Improved Hybridization of Evolutionary Algorithms with a Sensitivity-Based Decision-Making Technique for the Optimal Planning of Shunt Capacitors in Radial Distribution Systems

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Received: 18 January 2020; Accepted: 16 February 2020; Published: 19 February 2020

Abstract: In this paper, an improved hybridization of an evolutionary algorithm, named permutated oppositional differential evolution sine cosine algorithm (PODESCA) and also a sensitivity-based decision-making technique (SBDMT) are proposed to tackle the optimal planning of shunt capacitors (OPSC) problem in different-scale radial distribution systems (RDSs). The evolved PODESCA uniquely utilizes the mechanisms of differential evolution (DE) and an enhanced sine–cosine algorithm (SCA) to constitute the algorithm’s main structure. In addition, quasi-oppositional technique (QOT) is applied at the initialization stage to generate the initial population, and also inside the main loop. PODESCA is implemented to solve the OPSC problem, where the objective is to minimize the system’s total cost with the presence of capacitors subject to different operational constraints. Moreover, SBDMT is developed by using a multi-criteria decision-making (MCDM) approach; namely the technique for the order of preference by similarity to ideal solution (TOPSIS). By applying this approach, four sensitivity-based indices (SBIs) are set as inputs of TOPSIS, whereas the output is the highest potential buses for SC placement. Consequently, the OPSC problem’s search space is extensively and effectively reduced. Hence, based on the reduced search space, PODESCA is reimplemented on the OPSC problem, and the obtained results with and without reducing the search space by the proposed SBDMT are then compared. For further validation of the proposed methods, three RDSs are used, and then the results are compared with different methods from the literature. The performed comparisons demonstrate that the proposed methods overcome several previous methods and they are recommended as effective and robust techniques for solving the OPSC problem.

Keywords: radial distribution systems; shunt capacitors; differential evolution; sine cosine algorithm; sensitivity-based indices
1. Introduction

The numerous technical and operational problems that might easily occur in the vital radial distribution systems (RDSs) have forced the operators to make more efforts towards solving these problems effectively and efficiently. Those inevitable problems, such as high voltage drops, low voltage stability, bad quality and reliability of power delivered to the end consumers, and, as the main challenge, high power losses, have serious economical and functional impacts on the overall power system [1,2]. The presence of all those crucial problems in the RDS, which lacks any controllability due to the absence of active or reactive power generation, leads to critical operations of RDSs under high stress and near their permissible limits. As a result of that, many severe blackouts have happened in the last decades around the world. Most of the blackouts started because of voltage collapse issues in RDSs [3–5].

It is essential for the RDS’s operators to keep the system’s operation under safe and reliable conditions by overcoming the aforementioned problems. Sufficient planning of reactive power compensation (RPC) in RDSs by optimally installing and sizing shunt capacitor (SC) units at some of the system’s buses is one of the best ways that has been recently used to achieve the desirable optimal operation of RDSs. The improvement of the system’s voltage profile and stability, the enhancement of the delivered power quality and reliability, the decrement of total losses and costs are some of the benefits that could be achieved by the RPC in RDSs. The optimal planning of shunt capacitors (OPSC) includes deciding the most suitable buses as optimal locations for the installation of SCs along with their optimal sizes. The OPSC should be done so that a defined objective function (OF) is optimized (e.g., energy loss or total cost minimization) which is usually non-differentiable, while satisfying several constraints (such as voltage limits and power balance). Hence, the OPSC is regarded as a non-linear mixed-integer optimization problem, which is relatively hard to solve by the conventional optimization methods, especially with the exponential increasement of its size along with the increased RDS’s size [6,7].

Recently, several evolutionary algorithms (EA) have been applied on the OPSC problem. EA methods have shown their ability to find the global optimal solution. Some of the latest applied algorithms include cuckoo search algorithm (CSA) [8], bacterial foraging optimization algorithm (BFOA) [9], modified monkey search (MMS) algorithm [10], flower pollination algorithm (FPA) [11], and ant colony search (ACS) [12]. In [13], a comparison between five original EAs has been presented. With the diversified EA techniques that have been utilized to tackle the OPSC problem, different OFs have been studied, such as power loss minimization [2,9,14–16]. In [17], both power loss minimization and voltage profile improvement were included in the studied OF, whereas a combination between power loss reduction and voltage stability enhancement was constructed as the OF in [18].

However, as noticed from several papers in the literature, the total cost minimization was the most addressed OF regarding the OPSC problem in RDSs. Various formulas of this OF were studied utilizing many EA methods, as in [19], where minimizing the SC costs was a main part of the formulated bi-objective. The cost of both total installed capacitors and power loss was the considered OF in [20], where a fuzzy-based technique was used for solving the OPSC problem. Similar cost minimization OF was employed in some other studies but with a variety of implemented EAs, as for instance: novel improved differential evolution (HCODEQ) [21], whale optimization algorithm (WOA) [22], gravitational search algorithm (GSA) [23], ant colony optimization (ACO) [24], and FPA [25]. Subsequently, a more detailed and precise cost OF was built in order to represent all possible costs including loss, total installed capacitors, installation and operation costs. This OF was adopted in some of the latest research works [26–28].

The utilization of sensitivity-based indices (SBIs) has recently become a common procedure for significantly reducing the search space of the OPSC problem in RDSs. Those indicators are basically derived from the most critical aspects of RDSs, i.e., power losses and voltage profile, where the base-case load flow is used for their calculations. In [29], based on Lagrange multipliers, voltages, and reactive powers, an interior point optimal power flow method was developed to calculate the sensitivity indices. Power loss index (PLI) was used to identify the candidate buses for capacitor
allocation in [8,27,30]. Based on the active power loss formula in a distribution line, loss sensitivity factors (LSFs) were derived and then employed to reduce the search space by determining the highest potential buses for capacitor placement in [11,24,28]. In [31], a stability index was presented to find the weak buses. Different SBIs were also presented in several works, including combined loss sensitivity factor (CLSF) [32,33], index vector (IV) [32–34], voltage sensitivity index (VSenI) [32,33], voltage stability index (VSI) [32,35], and voltage stability margin (VSM) [32]. The combination between both LSF and VSM was used for selecting the candidate buses in [9,26].

As revealed by the literature reviewed in this paper, various approaches and techniques with their own advantages and drawbacks have been presented so far for solving the OPSC problem. In general, the main disadvantages that have been noticed in those methods can be summarized as follows:

- Only few previous works consider a comprehensive cost OF that includes all required costs especially for large-scale RDSs.
- Some EA approaches do not guarantee obtaining the optimal solutions especially for large-scale RDSs.
- Most of the methods utilize only one or two SBIs for reducing the search space of the OPSC problem.
- Some SBIs are employed to find the candidate buses for distributed generators (DGs) allocation (single or multiple DGs). However, they have to be tested for the OPSC problem as well, since the optimal locations for DG installation could not be the same as for SC installation.
- Some optimal locations for SC placement might be excluded from the reduced search space when only one or two SBIs are used, because of their limited ability, especially when different-scale RDSs are studied.

Hence, taking the aforementioned drawbacks under consideration, an improved hybridization of EA method called permuted oppositional differential evolution sine cosine algorithm (PODESCA) and a sensitivity-based decision-making technique (SBDMT) are proposed in this paper for solving the OPSC problem. The evolved PODESCA uniquely utilizes three effective search techniques in order to present a new and robust method, where the mechanisms of differential evolution (DE) and enhanced sine cosine algorithm (SCA) constitute the algorithm's main loop. In addition, to better improve the search ability, quasi-oppositional technique (QOT) is used in two positions throughout the algorithm; at the initialization stage to generate the initial population (IP), and also inside the main loop. PODESCA is implemented to tackle the OPSC problem in different-scale RDSs, where the objective is to minimize the system's total cost with the presence of SCs subject to different operational constraints. Furthermore, the SBDMT is developed by using a multi-criteria decision-making (MCDM) approach; namely the technique for the order of preference by similarity to ideal solution (TOPSIS). By applying this approach, four SBIs (VSI, PLI, VSenI, and VSM) are set as inputs of TOPSIS, while the output is the highest potential buses for SC placement. As a result, the search space of the OPSC problem is extensively and effectively reduced. Therefore, based on the reduced search space, PODESCA is reimplemented on the OPSC problem. The obtained results by the proposed algorithm without and with reducing the search space by the proposed SBDMT are then compared to validate their effectiveness. For further verification of the proposed methods, three RDSs; 69-bus, 85-bus, and large-scale 118-bus are used and then the results are compared with different previous methods in the literature.

