and Figure 8(d), respectively. Using $E_{(PV+BES)}^{(PV+BES)}$, the optimal $P_{PV}^{13}$ size can be obtained by applying (27) to (33).

Due to the intermittent nature of the PV power, it is considered a non-dispatchable generation unit. To convert a PV unit to dispatchable, a combination of PV and BES units is used to keep the system active power losses and voltage deviation for each load level at the minimum values. This combination can produce a daily amount of dispatchable energy, $E_{(PV+BES)}$, as shown in Figure 9(a). During a 24 h cycle, the PV unit produces an amount of energy, $E_{PV}$, based on the uncertainty model. A portion of this energy is delivered to the grid ($E_{PV}$). The remaining energy of the PV unit is used to charge the BES unit, when the PV output is high during the day. This stored energy is then discharged to the grid when the PV output is small or zero during the night.

The maximum charging BES power ($P_{max}^{BES} c$) can be achieved by assessing the maximum power value which should be curtailed from the $P_{PV}^{13}$ to satisfy the objective functions during 24 h. The same analysis is performed at buses 24 and 30, the optimal sizes of PV and BES power are summarised in Table 5.

The BES capacity is calculated based on the maximum charging energy during the 24 h. The charging/discharging power of the three installed BESs is shown in Figure 9(b). From this figure, it is observed that the discharging occurs between 1:00 and 6:00 h and in the second period from 19 to 24 h to keep the power losses and the voltage profile within the satisfied operator’s decision in case no PV power is delivered. On the other hand, a charging process happens from 7 to 18 h when high PV power is available.

### 8.3.4 Energy losses analysis

This analysis investigates the impact of the PV and BES on the total energy losses over a day. Table 6 gives the percentage of the total energy reduction when installing PV and PV + BES where the energy loss is 1613.45 MW h in case of no PV integration, however after integration of PV, the energy loss reduction reaches 20.69% and a significant reduction (57.40%) is achieved with incorporating PV + BES.

### 8.4 94-bus Portuguese RDS

The proposed MCSSA3 is applied to the real Portuguese RDS 94-bus system. The rated active and reactive loads are 4.797 MW and 2.3239 MVAR, respectively, and the base voltage is 15 kV. The single line diagram, line data, and load data are provided in [42]. The active and reactive powers losses of the base case are 362.8527 kW and 504.0351 kVAR, respectively. Due to the high length of the line branch and heavy load demand, the voltage profile of this system is not subject to the limits where the minimum voltage is 0.8485 p.u on bus #92. In this system, scenario 1 and scenario 3 are used with the three PV units which gives the best results.

#### 8.4.1 Scenario 1

Figure 10 displays the Pareto optimal front for the three objective functions to place three PV units, the best compromise solution obtained by the developed fuzzy logic decision-making is shown in the figure and Table 7. This table presents the optimal sizes and locations of the PV units and a comparison between the proposed MCSSA3 and MOPSO to

| Location | PV size (MW) | BES rated power (MW) | BES capacity (MW h) |
|----------|-------------|----------------------|---------------------|
| Bus 13   | 1.63        | 0.94                 | 7.18                |
| Bus 24   | 2.11        | 1.28                 | 10.30               |
| Bus 30   | 2.26        | 1.42                 | 11.83               |
validate the results. It is clear that by integrating three PV units at buses 21, 55, and 75 with 1276.78, 1937.40, and 1250.96 kW power generation, respectively, the obtained LR is 74.80%, and the minimum voltage increases to 0.9561 p.u compared with the MOPSO that gives 72.24% LR and minimum voltage 0.9481 p.u.

8.4.2 Scenario 3

Figure 11(a) shows the 94-bus voltage profile variation with respect to the changing on the load demand and it is obvious that many buses are not subject to the voltage boundary, therefore, the MCSSA3 is applied for the 24 h to optimally schedule the PV + BES to attain the objective functions.

As a result of utilising the proposed optimisation technique, the valuable improvement in the voltage profile is obtained as shown in Figure 11(b). The charging/discharging power of the three connected BESs is demonstrated in Figure 11(c), where the BES installed at bus #55, maintains the highest energy capacity due to the large PV size at this bus as summarised in Table 8.

8.4.3 Energy losses analysis

The energy loss reduction for the 94 bus system is given in Table 9. Similar to the previous test system, a considerable
energy losses reduction is obtained when integrating PV + BES which equals 52.19%.

9 | CONCLUSION

Here, a proposed MCSSA has been applied for optimal allocation of PV and BESs in RDS. Three objective functions (power loss, VD, and VSI) have been optimised through the presented study. A developed fuzzy logic decision-making has been utilised to achieve the best compromise solution from the Pareto optimal set. The proposed algorithm has been used to optimally schedule the charging/discharging BES power to enhance the system performance in the existence of intermittent PV generation power. The proposed algorithm has been validated based on three scenarios using standard IEEE 33-bus system. Hence, a comparison between the proposed method and the other well-known optimisation techniques has been presented. The results show that a significant loss reduction (63.26%) is achieved using the proposed MCSSA when installing three PV units. In addition, a significant energy loss reduction has been obtained using PV and BES which reached 57.40%. Besides, the proposed method has been applied to the practical 94-bus Portuguese and achieved 74% and 52.19% of the power and energy losses reductions, respectively. Consequently, the results proved the superiority of the proposed MCSSA for determining the optimal setting of PV and BES in RDS to minimise the total power and voltage deviation and enhance the overall voltage profile during 24 h.

In the future work, uncertainty model for the PV generation and load demand will be studied. In addition, a long-term analysis considering both capital and operational expenditure of the PV and BEES system will be optimised.

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