RESEARCH ARTICLE

# Taguchi-Based Parameter Tuning of PSO for Optimal Capacitor Placement in Unbalanced Distribution Systems

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## Abstract

**This paper presents a Taguchi-tuned Particle Swarm Optimization (PSO) approach for the optimal placement and sizing of shunt capacitor banks (CBs) in unbalanced distribution systems. The optimization aims to minimize the total operational cost by reducing power losses and improving voltage profile. A systematic parameter tuning was carried out using the Taguchi method based on an L25 orthogonal array, with five PSO parameters evaluated through Signal-to-Noise (SN) ratios and Analysis of Variance (ANOVA). The IEEE 13-bus test feeder was used as a benchmark. The results show that the installation of four optimally placed CBs reduces active power losses by 29.6% (from 133.16 kW to 93.71 kW), improves the minimum bus voltage from 0.942 p.u. to 1.014 p.u., and decreases operating costs by 6,144.55$ compared to the base case. Validation using DIgSILENT PowerFactory confirms the consistency of the proposed method. Moreover, the Taguchi-optimized PSO demonstrated superior performance over the classical PSO in terms of convergence speed, solution quality, and result consistency across multiple independent runs, confirming its effectiveness and robustness for practical distribution system optimization.**

**Keywords**: capacitor placement, particle swarm optimization (PSO), taguchi method, unbalanced systems.

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## 1 Introduction

The determination of optimal locations and sizes of capacitor banks (CBs) in distribution systems (DSs) represents a multidimensional engineering challenge with significant technical and economic implications. Proper sizing and strategic placement of these devices can improve voltage profiles, reduce power losses, and improve the efficiency of power transmission. Traditional approaches often rely on simplified models and assumptions, neglecting critical aspects such as network unbalance and temporal load variability, which are increasingly present in modern power systems.

Recent literature has explored various techniques for capacitor placement, ranging from classical deterministic methods to modern metaheuristic algorithms. Although the latter do not guarantee global optimality, they have demonstrated high effectiveness in solving complex, nonlinear optimization problems with acceptable computational overhead. Aman et al. [1] and Mostafa et al. [2] provided comprehensive reviews of over 250 relevant publications, addressing a wide range of objective

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functions, constraints, and solution strategies. Nevertheless, the majority of these studies are limited to balanced systems, despite the fact that practical DSs often operate under significantly unbalanced conditions due to asymmetric loading and feeder configurations.

Addressing this gap, several recent studies have proposed advanced methodologies tailored to unbalanced systems. Ahmadi et al. [3] implemented a multi-objective Particle Swarm Optimization (PSO)-based approach that simultaneously considers energy efficiency and operational cost minimization in CB placement, offering a more holistic perspective on system performance. Mondal et al. [4] developed a graph-theory-based framework for phase-wise capacitor deployment, aligning capacitor placement with feeder topology, while De Araujo et al. [5] proposed a time-series approach that considers daily load variation for the coordinated placement of fixed and switched CBs. Similarly, Asabere et al. [6] applied PSO for optimal CB sizing and placement, targeting power loss reduction in unbalanced networks. These contributions underscore a growing trend toward more realistic modeling and optimization frameworks that reflect actual operating conditions in DSs.

The PSO algorithm has emerged as a simple and efficient tool for solving complex optimization problems without requiring gradient information of the objective function. The success of PSO heavily depends on the proper selection of its parameters, namely, inertia weights ($w_0$, $w_1$), learning coefficients ($c_1$, $c_2$), and population size ($N$), as they directly influence the balance between global exploration and local exploitation [7]. To systematically identify optimal parameter settings and improve algorithmic robustness, this study employs the Taguchi method [8], a statistical design of experiments technique based on orthogonal arrays and Signal-to-Noise (S/N) ratios.

Unlike previous studies that typically rely on fixed or empirically selected PSO parameters, this work integrates Taguchi-based tuning to enhance solution quality and consistency. Building on this framework, a Taguchi-optimized PSO approach is developed for determining the optimal locations and sizes of CBs in unbalanced DSs. The IEEE 13-bus test feeder [9] is used as a benchmark system for evaluating the proposed method. The optimization objective is to minimize the system's operational cost. A total of 25 experiments, based on an L25 orthogonal array [10], were conducted to examine the influence of five PSO parameters. The results were analyzed using Analysis of Variance (ANOVA) [10], allowing for the identification of statistically significant factors and ensuring the reliability of the proposed optimization strategy. The statistical software Minitab [11] was used to compute the S/N ratios and to analyze the influence of each PSO parameter level within the Taguchi experimental framework.