The main contributions of this paper can be highlighted as follows:

- The proposed PODESCA is evolved by an improved hybridization of each of DE, SCA, and QOT, where their mathematical formulas are utilized in order to present a new, robust, and effective method.
- The developed SBDMT reduces the OPSC problem’s search space by utilizing four SBIs to be inputs of TOPSIS, which rearranges the system’s buses so that the most potential locations for SC placement are only kept in the search space.
• A comprehensive and detailed OF is employed to solve the OPSC problem in three different-scale RDSs, including one large-scale system, where various comparisons are presented.
• The OPSC is solved by PODESCA without and with reducing the search space by the SBDMT, and the results are then compared.
• The proposed methods are effective and robust especially for large-scale RDSs.

The rest of the paper is organized as follows: the mathematical formulation of the OPSC problem is addressed in Section 2. The main research steps and methodology of this paper are explained in Section 3. Then, the details of the proposed PODESCA and SBDMT with their implementation procedures on the OPSC problem are presented in Section 4. In Section 5, PODESCA’s performance analysis is performed by solving several benchmark functions and comparing the results with those from other novel algorithms. In Section 6, the results and comparisons are demonstrated and discussed. At last, the conclusions are pointed out in Section 7.

2. Mathematical Formulation of OPSC Problem

The OPSC problem basically aims at determining the locations, sizes, and types of SCs such that the main objective of this optimization problem is achieved. The system’s total annual cost is set as the objective function (OF). This OF includes the annual cost of active power loss (APL) in addition to the annual cost of SCs’ installation and operation. The decision variables required to be optimized are both locations and sizes of SCs, which are denoted as: \((LOC, \ SIZE)\), where the vector \(LOC: \{Loc_1, \ldots, Loc_{n_{SC}}\}\) is the SCs’ locations, the vector \(SIZE: \{Q_{SC_1}, \ldots, Q_{SC_{n_{SC}}}\}\) denotes the SCs’ sizes, and \(n_{SC}\) is the number of buses where SCs are installed. Hence, it is required to minimize the total cost according to those decision variables, subject to several equality and inequality constraints. The mathematical formulation of the OPSC problem can be expressed as the following [27]:

\[
\text{Cost}_{\text{tot}}(LOC, SIZE) = C_p \cdot APL \cdot T + D \cdot (C_i \cdot n_{SC} + C_o \cdot \sum_{i=1}^{n_{SC}} Q_{SC_i}) + C_a \cdot n_{SC} \quad (1)
\]

\[
\min \text{Cost}_{\text{tot}}(LOC, SIZE). \quad (2)
\]

Subject to

\[
P_{ss} = APL + \sum_{i=1}^{n_L} P_{L_i} \quad (3)
\]

\[
Q_{ss} + \sum_{i=1}^{n_{SC}} Q_{SC_i} = RPL + \sum_{i=1}^{n_{L}} Q_{L_i} \quad (4)
\]

\[
V_{\text{min}} \leq V_i \leq V_{\text{max}} \quad (5)
\]

\[
\sum_{i=1}^{n_{SC}} Q_{SC_i} \leq \sum_{i=1}^{n_{L}} Q_{L_i} \quad (6)
\]

\[
Q_{SC_{\text{min}}} \leq Q_{SC_i} \leq Q_{SC_{\text{max}}}. \quad (7)
\]

As given in (1) and (2), the total cost has to be effectively minimized, where \(T\) is the time (taking the total hours in a year), \(C_p\), \(C_i\), \(C_o\), and \(C_a\) represent the cost factors per kW-h, installation, kVar, and operation, respectively, \(D\) denotes the depreciation coefficient, and \(Q_{SC_i}\) is
the size of the installed SC’s at bus \( i \) in kVAR. All the constants’ values are taken as in [26–28] and also given in Table 1.

| Parameter | Value         |
|-----------|---------------|
| \( T \)   | 8760          |
| \( C_p \) | 0.06 $/kWh    |
| \( C_q \) | 25 $/kVAR     |
| \( D \)   | 0.2           |
| \( C_i \) | 1600 $        |
| \( C_o \) | 300 $/year/location |

It should be noted that the decision variables \( LOC \) indirectly contribute in the OF (\( Cost_{tot} \)), since according to those locations, the values of the decision variables \( SIZE \) will be determined. Equations (3) to (7) form the problem’s constraints. The power balance equality constraints formulated in (3) and (4) are the system’s load flow with the presence of SCs, where RPL denotes the reactive power loss, \( P_{ss} \) and \( Q_{ss} \) are the substation’s active and reactive powers, respectively, \( P_{i} \) and \( Q_{i} \) are the \( i \)th load’s active and reactive powers, and \( n_L \) is the total number of loads. The load flow in this paper is solved by a backward–forward sweep algorithm (BFSA). Furthermore, some inequality constraints are formulated as in (5) which represents the voltage limitation, where the voltages at all buses (\( V_i \); \( i = 1, ..., n \): total number of buses) should be remained within their permissible limits (the lower limit \( V_{min} = 0.9 \) p.u. and the upper limit \( V_{max} = 1.01 \) p.u.).

The total reactive power provided from the installed SCs must also be kept less or equal to the total reactive power of all loads, and at the same time, the individual \( Q_{Sc,i} \); \( i = 1, ..., n_{Sc} \) (which is taken as a discrete value by steps of 50 kVAR each) is maintained between minimum and maximum values \( Q_{Sc_{min}} = 50 \) kVAR, and \( Q_{Sc_{max}} = 1500 \) kVAR respectively. This is guaranteed by formulating the inequality constraints given in (6) and (7).

3. Research Steps and Methodology

Before getting through the proposed methods’ details and their implementations on the OPSC problem, a comprehensive overview of the main research methodology, including the whole steps followed in this paper, are illustrated in Figure 1.

Figure 1. Main research methodology.
As is shown in this figure, first, the mathematical model of the OPSC problem was built as presented in Section 2. Then, the proposed PODESCA was established by the unique hybridization between DE, SCA, and QOT, where the performance analysis of that algorithm was tested by solving benchmark functions and comparing the results with those from some other novel algorithms. After that, the proposed SBDMT was also constructed by utilizing four SBIs to be the inputs of TOPSIS, while the output was the best candidate buses for SC placement, so that the search space of the OPSC problem is extensively and effectively reduced. The OPSC problem was then solved for three RDSs; 33-bus, 69-bus, and 118-bus, where two cases were considered for each system; without reducing the search space, and with reducing the search space by SBDMT. For the best validation of the proposed methods’ effectiveness and robustness, the results obtained by only applying PODESCA on the OPSC problem were first compared with those from several previous methods in the literature, where those comparisons proved the superiority of the proposed algorithm over most of the other methods. Then, the results obtained by applying PODESCA without and with reducing the search space by SBDMT were also compared, where the achieved results for the three RDSs clearly verified the effectiveness of both proposed methods, especially for large-scale systems, where the SBDMT increases the consistency of PODESCA in obtaining the optimal solutions.

4. Description of PODESCA and SBDMT

4.1. Structure of PODESCA

The proposed PODESCA is constructed based on an improved hybridization between DE and SCA. In addition, QOT is used to generate the IP and also applied inside the main loop. DE was presented by Storn and Price [36]. This meta-heuristic algorithm is a simple-structured and fast method which was successfully applied in several applications. The three basic procedures of DE are the “mutation”, “crossover”, and “greedy selection”, which will be effectively used in the main body of PODESCA. Moreover, SCA was introduced by Mirjalili as a simple and efficient population-based algorithm [37]. It was designed by the sine and cosine functions to exploit the search space seeking better solutions. Enhanced functions of SCA will be also utilized inside the main loop of the proposed algorithm. The concept of QOT was originally evolved to accelerate the convergence and hence reduce the computational time of EAs [38,39]. It was proved that the quasi-opposite number is closer than its opposite number to the optimal solution. This concept was used to generate the initial population for some algorithms [40–42]. However, the QOT will be used in this paper not only at the initialization stage, but also inside PODESCA’s main loop. The steps of the proposed algorithm are highlighted as follows:

Step 1: generate population of random initial solutions (PIS) and use the considered OF to evaluate it.
Step 2: regenerate the PIS using QOT given by
\[ X^i_{QO} = \text{rand}(0.5 \ast (a^i + b^i), X^i_0), \]  
where \( X^i_{QO} \) are the quasi-opposite points in a multi-dimensional search space \( d \), and \( X^i_0 \) is given by
\[ X^i_0 = a^i + b^i - X^i; \ i = 1,2,...,d, \]  
where \( X^i_0 \in [a^i,b^i] \) are the opposite points in \( d \) [39,42]. Then, evaluate the resulted PIS again using the OF.
Step 3: execute the “DE’s greedy selection” to compare both PISs obtained in steps 1 and 2 and keep the best population, which will be set as the input PIS of PODESCA’s main loop.
Step 4: while termination criterion is not satisfied, do
Step 5: perform the “DE’s mutation” on the population by
\[ S_M = S_{Su} + F^H_{DE} \ast (S_{Rn_1} - S_{Rn_2} + S_{Rn_3} - S_{Rn_4}), \]  
where \( F^H_{DE} \) is the hybridization factor.
where $S_M$ is the mutant solution, the superior solution which is kept in each generation is denoted as $S_{Su}$, while $S_{Rn1}, S_{Rn2}, S_{Rn3},$ and $S_{Rn4}$ are random solutions, and $F_{DE}$ is a modified amplifying factor which is given by

$$F_{DE}^M = F_{max} - (It - 1) \times \frac{(F_{max} - F_{min})}{(It_{max} - 1)}, \quad (11)$$

where $F_{min} = 0.2$, $F_{max} = 2$, the iteration number is $It$ and its maximum is denoted by $It_{max}$. Then, evaluate the resulted solution using the OF.

Step 6: Perform the “DE’s crossover” by

$$T_{x1}^{It} = \begin{cases} S_{M1}^{It+1} & \text{if } r \leq cr \\ S_{1}^{It} & \text{if } r \geq cr \end{cases}, \quad (12)$$

where $T_{x1}^{It}$ are trial solutions, $cr$ denotes the crossover rate, and $r$ is in the range [0,1]. Then evaluate the obtained solution using the OF.

Step 7: Execute the “DE’s greedy selection” to compare both solutions obtained in steps 5 and 6 and keep the best population [36].

Step 8: Perform the SCA’s functions on the best population saved in step 7 by using a new enhanced SCA version which utilizes the local best solutions in addition to the global best solution in each iteration as:

$$S_{1}^{It+1} = \begin{cases} S_{1}^{It} + Rn_1 \times \sin(Rn_2) \times \left|Rn_3 \times P_{1}^{It} - S_{1}^{It}\right|, & Rn_4 < 0.5 \\ S_{1}^{It} + Rn_1 \times \cos(Rn_2) \times \left|Rn_3 \times P_{1}^{It} - S_{1}^{It}\right|, & Rn_4 \geq 0.5 \end{cases}, \quad (13)$$

where $S_{1}^{It}$ is the current local best solution, $P_{1}^{It}$ is the global best solution, $Rn_2$, $Rn_3$, and $Rn_4$ are random numbers, while $Rn_1$ is modified so that the exploration is balanced and hence improved:

$$Rn_1 = a - \frac{It}{It_{max}}, \quad (14)$$

where $a$ is a constant [37]. Then, evaluate the resulted solution using the OF.

Step 9: Perform the “DE’s crossover” on the saved population in step 8 again by (12) and reevaluate it using the OF.

Step 10: Execute the “DE’s greedy selection” to compare both solutions obtained in steps 8 and 9 and keep the best population.

Step 11: Apply the QOT on the population saved in step 10 by (8) and reevaluate it using the OF.

Step 12: Execute the “DE’s greedy selection” to compare both solutions obtained in steps 10 and 11 and keep the best population.

Step 13: End while

Step 14: Save the final solutions and results.

PODESCA’s implementation on the OPSC problem is also illustrated by the flowchart given in Figure 2.
Figure 2. Flowchart of the proposed permutated oppositional differential evolution sine cosine algorithm (PODESCA) and sensitivity-based decision-making technique (SBDMT).

4.2. Structure of SBDMT

The SBDMT is developed in this paper by utilizing four effective SBIs to be the inputs of TOPSIS, where this MCDM technique rearranged the buses depending on those four indices’ values. Then, the output of TOPSIS will be the most candidate buses that are suitable for SC placement.

4.2.1. Sensitivity-Based Indices

The SBIs are generally used to identify the most candidate buses for SC placement, where they are determined by the base-case load flow. Four indices are used in this paper; namely: VSI, PLI, VSenI, and VSM. Those indices are calculated as follows:

Voltage stability index (VSI)

Taking a distribution line between two buses $k$ and $k+1$, VSI at bus $k+1$ is calculated by [35]

$$VSI_{k+1} = \frac{4 \cdot X_l}{V_k^2} \cdot \left( \frac{P_{k+1}^2}{Q_{k+1}} + Q_{k+1} \right),$$

(15)

where $X_l$ denotes the line reactance, $V_k$ is the voltage at bus $k$, $P_{k+1}$ and $Q_{k+1}$ are the active and reactive powers at bus $k+1$, respectively. The candidate buses for SC placement are selected according to the highest VSI values [35].

Power loss index (PLI)

Considering one bus at a time (the slack bus is excluded), PLI is calculated by removing the reactive part of the load at that bus and then finding the active loss reduction (LR). Hence, it is given at bus $k$ by [30]
The buses are then sorted from the highest to the lowest values, where the first sorted buses are taken as the candidates for SC placement [30].

Voltage sensitivity index (VSenI)

According to this index, the most voltage-sensitive buses are identified, which is a significant issue since those critical buses might put the system under the risk of collapse. By adding a SC with a size equal to 25% of the total system capacity and considering one bus at a time, VSenI at bus \( k \) is defined by [32]

\[
V_{SenI_k} = \sqrt{\frac{\sum_{i=1}^{n}(1-V_i)^2}{n}}. 
\]  

(17)

The candidate buses for SC placement are selected here according to the lowest VSenI values [32].

Voltage stability margin (VSM)

This index also defines the “near-collapse” or “weak” buses in the system, where those buses might threaten the system’s stability. It is determined at bus \( k + 1 \) by [26,32]

\[
V_{SM_{k+1}} = |V_k|^4 - 4 \times (P_{k+1}X_l - Q_{k+1}R_l)^2 - 4 \times (P_{k+1}R_l + Q_{k+1}X_l) \times |V_k|^2, 
\]  

(18)

where \( R_l \) denotes the line resistance. According to the lowest VSM values, the candidate buses for SC placement are selected [26,32].

After determining the indices’ values, they are all normalized to be in the same domain between 0 and 1. Then, they are arranged in a \((N \times M)\) matrix; \((N\) is the total number of buses and \(M\) is the number of indices). This matrix is the input of TOPSIS.

4.2.2. TOPSIS

TOPSIS was originally presented by Hwang and Yoon [43]. This MCDM technique selects two sets of solutions (the positive and negative ideal solutions: \( I^+ \), \( I^- \)) from a decision matrix with \( N \) number of alternatives (total number of the RDS’s buses) and \( M \) number of attributes (number of indices). From all the alternatives, \( I^+ \) has the best data; while \( I^- \) has the worst data. By calculating the Euclidean distance of all points (taking a pair of positive and negative solutions at a time) and comparing them, the best point is determined which has the least distance from \( I^+ \) and the longest distance from \( I^- \). The steps of TOPSIS are given as follows [43]:

Step 1: set the \( N \times M \) input matrix \((S_i)\).

Step 2: find the normalized decision matrix (NDM) \( (S_{Nij}) \) from the input matrix in step 1 so that the dimensional problem is converted into nondimensional

\[
S_{Nij} = \frac{S_{ij}}{\sqrt{\sum_{i=1}^{N} x_{ij}^2}}. 
\]  

(19)

where \( i = 1, ..., N \) and \( j = 1, ..., M \).