The key contributions of this study include:

- Development of a Taguchi-tuned PSO algorithm specifically tailored for unbalanced DSs;
- Systematic evaluation of PSO parameter influence using S/N ratio analysis and ANOVA;
- Application of the method to the IEEE 13-bus feeder to determine optimal capacitor placements that minimize operational cost;
- Comprehensive performance evaluation of different CB installation scenarios (from one to four banks), providing detailed insights into technical (voltage profile, losses) and economic (investment cost, savings) trade-offs.
- Validation of optimization results using DIgSILENT PowerFactory [12] simulations to confirm the accuracy of the Backward/Forward Sweep (BFS) power flow method [13].

## 2 Problem formulation

The problem of optimal CB placement and sizing is formulated as a constrained optimization problem, wherein the objective is to minimize (or maximize) a predefined objective function $f(x, u)$ by determining the optimal values of the control variables $u$ within the admissible set $U$ (i.e., $u \in U$), where $x$ denotes the vector of state variables. The solution must satisfy a set of equality constraints $g(x, u) = 0$, and inequality constraints $h(x, u) \leq 0$.

The state variable vector $x$ consists of the RMS bus voltage magnitude $V_{ip}$ at each node $i$ and phase $p$ (where $p$ corresponds to phases A, B, or C). The control variable vector $(u)$ includes the candidate installation points for CBS, specified by both node (bus) and phase indices, along with their corresponding reactive power ratings $(Q_c)$.

### 2.1 Objective function

The objective function consists of two components: the cost of active power losses in the DS and the cost of reactive power supplied by the installed CBs. It can be expressed as follows [14, 15]:

$$F(x,u) = C_P P_{\text{loss}} + \sum_{i=1}^{N_C} (C_{C,i} Q_{C,i}) \tag{1}$$

where $C_P$ represents the cost coefficient of active power losses (\$/kW), $P_{\text{loss}}$ denotes the total active power losses in the DS (kW), $C_{C,i}$ is the cost of the $i$th CB (\$/kVAr), $Q_{C_i}$ is the reactive power provided by the $i$th CB (kVAr), and $N_C$ is the total number of installed CBs. In this study, a single fixed load level is assumed for the power-flow and optimization analysis, following the approach in [14, 15].

It is worth noting that the control variables are inherently constrained. On the other hand, the inequality constraints related to the state variables are incorporated into the objective function using a quadratic penalty method. Accordingly, the original objective function is augmented to penalize violations of these constraints, resulting in the following expanded formulation to be minimized:

$$F_e(x,u) = F(x,u) + \lambda_V \sum_{i=1}^{N_{bus}} \left( V_{i,p} - V_{i,p}^{\text{lim}} \right)^2 \tag{2}$$

where $F_e$ is the expanded objective function, $\lambda_V$ is the penalty coefficient, and $V_{i,p}^{\text{lim}}$ denotes the limiting value of the RMS bus voltage magnitude for node $i$ and phase $p$.

The voltage limit is defined as follows:

$$V_{i,p}^{\text{lim}} = \begin{cases} V^{\max} & \text{if } V_{i,p} > V^{\max} \\ V^{\min} & \text{if } V_{i,p} < V^{\min} \end{cases} \tag{3}$$

where $V^{\min} = 0.9\,\text{p.u.}$ and $V^{\max} = 1.1\,\text{p.u.}$ denote the minimum and maximum allowable bus voltage magnitudes, respectively. In this study, a penalty factor of $10^6$ is used for all the inequality constraints.