Step 3: get the weighted NDM \((WS_{Nij})\) by

\[
WS_{Nij} = w_j \times S_{Nij}, 
\]  

(20)

where \( \sum_{j=1}^{M} w_j = 1 \) represent the assumed weights.
Step 4: define the positive and negative ideal solutions ($IS^+$, $IS^-$) by

$$\begin{align*}
IS^+ &= \{WS_{N_1}^+, \ldots, WS_{N_M}^+\} \\
IS^- &= \{WS_{N_1}^-, \ldots, WS_{N_M}^-\}
\end{align*}$$

where

$$\begin{align*}
WS_{N_j}^+ &= \{\max_i WS_{N_{ij}} \mid j \in J, \min_i WS_{N_{ij}} \mid j \in J'\} \\
WS_{N_j}^- &= \{\min_i WS_{N_{ij}} \mid j \in J, \max_i WS_{N_{ij}} \mid j \in J'\}
\end{align*}$$

where $J$ denotes the set of benefit attributes and $J'$ is the set of cost attributes.

Step 5: find the distances $D_i^+$ and $D_i^-$ from $IS^+$ and $IS^-$, respectively.

$$\begin{align*}
D_i^+ &= \sqrt{\sum_{j=1}^{M} (WS_{N_j}^+ - WS_{N_{ij}})^2} \\
D_i^- &= \sqrt{\sum_{j=1}^{M} (WS_{N_j}^- - WS_{N_{ij}})^2}
\end{align*}$$

Step 6: calculate the relative closeness of alternatives to the ideal solutions $RC_i^+$ by

$$RC_i^+ = \frac{D_i^-}{D_i^- + D_i^+}$$

where $RC_i^+ \in [0,1]$, and the relative closeness of the best solutions should be the closest to 1 [43].

Furthermore, the utilization of SBDMT for reducing the OPSC problem’s search space is shown in the flowchart of Figure 2.

5. Performance Analysis of PODESCA

When developing a new evolutionary algorithm, it is essential to analyze its performance by solving some of the most important benchmark test functions (BTFs). Therefore, ten BTFs are utilized in this paper in order to study PODESCA’s performance. Those BTFs are: $f_1$: Ackley, $f_2$: Griewank, $f_3$: Rastrigin, $f_4$: Levy, $f_5$: Perm 0, $d$, $\beta$, $f_6$: Sum squares, $f_7$: Rotated hyper-ellipsoid, $f_8$: Power sum, $f_9$: Rosenbrock, and $f_{10}$: Dixon-Price, where their detailed formulas and all needed data can be found in [42,44]. The proposed algorithm’s results are also compared with those from six other novel algorithms; PSO, GA, ABC, firefly algorithm (FA), DE, and SCA. The number of evaluations for all algorithms was set to 40,000. All the BTFs were minimized so that their optimal values were zero. The obtained results are illustrated in Table 2.

| Function | PSO | GA | ABC | FA | DE | SCA | PODESCA |
|----------|-----|----|-----|----|----|-----|---------|
| $f(x)$   | Min. 7.9936×10^{-10} | 0.001500000 | 0.001499 | 3.5994×10^{-6} | 5.5078×10^{-5} | 3.3672×10^{-5} | 8.88178×10^{-16} |
|          | Max. 1.5099×10^{-14} | 1.501800000 | 0.005632 | 9.1151×10^{-5} | 0.00136427 | 8.88178×10^{-5} | 8.88178×10^{-16} |
|          | Mean 1.1546×10^{-14} | 0.494010000 | 0.003136 | 4.3945×10^{-5} | 7.7296×10^{-5} | 0.00052707 | 8.88178×10^{-16} |
|          | SD 3.7449×10^{-15} | 0.650915210 | 0.001235 | 4.1056×10^{-6} | 1.3982×10^{-5} | 0.00039639 | 0 |
| $f(x)$   | Min. 1.85×10^{-13} | 1.67057×10^{-7} | 0.023929 | 4.48524×10^{-8} | 1.89310×10^{-6} | 3.53044×10^{-5} | 0 |
|          | Max. 0.058921 | 0.007396679 | 0.305490 | 0.009864731 | 6.47944×10^{-5} | 0.260080741 | 0 |
|          | Mean 0.026802 | 0.00740400 | 0.089867 | 0.002465738 | 1.42411×10^{-5} | 0.079647319 | 0 |
|          | SD 0.019734 | 0.00238778 | 0.085039 | 0.00426563 | 1.85757×10^{-5} | 0.105481599 | 0 |
| $f(x)$   | Min. 0 | 0.994959 | 0.205000 | 0.994959 | 2.01×10^{-11} | 0 | 0 |
|          | Max. 1.989918 | 5.969749 | 1.657200 | 5.969754 | 1.15×10^{-10} | 9.32×10^{-11} | 1.42109×10^{-14} |
|          | Mean 0.596795 | 2.984877 | 0.768219 | 3.28365 | 3.80×10^{-10} | 9.40×10^{-12} | 2.13613×10^{-15} |
|          | SD 0.039623 | 1.483196 | 0.537652 | 1.410988 | 3.53×10^{-11} | 2.94×10^{-11} | 4.66789×10^{-16} |
| $f(x)$   | Min. 3.28×10^{-10} | 3.02×10^{-10} | 3.02×10^{-10} | 9.21×10^{-10} | 6.41×10^{-10} | 1.05693 | 7.15×10^{-10} |
|          | Max. 3.91×10^{-10} | 0.9948176 | 0.001058 | 1.33×10^{-10} | 2.05×10^{-10} | 1.279176 | 0.722374 |
|          | Mean 2.65×10^{-10} | 0.172109 | 0.000406 | 1.19×10^{-10} | 1.14×10^{-10} | 1.180877 | 0.360174 |
|          | SD 1.52×10^{-10} | 0.335319 | 0.000265 | 1.27×10^{-11} | 4.79×10^{-14} | 0.085863 | 0.189337 |
| $f(x)$   | Min. 3.50×10^{-13} | 0.000224 | 0.001526 | 8.36×10^{-14} | 0.003839 | 0.204203 | 4.81×10^{-16} |
Table 2 includes the minimum (Min.), maximum (Max.), mean, and standard deviation (SD) for each function. As is remarked from Table 2 for most of the BTFs, PODESCA’s results are much better than those from the other algorithms. This validates the effectiveness of the proposed algorithm.

Remarks
1. The QOT has been employed to enhance the exploration and search ability of some algorithms by generating their initial populations as in [40–42]. However, this concept is applied at the initialization stage as well as inside the main loop of the proposed PODESCA in this paper.
2. The proposed PODESCA applies two main global optimization frameworks, namely the DE and an enhanced version of SCA algorithm. Compared to the original DE algorithm previously applied for balanced systems [30], the implementation of PODESCA insures the convergence towards the optimum rapidly and reliably. The combined techniques also keep the elite solutions in each generation which guarantees their flexible flow to the optimal region inside the search space. The developed paradigm combining the above superior features is also suitable to be utilized in various engineering applications.
3. The proposed SBDMT exploits four well-known SBIs’ abilities to identify the weak buses by merging their values using TOPSIS. This technique helps extensively and effectively reducing the OPSC problem’s search space while keeping the most potential buses suitable for SC placement, unlike other methods which utilize only one or two SBIs to reduce the search space and thus some critical buses are excluded from the search space, as in [26,28,30–35].

6. Results and Discussions
The proposed PODESCA and SBDMT have been applied on the 69-bus, 85-bus, and 118-bus RDSs. As mentioned before, BFSA was used to perform the load flow. For every system, the OPSC problem is solved by minimizing the system’s total annual cost given in (2) considering the constraints given from (3) to (7).

PODESCA is first applied without reducing the search space, i.e., the search space of the problem includes all the system’s buses (excluding the slack bus), and the obtained results are then compared with those from several methods in the literature. After that, the proposed algorithm is reapplied but this time with reducing the search space by the SBDMT, where the results are thus compared without and with reducing the search space by the SBDMT. Furthermore, for every system, three different load levels are considered; light-, medium-, and full-load, with values of 50%, 75%, and 100% of the base-case, respectively. Thus, a comprehensive planning schedule is provided by deciding the locations and sizes of both fixed and switched SCs.
According to the system’s scale, PODESCA’s parameters are set using a step-wise variation of stochastic parameters so that the best performance is achieved. For each system, 50 independent runs are executed to obtain the best solutions. Matlab-R2016a is used for coding and running the programs on a PC with an Intel Core processor (TM) i7, 3.2 GHz speed and 8 GB RAM.

6.1. 69-Bus System

This system’s load and line data are taken as in [45]. The base values of voltage and power are 12.66 kV and 100 MVA, respectively. The total system’s loads are 3.80 MW (active) and 2.69 MVAr (reactive). By performing the base-case load flow (with full-load level), the active and reactive power losses are 225 kW and 102.16 kVAr, respectively. The base-case minimum voltage \( V_{min} \) is 0.9092 p.u., the voltage deviation (VD) (which is calculated by \( VD = \sum_{i=1}^{n} (V_i - 1)^2 \)) is 0.0993 p.u., and the annual cost is 118,270.5 ($/year).

6.1.1. Results without Reducing the Search Space

The search space in this case includes all the system’s buses (excluding the slack bus); i.e., 68 buses. PODESCA decides the optimal locations and sizes of the added SCs, where only two locations are considered. The obtained results of full-load level are given in Tables 3 and 4. As shown in those two tables, the proposed algorithm’s results are also compared to those from other methods in [27,30,46–48].

The optimal locations are 20 and 61 with total installed capacity equal to 1400 kVAR, which is less than those from the other methods. Moreover, by applying PODESCA, \( V_{min} \) and VD are improved to 0.9302 p.u. and 0.0622 p.u., respectively. The APL is also reduced to 147.78 kW with a loss reduction (LR) percentage of 34.3%. Those values are better than those obtained from particle swarm optimization (PSO), fuzzy genetic algorithm (FGA), heuristic method (HM), and DE.

However, although the APL obtained from improved harmony algorithm-power loss index (IHA-PLI) (145.32 kW) is still lower than that from PODESCA, the annual cost (ann. cost) is higher (86,122.10 $/year), while the annual cost by the proposed algorithm reaches 85,913.48 $/year. Consequently, the net savings (net sav. = 32,356.5 $/year) are also better than that from IHA-PLI (32,082.7 $/year). Therefore, the compromised results obtained by applying the proposed PODESCA are better than most of the other results considered in the comparison, which proves the algorithm’s effectiveness. Additionally, the small SD value (0.01133) shown in Table 4 validates the method’s consistency, especially when it is compared to the SD value of IHA-PLI method (832.16).

The optimal results for different load levels are also obtained as given in Table 5, where, according to those levels, only a fixed SC of 550 kVAR is needed at bus 61, whereas two switched SCs of 250 kVAR at bus 20 and 600 kVAR at bus 61 are required to cover the three load levels.

| Method          | PSO [46] | FGA [47] | HM [48] | DE [30] | IHA-PLI [27] | PODESCA |
|-----------------|----------|----------|---------|---------|--------------|---------|
| SCs locations   | 46       | 47       | 47      | 47      | 47           | 47      |
| SCs sizes (kVAR)| 241      | 365      | 365     | 365     | 365          | 365     |
| Total No. of locations | 3 locations | 3 locations | 3 locations | 5 locations | 2 locations | 2 locations |
| Total kVAR     | 1621     | 1600     | 1800    | 1450    | 1700         | 1400    |
### Table 4. Comparison of results between PODESCA and other methods for the 69-bus system.

| Method | APL (kW) | LR (%) | $V_{min}$ (p.u.) | VD (p.u.) | Ann. cost ($/year) | Net sav. ($/year) | Net sav. (%) | SD |
|--------|----------|--------|-----------------|----------|-------------------|------------------|--------------|----|
| Without SCs | 225.02 | - | 0.9092 | 0.0993 | 118,270.5 | - | - | - |
| PSO [46] | 152.48 | 32.2 | - | - | 90,108.50 | 28,096.3 | 23.77 | - |
| FGA [47] | 156.62 | 30.4 | 0.9369 | - | 92,179.50 | 26,025.3 | 22.02 | - |
| With SCs | 148.48 | 34.0 | 0.9305 | - | 88,901.10 | 29,303.7 | 24.79 | - |
| HM [48] | 151.38 | 32.7 | 0.9311 | - | 89,913.40 | 28,291.4 | 23.93 | - |
| DE [30] | 145.32 | 35.4 | 0.9370 | - | 86,122.10 | 32,082.7 | 27.14 | 832.160 |
| IHA-PLI [27] | 147.78 | 34.3 | 0.9302 | 0.0622 | 85,913.48 | 32,356.5 | 27.36 | 0.01133 |

### Table 5. Optimal results of PODESCA for the 69-bus system considering different load levels.

| Load level | Description | Without SCs | With SCs Installed SCs (kVar) |
|------------|-------------|-------------|-----------------------------|
| 100% | $V_{min}$ (p.u.) | 0.9092 | 0.9302 |
| | VD (p.u.) | 0.0993 | 0.0622 |
| | APL (kW) | 225.02 | 147.78 |
| | RPL (kVar) | 102.10 | 68.90 |
| | Ann. cost ($/year) | 118,270.5 | 85,913.48 |
| | Net sav. ($/year) | - | 32,356.50 |
| 75% | $V_{min}$ (p.u.) | 0.9335 | 0.9476 |
| | VD (p.u.) | 0.0536 | 0.0365 |
| | APL (kW) | 121.04 | 83.065 |
| | RPL (kVar) | 55.065 | 38.643 |
| | Ann. cost ($/year) | 63,618.62 | 48,779 |
| | Net sav. ($/year) | - | 14,839.62 |
| 50% | $V_{min}$ (p.u.) | 0.9567 | 0.9650 |
| | VD (p.u.) | 0.0229 | 0.0162 |
| | APL (kW) | 51.610 | 36.057 |
| | RPL (kVar) | 23.537 | 16.824 |
| | Ann. cost ($/year) | 27,126.32 | 22,321.64 |
| | Net sav. ($/year) | - | 4804.68 |

### 6.1.2. Results with Reducing the Search Space by SBDMT

PODESCA is applied again on the OPSC problem but in this case with a reduced search space by the proposed SBDMT. By applying this technique, the search space is significantly reduced, where only 15 buses are considered for selecting the optimal locations of SCs. For further validation of the proposed SBDMT, the obtained search space is compared to that from CLSF and PLI as illustrated in Table 6.

#### Table 6. The reduced search space by SBDMT comparing to combined loss sensitivity factor (CLSF) and power loss index (PLI) for the 69-bus system.

| Technique | The reduced search space: Total: 15 buses |
|-----------|------------------------------------------|
| CLSF      | 57 58 7 6 61 60 10 59 55 56 49 12 54 13 14 |
| PLI       | 61 64 59 65 21 12 11 62 17 18 16 8 24 68 69 |
| SBDMT     | 61 49 64 65 62 59 63 60 58 66 57 21 17 20 18 |

It can be easily seen that the three techniques give different locations. It is also clear that the selected locations by PODESCA in the first case are included in the search space. By utilizing the SBDMT’s search space, PODESCA’s results are obtained. It is observed that the same optimal locations and sizes are selected by the proposed algorithm. Accordingly, the same results are attained as presented in Tables 3–5.
Nevertheless, the SD in this case is smaller than that obtained without using the SBDMT, where it reached the value of 0.00443. Those results prove that SBDMT effectively reduces the search space while keeping the most critical and suitable buses for SC placement.

This technique also helps to increase PODESCA’s consistency by reducing the SD. In addition to that, the convergence characteristics of the proposed algorithm are plotted and compared without and with utilizing the SBDMT as depicted in Figure 3. This figure clearly demonstrates that the same OF’s value (85,913.48 $/year) is achieved in both cases but with different convergence rates, where 30 iterations are needed to reach the optimal value without reducing the search space. On the other hand, only 13 iterations are needed to get to the optimal value if the search space is reduced by the proposed SBDMT. Those results verify the effectiveness and robustness of both proposed PODESCA and SBDMT for solving the OPSC problem.

Finally, Figure 4 shows the voltages along the 69-bus system considering the full-load level, where it can be obviously remarked that a good enhancement in voltages is achieved after adding the optimal SCs.

![Figure 3. Convergence characteristics of PODESCA for the 69-bus system.](image1)

![Figure 4. Voltage profile of the 69-bus system considering full-load level using PODESCA.](image2)
6.2. 85-Bus System

This system’s load and line data are taken as in [26]. The base values of voltage and power are 11 kV and 100 MVA, respectively. The total system’s loads are 2.57 MW (active) and 2.62 MVAr (reactive). The base-case load flow values regarding the active and reactive power losses are 315.714 kW and 198.37 kVAr, respectively. The base-case values of \( V_{\text{ref}} \), \( V_D \), and annual cost are 0.8713 p.u., 0.8203 p.u., and 165,939.28 ($/year), respectively.