### 2.2 Constraints

The equality constraints $g(x,u) = 0$ represent the nonlinear power flow balance equations, which are solved in this study using the BFS method [13, 16]. The inequality constraints $h(x,u) \leq 0$ define the permissible operating ranges for the state variables (node voltages), with particular emphasis on maintaining acceptable voltage magnitudes at all buses in the system. These constraints include the following voltage magnitude limits at each bus $i$ and phase $p$:

$$V^{\min} \leq V_{i,p} \leq V^{\max} \tag{4}$$

The constraints formulated by equation $u \in U$ define the admissible range of control variables. In a radial DS, each bus is considered a potential location for the installation of a CB, subject to the constraint that no more than one CB can be installed per phase at each bus. The allowable locations are selected from a predefined set of admissible node and phase combinations. This constraint is mathematically expressed as:

$$(i,p) \in L, \qquad \sum_{p \in \{A,B,C\}} \delta_{i,p} \leq 1, \quad \forall i \in N_b \tag{5}$$

where $i$ denotes the bus index, $p$ the phase index (A, B, C), $L$ the set of admissible installation locations, and $\delta_{i,p} = 1$ if a CB is installed at bus $i$ on phase $p$, otherwise $\delta_{i,p} = 0$. $N_b$ denotes the set of all buses in the DS.

The selection of CB sizes is limited to discrete, commercially available units. The standard CB ratings used in this study, along with their associated installation costs, are listed in Table 1. Following the approach described in [14, 15], the reactive power compensation at each bus $i$ and phase $p$ is subject to the following constraint:

$$Q_{C,i,p} = k \cdot Q_C^{\min}, \quad k \in \{0,1,2,\ldots\}, \quad 0 \leq Q_{C,i,p} \leq Q_C^{\max} \tag{6}$$

where $Q_{C,i,p}$ is the reactive power of the CB installed at bus $i$ and phase $p$; $k$ is an integer multiplier representing the number of minimum-size CB units; $Q_C^{\min}$ is the minimum available CB size (i.e., 150 kVAr); and $Q_C^{\max}$ is the maximum allowed reactive power of CBs.

## 3 Optimization algorithm

The PSO algorithm dates back to 1995 and was primarily developed by Kennedy and Eberhart, as introduced in [17]. The algorithm is inspired by the social behavior observed in flocks of birds or schools of fish that move within a bounded space in search of food. Each particle (individual) in the swarm represents a candidate solution and navigates through the search space by utilizing both

**Table 1.** Commercially available CB ratings and corresponding installation costs [14].

| QC (kVAr) | 150 | 300 | 450 | 600 | 750 | 900 | 1050 | 1200 | 1350 | 1500 | 1650 | 1800 | 1950 | 2100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CC ($/kVAr) | 0.5 | 0.35 | 0.253 | 0.22 | 0.276 | 0.183 | 0.228 | 0.17 | 0.207 | 0.201 | 0.193 | 0.187 | 0.211 | 0.176 |

its own experience and the experiences of neighboring particles. Individuals in the swarm are characterized by their position and velocity. During the search for the optimal solution, the position of each particle in the population is updated based on its own best-found position and the best-known position among all particles in the swarm. The PSO algorithm is initialized with a population of randomly generated solutions, where each particle is placed at a randomly selected position $x$ and assigned a randomly chosen velocity $v$.

The velocity of each particle in the next iteration $(t+1)$, as well as the position update of particle $i$, is defined as follows:

$$\begin{aligned} v_i(t+1) = w(t)v_i(t) + c_1 r_1 \left(\text{pbest}_i(t) - x_i(t)\right) \\ + c_2 r_2 \left(\text{gbest}(t) - x_i(t)\right) \end{aligned} \tag{7}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{8}$$

where $w(t)$ is the inertia weight in iteration $t$, which controls the influence of a particle's previous velocities on its current velocity; $v_i(t)$ is the current velocity of particle $i$; $x_i(t)$ is the current position of the particle (i.e., the current solution); $r_1$ and $r_2$ are randomly selected numbers in the range $[0, 1]$; $c_1$ is the cognitive acceleration coefficient (representing the influence of the particle's own experience); $c_2$ is the social acceleration coefficient (representing the influence of the swarm's experience); $\text{pbest}_i(t)$ is the best position visited by particle $i$ during its movement, and $\text{gbest}(t)$ is the best position found by the entire swarm.