6.2.1. Results without Reducing the Search Space

PODESCA is applied on the OPSC problem in this case with a search space containing 84 buses. Considering five locations for SC placement, the results of full-load level are obtained and listed in Tables 7 and 8. As demonstrated in those tables, the results of PODESCA are compared to those from other methods in the literature [2,23,26,28]. The optimal selected locations are 12, 30, 49, 60, and 69 with total installed capacity equal to 2000 kVAr, which is less than those from the other methods.

In addition, both values of \( V_{\text{ref}} \) and \( V_D \) are improved to 0.9207 p.u. and 0.3121 p.u., respectively. The APL is decreased to 148.25 kW, which is lower than those obtained from plant growth simulation algorithm (PGSA) and MBA. However, this value is still higher than those from direct search algorithm (DSA), teaching learning-based optimization (TLBO), GSA, and improved harmony algorithm (IHA). Nevertheless, the annual cost obtained by the proposed algorithm (91,018.47 $/year) is less than the costs from the all other algorithms addressed in this comparison, which consequently led to the highest annual savings as well (74,920.8 $/year). Hence, by compromising the overall solutions, it can be noticed that PODESCA’s results are regarded as better solutions than most of the other methods’ solutions from the literature. Thus, the obtained results given in Tables 7 and 8 validate the proposed algorithm’s effectiveness as well as its consistency especially when comparing the small SD value (0.01208) to that from IHA (358.240).

Table 7. Optimal locations and sizes of SCs by PODESCA comparing to other methods for the 85-bus system.

| Method | PGSA [26] | DSA [26] | TLBO [2] | GSA [23] | IHA [26] | MBA [28] | PODESCA |
|--------|-----------|----------|----------|----------|----------|----------|---------|
| SCs locations and sizes (kVAr) | 7 200 | 6 150 | 4 300 | 8 150 | 8 250 | 8 800 | 12 450 |
| | 8 1200 | 8 150 | 7 150 | 12 150 | 29 350 | 27 300 | 30 450 |
| | 58 908 | 14 150 | 9 300 | 29 350 | 34 400 | 34 400 | 49 350 |
| | - - | 17 150 | 21 150 | 36 450 | 54 150 | 58 400 | 60 500 |
| | - - | 18 150 | 26 150 | 68 450 | 58 350 | 64 300 | 69 250 |
| | - - | 20 150 | 31 300 | 83 1050 | 64 500 | - - | - - |
| | - - | 26 150 | 45 150 | - - | 83 250 | - - | - - |
| | - - | 30 300 | 49 150 | - - | - - | - - | - - |
| | - - | 36 450 | 55 150 | - - | - - | - - | - - |
| | - - | 57 150 | 61 300 | - - | - - | - - | - - |
| | - - | 61 150 | 68 300 | - - | - - | - - | - - |
| | - - | 66 150 | 83 150 | - - | - - | - - | - - |
| | - - | 69 300 | 85 150 | - - | - - | - - | - - |
| | - - | 80 150 | - - | - - | - - | - - | - - |
| Total No. of locations | 3 14 | 13 6 | 7 5 | 5 5 |
| Total kVAr | 2308 | 2700 | 2700 | 2600 | 2250 | 2200 | 2000 |
Table 8. Comparison of results between PODESCA and other methods for the 85-bus system.

| Method           | APL (kW) | LR (%) | $V_{min}$ (p.u.) | VD (p.u.) | Ann. cost ($/year) | Net sav. ($/year) | Net sav. (%) | SD |
|------------------|----------|--------|------------------|----------|-------------------|------------------|--------------|----|
| Without SCs      | 315.714  | -      | 0.8713           | 0.8203   | 165,939.28        | -                | -            | -  |
| With SCs         |          |        |                  |          |                   |                  |              |    |
| PGSA [26]        | 161.40   | 48.88  | -                | -        | 98,231.80         | 67,707.4         | 40.8         | -  |
| DSA [26]         | 144.01   | 54.39  | 0.9224           | -        | 97,871.70         | 68,067.6         | 41.02        | -  |
| TLBO [2]         | 143.18   | 54.65  | 0.9242           | -        | 96,815.40         | 69,123.9         | 41.66        | -  |
| GSA [23]         | 143.09   | 54.69  | -                | -        | 91,890.80         | 74,048.5         | 44.62        | -  |
| IHA [26]         | 144.72   | 54.16  | 0.9370           | -        | 91,654.80         | 74,284.4         | 44.76        | -  |
| MBA [28]         | 149.79   | 52.55  | 0.9300           | -        | 92,831.67         | 73,107.6         | 44.06        | -  |
| PODESCA          | 148.25   | 53.04  | 0.9207           | 0.3121   | 91,018.47         | 74,920.8         | 45.15        | 0.01208 |

Furthermore, Table 9 gives the optimal results for different load levels, where three fixed SCs with sizes of 250, 350, and 300 kVAr are injected at buses 12, 30, and 60, respectively. While the switched SCs are distributed as 200, 200, 350, 200, and 250 kVAr, respectively, at buses 12, 30, 49, 60, and 69.

Table 9. Optimal results of PODESCA for the 85-bus system considering different load levels.

| Load level | Description | Without SCs | With SCs | Installed SCs (kVAr) |
|------------|-------------|-------------|----------|----------------------|
| 100%       | $V_{min}$ (p.u.) | 0.8713      | 0.9207   | 5 locations         |
|            | VD (p.u.)    | 0.8203      | 0.3121   | Total: 2000         |
|            | APL (kW)     | 315.714     | 148.25   |                      |
|            | RPL (kVAR)   | 198.370     | 92.520   |                      |
|            | Ann. cost ($/year) | 165,939.28 | 91,018.47 |                      |
|            | Net sav. ($/year) | -         | 74,920.80 |                      |
| 75%        | $V_{min}$ (p.u.) | 0.9068      | 0.9355   | 12 (350)            |
|            | VD (p.u.)    | 0.4323      | 0.1888   | 30 (550)            |
|            | APL (kW)     | 166.76      | 85.0098  | 60 (500)            |
|            | RPL (kVAR)   | 104.83      | 52.4542  | Total: 1400         |
|            | Ann. cost ($/year) | 87,649.06  | 53,541   |                      |
|            | Net sav. ($/year) | -         | 34,108.06 |                      |
| 50%        | $V_{min}$ (p.u.) | 0.9397      | 0.9573   | 12 (250)            |
|            | VD (p.u.)    | 0.1811      | 0.0834   | 30 (350)            |
|            | APL (kW)     | 70.015      | 36.7358  | 60 (300)            |
|            | RPL (kVAR)   | 44.034      | 22.6901  | Total: 900          |
|            | Ann. cost ($/year) | 36,800     | 25,668   |                      |
|            | Net sav. ($/year) | -         | 11,132   |                      |

6.2.2. Results with Reducing the Search Space by SBDMT

The implementation of PODESCA on the OPSC problem is performed again with a reduced search space by the proposed SBDMT (reduced to 20 buses), with five locations also considered for SC placement. The comparison between the obtained search spaces by SBDMT, CLSF, and PLI is shown in Table 10, where it clearly demonstrates the difference between the three techniques. It also shows that the selected locations by PODESCA in the first case are all included in the search space.

The obtained results by re-implementing PODESCA and utilizing the SBDMT’s search space indicate that the same locations and sizes of SCs are selected.
Table 10. The reduced search space by SBDMT comparing to CLSF and PLI for the 85-bus system.

| Technique | The reduced search space: Total: 20 buses |
|-----------|------------------------------------------|
| CLSF      | 8  6  7  4  58  27  3  25  29  34  30  26  60  64  2  5  10  68  52  28 |
| PLI       | 54  55  51  76  69  74  39  72  66  28  62  38  61  60  59  82  37  26  80  11 |
| SBDMT     | 69  62  38  61  80  8  76  54  55  51  60  44  39  78  75  30  46  45  12  49 |

As a consequence, the results given in Tables 7–9 are attained again. However, those results are achieved with smaller SD (0.00725) comparing to its value without reducing the search space (0.01208), which means that the SBDMT increases PODESCA’s consistency when solving the OPSC problem. Additionally, the convergence characteristics illustrated in Figure 5 show the difference between PODESCA’s convergence rates without and with the SBDMT’s search space. As depicted in this figure, the minimum total cost (91,018.47 $/year) is reached in both cases, but at the 51st iteration without reducing the search space, and at the 23rd iteration with the reduced search space. Those results validate the effectiveness as well as the robustness of each of the proposed PODESCA and SBDMT. Finally, the voltages along the 85-bus system considering the full-load level are depicted in Figure 6.