The inertia weight $w(t)$ is used to regulate the exploration capabilities of the swarm and typically ranges from 0.4 to 0.9. Assigning higher values promotes global exploration, whereas lower values facilitate local search. In the traditional PSO algorithm [17], the inertia weight $w(t)$ is linearly decreased during the iterative process from an initial or maximum value $(w_0)$ to a final or minimum value $(w_1)$, according to the following expression:

$$w(t) = w_0 - (w_0 - w_1)\,\frac{t}{t_{\max}} \tag{9}$$

where $t$ is the current iteration, and $t_{\max}$ is the maximum number of iterations. In addition to the linear variation of the inertia weight $w(t)$ during the optimization process, other schemes can also be employed, such as random [18], nonlinear (quadratic) [19], asymptotic [19], and exponential [20].

The acceleration coefficients $c_1$ and $c_2$ represent the attraction factors and influence the strength of the attractive force between particles in the swarm and the best solution found. Typical values for these coefficients are in the range $0 \leq c_1, c_2 \leq 2$ [17]. In certain variants of the PSO algorithm [21], different values are assigned to these weights $(c_1 \neq c_2)$, which allows for better control of the algorithm and enhances its exploration capabilities.

The overall performance of the PSO algorithm is highly sensitive to the selection of control parameters, including the population size $N$, inertia weights $(w_0, w_1)$, and acceleration coefficients $(c_1, c_2)$. These parameters directly affect the algorithm's ability to balance global search and local convergence. To systematically tune these parameters and improve the reliability and robustness of the optimization process, the Taguchi method is applied in this study.

## 4 Taguchi method

The Taguchi method [8] is a statistically grounded technique for Design of Experiments (DoE), employing orthogonal arrays and S/N ratios to evaluate system performance under uncertainty. Its strength lies in achieving a comprehensive analysis of multiple parameters using a minimal number of simulations. By using orthogonal arrays, it becomes possible to identify a robust configuration with a minimal number of experiments (e.g., 25 instead of 3125 for 5 factors at 5 levels each). In this study, the Taguchi method is used to tune PSO parameters, targeting improved robustness and convergence consistency. Random selection of inertia weights and learning coefficients often results in suboptimal and unstable behavior due to stochastic effects. To overcome this, a systematic experimental plan is developed to find parameter settings that yield high-quality, noise-tolerant solutions. Five PSO control parameters are considered: $w_0$, $w_1$, $c_1$, $c_2$, and $N$. Each parameter is tested at five levels, as summarized in Table 2. The L25 orthogonal array is used to structure the experiments, ensuring that all

**Table 2.** PSO parameters and levels used in the Taguchi design [10].

| Parameter | Description | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 |
|---|---|---|---|---|---|---|
| $w_0$ | Initial inertia weight | 0.9 | 0.7 | 0.5 | 0.3 | 0.1 |
| $w_1$ | Final inertia weight | 0.1 | 0.3 | 0.5 | 0.7 | 0.9 |
| $c_1$ | Cognitive coefficient | 0.5 | 1 | 1.5 | 2 | 2.5 |
| $c_2$ | Social coefficient | 0.5 | 1 | 1.5 | 2 | 2.5 |
| $N$ | Population size | 10 | 20 | 30 | 40 | 50 |

combinations are uniformly and efficiently explored.

The proposed methodology involves the following steps [10]:

- **Step 1:** Define the objective (fitness) function as given in Eq. (2);
- **Step 2:** Choose parameter levels (Table 2);
- **Step 3:** Construct the L25 orthogonal array (Table 3);
- **Step 4:** Run each of the 25 experiments 10 times to account for stochastic variation;
- **Step 5:** Evaluate robustness using the Smaller-the-Better (STB) S/N ratio:

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} F_i^2\right) \tag{10}$$

where $n = 10$ is the number of repeated runs per experiment.

This method enables the identification of the most influential control factors affecting both solution quality, as measured by the average objective function value, and solution robustness, as quantified by the S/N ratio.

## 5 Results and discussion

The proposed Taguchi-based PSO optimization framework was tested and validated on the standard IEEE 13-bus unbalanced three-phase DS [9]. In this study, system loads were represented using a combination of constant power, constant impedance, and constant current models, thereby reflecting typical behavior observed in real-world networks. CBs were modeled as grounded wye-connected constant impedance elements, enabling phase-specific injection of reactive power. The IEEE 13-bus feeder, operating at a nominal voltage level of 4.16 kV, comprises a diverse mix of network components, including voltage regulators, single- and three-phase overhead lines and underground cables, spot and distributed loads, and CBs. Under base-case conditions, the system exhibits a total active and reactive power demand of 3.466 MW and 2.102 MVAr, respectively.