![Figure 5](image1.png)

**Figure 5.** Convergence characteristics of PODESCA for the 85-bus system.

![Figure 6](image2.png)

**Figure 6.** Voltage profile of the 85-bus system considering full-load level using PODESCA.
It can be clearly noted from Figure 6 that the voltages are well enhanced after adding the optimal SCs.

6.3. 118-Bus System

This system’s data are taken from [8]. The base values of voltage and power are 11 kV and 100 MVA, respectively. The total system’s loads are 22.710 MW (active) and 17.041 MVAr (reactive). By performing the base-case load flow, the active and reactive power losses are 1297.95 kW and 978.54 kVAR, respectively. The base-case values of $V_{\text{min}}$, $V_D$, and annual cost are 0.8688 p.u., 0.3576 p.u., and 682,202.52 ($/year), respectively.

6.3.1. Results without Reducing the Search Space

In this case, the OPSC problem is solved by PODESCA with a search space of 117 buses. Considering nine locations for SC placement, the obtained results of full-load level are presented in Tables 11 and 12. As is shown in those tables, the results of PODESCA are compared to those from other methods [8,26,27]. The optimal locations selected by the proposed algorithm are 5, 34, 39, 48, 74, 86, 91, 109 and 118 with total installed capacity equal to 9150 kVAR, which is less than those from the other methods except for CSA. It is obvious that bus 5 has only a small impact on the results since only 50 kVAR is injected at that location.

| Method       | CSA [8] | ABC [27] | HSA [27] | IHA [26] | IHA-PLI [27] | PODESCA |
|--------------|---------|----------|----------|----------|--------------|---------|
|              | 32      | 1500     | 32       | 850      | 32           | 1500    |
|              | 39      | 1500     | 35       | 1050     | 32           | 1500    |
|              | 40      | 550      | 40       | 1300     | 35           | 1050    |
|              | 70      | 950      | 50       | 800      | 40           | 1300    |
|              | 74      | 750      | 70       | 550      | 50           | 165     |
|              | 74      | 750      | 70       | 550      | 53           | 425     |
|              | 86      | 1050     | 73       | 1300     | 54           | 377     |
|              | 108     | 1500     | 79       | 1200     | 56           | 375     |
|              | 118     | 1200     | 105      | 700      | 70           | 626     |
| Total kVAR   | 9000    | 10,000   | 9928     | 9400     | 9800         | 9150    |

Furthermore, $V_{\text{min}}$ and $V_D$ are well enhanced to 0.9072 p.u. and 0.1771 p.u., respectively. The APL and annual cost obtained by the proposed algorithm are reduced to 842.16 kW and 493,969.50 $/year, respectively. As is easily seen from Table 12, those two values are less than those obtained
from the all other methods, where the highest annual savings are recorded as well (188,233.02 $/year). Hence, it can be clearly noticed that PODESCA’s results are better than those from other methods in the literature. Therefore, they highly validate the proposed algorithm’s effectiveness as well as its consistency especially when comparing the small SD value (184.433) to that from IHA (1051.6) and IHA-PLI (550.70).

Table 12. Comparison of results between PODESCA and other methods for the 118-bus system.

| Method         | APL (kW) | LR (%) | $V_{\min}$ (p.u.) | $V_D$ (p.u.) | Ann. cost ($/Year) | Net sav. ($/Year) | Net sav. (%) | SD       |
|----------------|----------|--------|-------------------|--------------|-------------------|-------------------|--------------|----------|
| Without SCs    | 1297.95  | 0.8688 | 0.3576            | 682,202.52   | -                 | -                 | -            | -        |
| CSA [8]        | 858.89   | 33.64  | 0.9060            | -            | 501,392.60        | 178,917.80        | 26.30        | -        |
| ABC [27]       | 854.39   | 33.99  | 0.9089            | -            | 505,887.40        | 174,423.00        | 25.64        | -        |
| With SCs       |          |        |                   |              |                   |                   |              |          |
| HSA [27]       | 926.10   | 28.26  | -                 | -            | 549,418.20        | 130,892.20        | 19.24        | -        |
| IHA [26]       | 853.46   | 34.06  | 0.9004            | -            | 501,160.31        | 179,150.05        | 26.33        | 1051.6   |
| IHA-PLI [27]   | 843.15   | 34.85  | 0.9020            | -            | 497,737.50        | 182,572.80        | 26.80        | 550.70   |
| PODESCA        | 842.16   | 35.12  | 0.9072            | 0.1771       | 493,969.50        | 188,233.02        | 27.59        | 184.433  |

6.3.2. Results with Reducing the Search Space by SBDMT

PODESCA is reapplied on the OPSC problem with a reduced search space by the SBDMT, where it is limited to only 25 buses. The search spaces of SBDMT, CLSF, and PLI are compared in Table 13, where this comparison demonstrates the difference between the three techniques. It also shows that only bus 5 among the selected locations by PODESCA in the first case is not included in the search space.

Table 13. The reduced search space by SBDMT comparing to CLSF and PLI for the 118-bus system.

| Technique | The reduced search space: Total: 25 buses |
|-----------|-----------------------------------------|
| CLSF      | 70 68 104 89 65 64 30 69 67 78 101 31 106 108 48 |
|           | 103 33 66 34 110 23 102 44 105 36 |
| PLI       | 118 39 74 70 109 107 71 111 43 110 86 32 76 91 108 |
|           | 40 85 72 31 102 56 97 46 61 48 |
| SBDMT     | 70 48 74 39 118 76 71 77 75 72 73 109 43 107 56 |
|           | 111 85 86 110 78 69 34 40 108 91 |

By using the SBDMT’s search space, PODESCA’s results are obtained, where the selected locations in this case are: 34, 39, 48, 72, 74, 85, 91, 108, and 118. It is clear that some selected locations and sizes of SCs are different from the first case (without reducing the search space). Therefore, a comparison between the obtained results without and with reducing the search space is required as presented in Tables 14 and 15. As is seen in those two tables, the total installed capacity is 9250 kVAr with the reduced search space, which is slightly higher than that in the first case.

Table 14. Comparison between the optimal locations and sizes of SCs by PODESCA for the 118-bus system with and without reducing the search space by SBDMT.

| Description | Without SBDMT | With SBDMT |
|-------------|---------------|------------|
| 5           | 50            | 34         |
| 34          | 1150          | 39         |
| 39          | 1500          | 48         |
| 48          | 600           | 72         |
| 74          | 1500          | 74         |
| 86          | 850           | 85         |
| 91          | 1200          | 91         |
| 109         | 1150          | 108        |
| 118         | 1150          | 118        |
| Total No. of locations | 9 locations | 9 locations |
| Total kVAr   | 9150         | 9250       |
Table 15. Comparison of PODESCA’s results for the 118-bus system without and with reducing the search space by SBDMT.

| Method            | APL (kW) | LR (%) | $V_{\text{min}}$ (p.u.) | VD (p.u.) | Ann. cost ($/\text{Year}$) | Net sav. ($/\text{Year}$) | Net sav. (%) | SD   |
|-------------------|----------|--------|--------------------------|-----------|----------------------------|---------------------------|--------------|------|
| Without SCs       | 1297.95  | -      | 0.8688                   | 0.3576    | 682,202.52                 | -                         | -            | -    |
| With SCs          |          |        |                          |           |                            |                           |              |      |
| Without SBDMT     | 842.16   | 35.12  | 0.9072                   | 0.1771    | 493,969.50                 | 188,233.02                | 27.59        | 184.433 |
| With SBDMT        | 837.89   | 35.45  | 0.9068                   | 0.1761    | 492,225.66                 | 189,976.86                | 27.85        | 110.371 |

However, comparing to the first case, it is obvious that better results are attained regarding the distribution of the SCs’ sizes along the selected locations, the APL (837.89 kW), VD (0.1761 p.u.), the annual cost (492,225.66 $/year), and the annual savings (189,976.86 $/year), with a slightly lower $V_{\text{min}}$ (0.9068 p.u.). Moreover, those results are achieved with much smaller SD than that obtained in the first case, where it reaches the value of 110.371. Those results manifest the effectiveness of the proposed methods even for a heavy-loaded large-scale RDS as the 118-bus system, where due to the increasement of the problem’s complexity and its wide search space, several possibilities for selecting the optimal locations can be found with more than one feasible solution as is already achieved in both studied cases for this system. Consequently, without reducing the search space, PODESCA selects the optimal locations (including the limited-impact bus 5) with better results than those from the all other methods. Furthermore, when utilizing the reduced search space by the SBDMT, the most potential buses for SC placement are kept (bus 5 is excluded). Hence, much better results than those in the first case are obtained with better consistency as well. In other words, the best results are obtained by applying the PODESCA while using the SBDMT’s reduced search space.

In addition, the convergence characteristics of the proposed algorithm are compared without and with utilizing the SBDMT as illustrated in Figure 7, where it is obvious that the initial solutions in both cases are different due to the big difference in the search space’s size, and the OF’s values are reached with different convergence rates, where 103 iterations are required to obtain the optimal value (493,969.50 $/year) without reducing the search space. However, if the search space is reduced by the SBDMT, only 59 iterations are needed to reach the optimal value (492,225.66 $/year). Those results highly validate the effectiveness and robustness of both PODESCA and SBDMT for solving the OPSC problem for large-scale RDSs.

Figure 7. Convergence characteristics of PODESCA for the 118-bus system.
Hence, since the best solutions are obtained by utilizing both PODESCA and SBDMT together for this system, the optimal results for different load levels are determined according to the reduced search space and listed in Table 16, where four fixed SCs with sizes of 950, 700, 300, and 900 kVar are injected at buses 39, 72, 85, and 118, respectively. Whereas, the switched SCs are placed as 1150, 550, 600, 400, 850, 600, 1200, 1100 and 600 kVar respectively at buses 34, 39, 48, 72, 74, 85, 91, 108 and 118.

At last, the voltages along the 118-bus system considering the full-load level (obtained by the best solutions) are depicted in Figure 8, where a good improvement in voltages is achieved after adding the optimal SCs.

![Figure 8. Voltage profile of the 118-bus system considering full-load level using PODESCA and SBDMT.](image)

**Table 16.** Optimal results of PODESCA and SBDMT for the 118-bus system considering different load levels.

| Load level | Description | Without SCs | With SCs | Installed SCs (kVar) |
|------------|-------------|-------------|----------|---------------------|
| 100%       | $V_{\text{min}}$ (p.u.) | 0.8688      | 0.9068   | 9 locations         |
|            | $V_D$ (p.u.)      | 0.3576      | 0.1761   | Total: 9250         |
|            | APL (kW)          | 1297.95     | 837.89   |                     |
|            | RPL (kVar)        | 978.54      | 630.72   |                     |
|            | Ann. cost ($/year) | 682,202.52  | 492,225.66 |                     |
|            | Net sav. ($/year) | -           | 189,976.86 |                     |
| 75%        | $V_{\text{min}}$ (p.u.) | 0.9049      | 0.9288   | 39 (1500)           |
|            | $V_D$ (p.u.)      | 0.1896      | 0.1067   | 72 (1100)           |
|            | APL (kW)          | 697.24      | 479.34   | 85 (600)            |
|            | RPL (kVar)        | 527.16      | 362.01   | 91 (750)            |
|            | Ann. cost ($/year) | 36,646.93   | 282,290  | 118 (1500)          |
|            | Net sav. ($/year) | -           | 84,179.3 | Total: 5450         |
| 50%        | $V_{\text{min}}$ (p.u.) | 0.9385      | 0.9517   | 39 (950)            |
|            | $V_D$ (p.u.)      | 0.0806      | 0.0504   | 72 (700)            |
|            | APL (kW)          | 297.13      | 214.43   | 85 (300)            |
|            | RPL (kVar)        | 225.2       | 163.46   | 118 (900)           |
|            | Ann. cost ($/year) | 156,171.5   | 129,430  | Total: 2850         |
|            | Net sav. ($/year) | -           | 26,741.5 |                     |

Fixed (Location, kVar) (39, 950), (72, 700), (85, 300), (118, 900)

Switched (Location, kVar) (34, 1150), (39, 550), (48, 600), (72, 400), (74, 850), (85, 600), (91, 1200), (108, 1100), (118, 600)
After testing the proposed methods on three different-scale RDSs, the following advantages can be pointed out:

1. The rapid convergence towards the global optimal solutions is guaranteed by PODESCA due to its robust structure, which efficiently combines the mechanisms of DE, SCA, and QOT. By its unique hybridization, the search exploration and diversity are increased. It reliably keeps the best solutions in every generation and thus ensures their flexible flow to the optimal region inside the search space.

2. The consistency and robustness of PODESCA are verified by indicating the small standard deviations and fast convergence rates.

3. The effectiveness of the SBDMT is validated since it reduces the OPSC problem’s search space extensively and at the same time keeps the most suitable buses for SC placement. In addition, this technique is easy to implement due to the simple formulation of TOPSIS as well as the SBIs.

4. The utilization of both PODESCA and SBDMT to solve the OPSC problem is very effective especially for large-scale RDSs, where they guarantee obtaining the optimal solutions and further increase the convergence rate and standard deviation of the obtained solutions.

Nevertheless, some disadvantages and recommendations can be outlined as follows:

1. Due to the hybridization between three mechanisms and applying the “greedy selection” several times, PODESCA suffers from a slightly higher computational time comparing to some other methods in the literature. However, this issue can be managed using a more powerful PC. Besides that, in offline planning applications, it is more essential to obtain much better solutions than suffer from a slightly higher computational time.

2. The SBDMT effectively keeps the most potential locations for SC placement in the search space, but it could be further tested for identifying the suitable locations DGs as well.

As a future work, the proposed algorithm can be considered and adopted for other fields, which are innovative and new, like that of micro-nanofluidics networks [49]. The proposed algorithm can be adopted for solving problems in different aspects and fields in engineering and sciences.

7. Conclusions

The proposed PODESCA and SBDMT have been implemented in this paper to tackle the OPSC problem in different-scale RDSs, where the system’s total annual cost has been minimized considering different operational constrains. The effectiveness of the proposed methods has been validated by testing them on the 69-bus, 85-bus, and large-scale 118-bus RDSs. Moreover, several comparisons have been performed with different previous methods from the literature, where those comparisons have signified that, comparing to most of the other methods, a lower system’s annual cost as well as higher annual savings can be achieved by less amount of total injected reactive power, especially for the large-scale 118-bus system. In addition, the consistency and robustness of the proposed PODESCA have been verified by indicating the small standard deviations and fast convergence rates. Furthermore, the proposed SBDMT has extensively reduced the OPSC problem’s search space while keeping the most suitable locations for SC placement, which led to attain better results by the PODESCA with smaller standard deviations and faster convergence rates especially for the large-scale 118-bus system. Thus, the proposed PODESCA and SBDMT are recommended as robust methods for solving the OPSC problem. However, more investigations are suggested to check PODESCA’s performance on other engineering applications, and further tests might be explored on the SBDMT to effectively reduce the search space of the optimal planning of DGs problem as well.

**Author Contributions:** R.J.M. and N.F.A. did the methodology, simulation and validation. R.J.M. and N.F.A. did the analysis and wrote the paper. Conceptualization, R.J.M., N.F.A. and Y.S.; software, R.J.M., N.F.A. and Y.S.; investigation, R.J.M. and N.F.A.; resources, R.J.M., N.F.A. and Y.S.; data curation, R.J.M., N.F.A. and Y.S.; writing—original draft preparation, R.J.M.; writing—review and editing, N.F.A., Y.S., H.H.A., P.S. and M.P.; visualization, R.J.M., N.F.A., Y.S., H.H.A., P.S. and M.P.; supervision, Y.S. and P.S.; project administration, Y.S.;
funding acquisition, Y.S. and H.H.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported in part by the National Natural Science Foundation of China under Grant 61673161, and in part by Six Talent Peaks High Level Project of Jiangsu Province under Grant 2017-XNY-004.

**Conflicts of Interest:** The authors declare no conflict of interest.

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