To evaluate the performance of the proposed optimization strategy, simulations were conducted for multiple scenarios involving the installation of one to four CBs. For each scenario, the PSO algorithm was executed under identical stopping criteria and control constraints, and the results were compared to a baseline configuration in which no CBs were installed. The cost of real power losses is assumed to be 168 $/kW, while the cost of installed CBs is treated as a function of their rated reactive power capacity. For the specific case involving four CBs, a preliminary parameter tuning phase was conducted using the Taguchi method. An L25 orthogonal array [10] design was employed to systematically explore the influence of five key PSO parameters: the initial and final inertia weights ($w_0$ and $w_1$), the cognitive and social acceleration coefficients ($c_1$ and $c_2$), and the population size (N), on the optimization performance. Each of the 25 experiments defined by the array was executed 10 times to account for the stochastic nature of the PSO algorithm. The maximum number of iterations per run was set to 100. The average values of the objective function obtained from these runs are presented in Table 3.

To assess both performance and robustness, the S/N ratios were calculated using the STB formulation, which is suitable for minimization objectives. The statistical software Minitab (version 15) [11] was used to compute the S/N ratios and to analyze the influence of each PSO parameter level. The results of this analysis are shown in Table 3. The values in Table 3 represent the average S/N ratios for each parameter level, calculated according to the procedure described in [10] based on the results from Table 3. The optimal PSO parameter configuration was determined by selecting the levels corresponding to the highest S/N ratios, in accordance with Taguchi's robustness principle [8].

As for parameter significance, Table 4 indicates that

**Table 3.** Taguchi-based PSO optimization results with four CBs installed.

| DoE | $w_0$ | $w_1$ | $c_1$ | $c_2$ | $N$ | $F_{mean}$ | S/N |
|---|---|---|---|---|---|---|---|
| 1 | 0.9 | 0.1 | 0.5 | 0.5 | 10 | 17132.22 | -84.68 |
| 2 | 0.9 | 0.3 | 1 | 1 | 20 | 16496.97 | -84.35 |
| 3 | 0.9 | 0.5 | 1.5 | 1.5 | 30 | 16490.43 | -84.34 |
| 4 | 0.9 | 0.7 | 2 | 2 | 40 | 16818.67 | -84.52 |
| 5 | 0.9 | 0.9 | 2.5 | 2.5 | 50 | 17087.13 | -84.65 |
| 6 | 0.7 | 0.1 | 1 | 1.5 | 40 | 16402.97 | -84.30 |
| 7 | 0.7 | 0.3 | 1.5 | 2 | 50 | 16357.76 | -84.27 |
| 8 | 0.7 | 0.5 | 2 | 2.5 | 10 | 17139.14 | -84.68 |
| 9 | 0.7 | 0.7 | 2.5 | 0.5 | 20 | 16539.93 | -84.37 |
| 10 | 0.7 | 0.9 | 0.5 | 1 | 30 | 16430.34 | -84.31 |
| 11 | 0.5 | 0.1 | 1.5 | 2.5 | 20 | 16425.97 | -84.31 |
| 12 | 0.5 | 0.3 | 2 | 0.5 | 30 | 16452.53 | -84.32 |
| 13 | 0.5 | 0.5 | 2.5 | 1 | 40 | 16281.61 | -84.23 |
| 14 | 0.5 | 0.7 | 0.5 | 1.5 | 50 | 16489.57 | -84.34 |
| 15 | 0.5 | 0.9 | 1 | 2 | 10 | 16804.77 | -84.51 |
| 16 | 0.3 | 0.1 | 2 | 1 | 50 | 16394.97 | -84.29 |
| 17 | 0.3 | 0.3 | 2.5 | 1.5 | 10 | 16605.76 | -84.41 |
| 18 | 0.3 | 0.5 | 0.5 | 2 | 20 | 16856.30 | -84.54 |
| 19 | 0.3 | 0.7 | 1 | 2.5 | 30 | 16382.66 | -84.29 |
| 20 | 0.3 | 0.9 | 1.5 | 0.5 | 40 | 16494.65 | -84.35 |
| 21 | 0.1 | 0.1 | 2.5 | 2 | 30 | 16431.16 | -84.31 |
| 22 | 0.1 | 0.3 | 0.5 | 2.5 | 40 | 16446.52 | -84.32 |
| 23 | 0.1 | 0.5 | 1 | 0.5 | 50 | 16901.37 | -84.56 |
| 24 | 0.1 | 0.7 | 1.5 | 1 | 10 | 18352.15 | -85.27 |
| 25 | 0.1 | 0.9 | 2 | 1.5 | 20 | 16429.77 | -84.31 |

population size exhibited the most substantial impact on optimization results, followed in order by the final inertia weight, initial inertia weight, social coefficient, and cognitive coefficient. The corresponding delta values, which represent the range of S/N ratios across parameter levels and reflect their relative influence, were 0.39, 0.22, 0.21, 0.15, and 0.11, respectively. These values confirm that population size was the dominant factor affecting PSO performance, while the cognitive component had the least effect.

**Table 4.** SN ratios for each PSO parameter at five levels using the STB criterion, along with delta values and ranks.

| Level | $w_0$ | $w_1$ | $c_1$ | $c_2$ | $N$ |
|---|---|---|---|---|---|
| 1 | -84.56 | -84.38 | -84.44 | -84.46 | -84.71 |
| 2 | -84.37 | **-84.33** | -84.41 | -84.49 | -84.38 |
| 3 | **-84.34** | -84.47 | -84.51 | **-84.34** | **-84.32** |
| 4 | -84.39 | -84.56 | -84.43 | -84.43 | -84.34 |
| 5 | -84.51 | -84.43 | **-84.4** | -84.45 | -84.42 |
| Delta | 0.21 | 0.22 | 0.11 | 0.15 | 0.39 |
| Rank | 3 | 2 | 5 | 4 | 1 |

Figure 1 presents the main effects plot for the S/N ratios corresponding to each PSO parameter. According to the Taguchi method, the optimal parameter setting is identified by selecting the level of each factor that yields the highest S/N ratio, thereby ensuring both low average objective values and reduced variability. As shown in Figure 1 and Table 4, the optimal values are: $w_0 = 0.5\,(\text{Level}\,3)$, $w_1 = 0.3\,(\text{Level}\,2)$, $c_1 = 2.5\,(\text{Level}\,5)$, $c_2 = 1.5\,(\text{Level}\,3)$, and $N = 30\,(\text{Level}\,3)$. This combination of PSO parameters was used in the final optimization runs to ensure enhanced convergence behavior and robust performance.

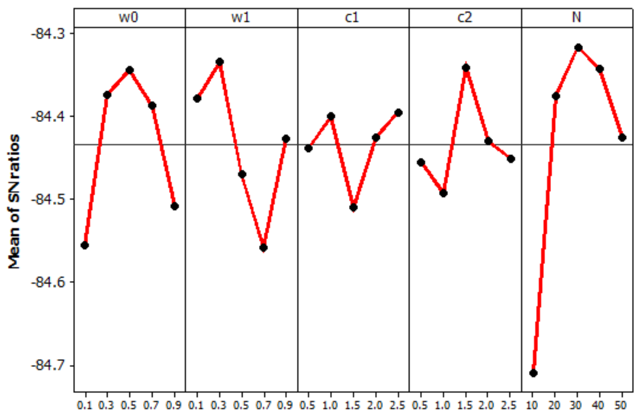


**Figure 1.** Main effects plot of S/N ratios for PSO control parameters using the STB criterion.

ANOVA was performed at a 95% confidence level to evaluate the relative significance of the PSO control parameters. The results are summarized in Table 5. In this context, the abbreviation DF (Degrees of Freedom) refers to the number of independent values that can vary without violating given constraints. DF values are used to compute the Mean Square (MS) for each factor, which is then employed in the F-test to determine statistical significance by comparing it to the residual variance. A higher F-value generally indicates a stronger influence on the optimization outcome. The p-value represents the probability that the observed F-value could occur by chance; values less than 0.05 typically indicate statistical significance at the 95% confidence level. The Sequential Sum of Squares (Seq. SS) quantifies the portion of the total variance explained by each factor when it is added to the model sequentially, while the Adjusted Mean Square (Adj. MS) is calculated by dividing the sum of squares by the corresponding degrees of freedom, and serves as the basis for the F-test [22].

Among the examined parameters, population size exhibited the most significant influence on the PSO performance, with an F-value of 2.22 and a

**Table 5.** ANOVA results for S/N ratio analysis of PSO parameter tuning.

| Parameter | DF | Seq. SS | Adj. MS | F-value | p-value | Contribution (%) |
|---|---|---|---|---|---|---|
| $w_0$ | 4 | 666352 | 166588 | 0.76 | 0.603 | 14.75 |
| $w_1$ | 4 | 585609 | 146402 | 0.67 | 0.649 | 12.96 |
| $c_1$ | 4 | 179895 | 44974 | 0.20 | 0.923 | 3.98 |
| $c_2$ | 4 | 257162 | 64291 | 0.29 | 0.87 | 5.69 |
| $N$ | 4 | 1949945 | 487486 | 2.22 | 0.23 | 43.15 |
| Error | 4 | 879832 | 219958 | - | - | 19.47 |
| Total | 24 | 4518796 | - | - | - | - |

**Table 6.** Comparison of system performance with different CB configurations.

| Control variables, state variables, and objective function | Case | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Base case | 1 CB | 2 CBs | | 3 CBs | | | 4 CBs | | |
| Min. *VRMS* (p.u.) | 0.942 | 0.964 | 0.993 | | 1.014 | | | 1.014 | | |
| Max.*VRMS* (p.u.) | 1.04 | 1.069 | 1.069 | | 1.069 | | | 1.069 | | |
| *Ploss* (kW) | 133.16 | 112.15 | 102.96 | | 94.83 | | | 93.71 | | |
| *Qloss* (kVAr) | 391.41 | 321.37 | 287.22 | | 273.88 | | | 273.48 | | |
| | | 692 | 671 | 692 | 692 | 692 | 671 | 671 | 692 | 692 | 675 |
| Location (bus and phase) and size of CBs (kVAr) | - | C | A | C | A | B | C | C | A | B | C |
| | | 600 | 450 | 750 | 600 | 450 | 900 | 600 | 600 | 450 | 300 |
| CBs Injection (kVAr) | - | 600 | 1200 | | 1950 | | | 1950 | | | |
| CBs costs ($) | - | 132 | 320.85 | | 410.55 | | | 482.85 | | | |
| Costs ($) | 22,370.71 | 18,973.19 | 17,617.45 | | 16,342.16 | | | 16,226.16 | | | |
| Benefits ($) | | 3,397.52 | 4,753.26 | | 6,028.55 | | | 6,144.55 | | | |

contribution of 43.15%. This was followed by the initial inertia weight (F = 0.76, 14.75%), final inertia weight (F = 0.67, 12.96%), social coefficient (F = 0.29, 5.69%), and cognitive coefficient (F = 0.20, 3.98%). The residual error accounted for 19.47% of the total variation, indicating a reasonably good model fit and suggesting that the majority of the variability in the response can be attributed to the selected control factors.

The optimal CB configurations, including their locations, reactive power ratings, and the corresponding values of bus voltages, along with the resulting reductions in operational cost, are summarized in Table 6. This table provides a comparative assessment of the system's electrical and economic performance across several scenarios involving the installation of one to four shunt CBs, in addition to the base case with no compensation.

In the base case, the minimum bus voltage is 0.942 p.u., while the active and reactive power losses are 133.16 kW and 391.41 kVAr, respectively. The total operational cost in this configuration amounts to 22,370.71 $. When a single CB of 600 kVAr is installed at bus 692, phase C, the minimum voltage rises to 0.964 p.u., and losses are reduced to 112.15 kW and 321.37 kVAr. This leads to a cost saving of 3,397.52 $. With two CBs – 450 kVAr at bus 671, phase A, and 750 kVAr at bus 692, phase C – the minimum voltage further improves to 0.993 p.u., with active and reactive power losses reduced to 102.96 kW and 287.22 kVAr, respectively. The resulting cost drops to 17,617.45 $, offering a net benefit of 4,753.26 $. In the three- CB case: 600 kVAr and 450 kVAr at bus 692, phases A and B, respectively, and 900 kVAr at bus 671, phase C, the voltage profile reaches 1.014 p.u., while power losses are reduced to 94.83 kW and 273.88 kVAr. The operating cost is 16,342.16 $, yielding a benefit of 6,028.55 $. Finally, the configuration with four CBs: 600 and 450 kVAr at phases A and B of bus 692, 300 kVAr at phase C of bus 675, and 600 kVAr at phase C of bus 671, maintains the minimum voltage at 1.014 p.u., with losses further reduced to 93.71 kW and 273.48 kVAr. Despite the highest CB investment cost (482.85 $), this scenario achieves the lowest system cost of 16,226.16 $, delivering the maximum economic benefit of 6,144.55 $ compared to the base case. These findings confirm the effectiveness of optimal CB placement and sizing in improving voltage regulation, minimizing losses, and enhancing the economic efficiency of unbalanced DSs. Consequently, the optimization was limited to configurations with up to four CBs, as the addition of a fifth unit provided less than 1 kW of additional loss reduction – a marginal gain deemed technically and economically insignificant for practical DS applications.

To evaluate the effectiveness of the proposed parameter

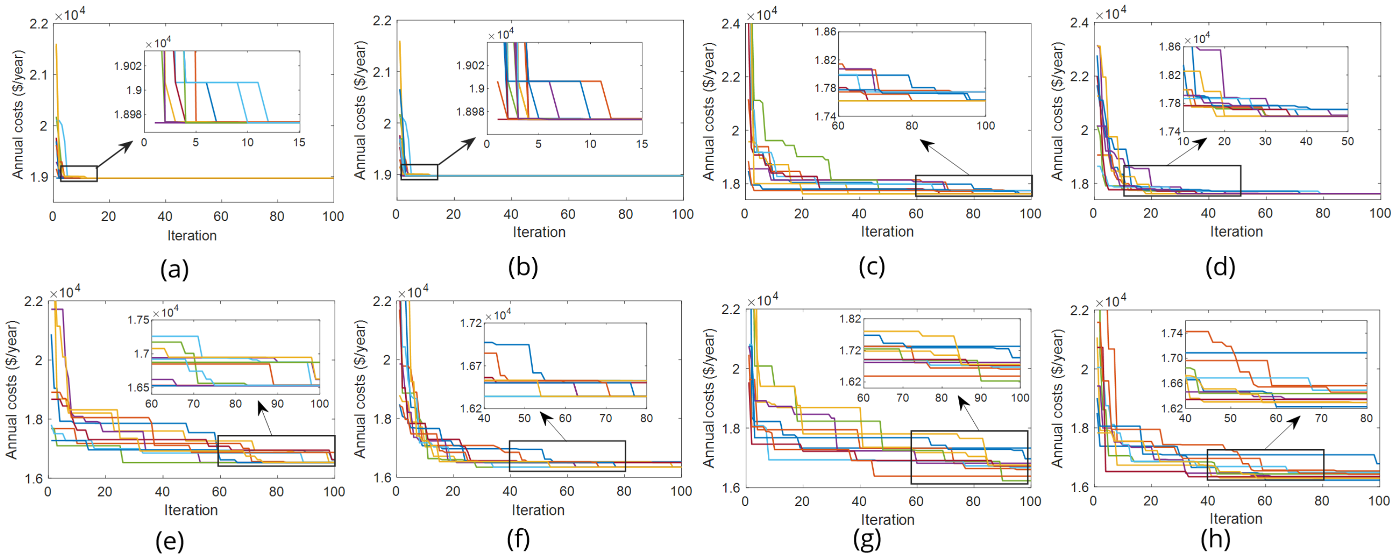


**Figure 2.** Convergence profiles of the PSO algorithm across different CB configurations. Subfigures (a), (c), (e), and (g) show results obtained using the classic PSO, while (b), (d), (f), and (h) correspond to the Taguchi-based PSO for cases involving 1, 2, 3, and 4 CBs, respectively.

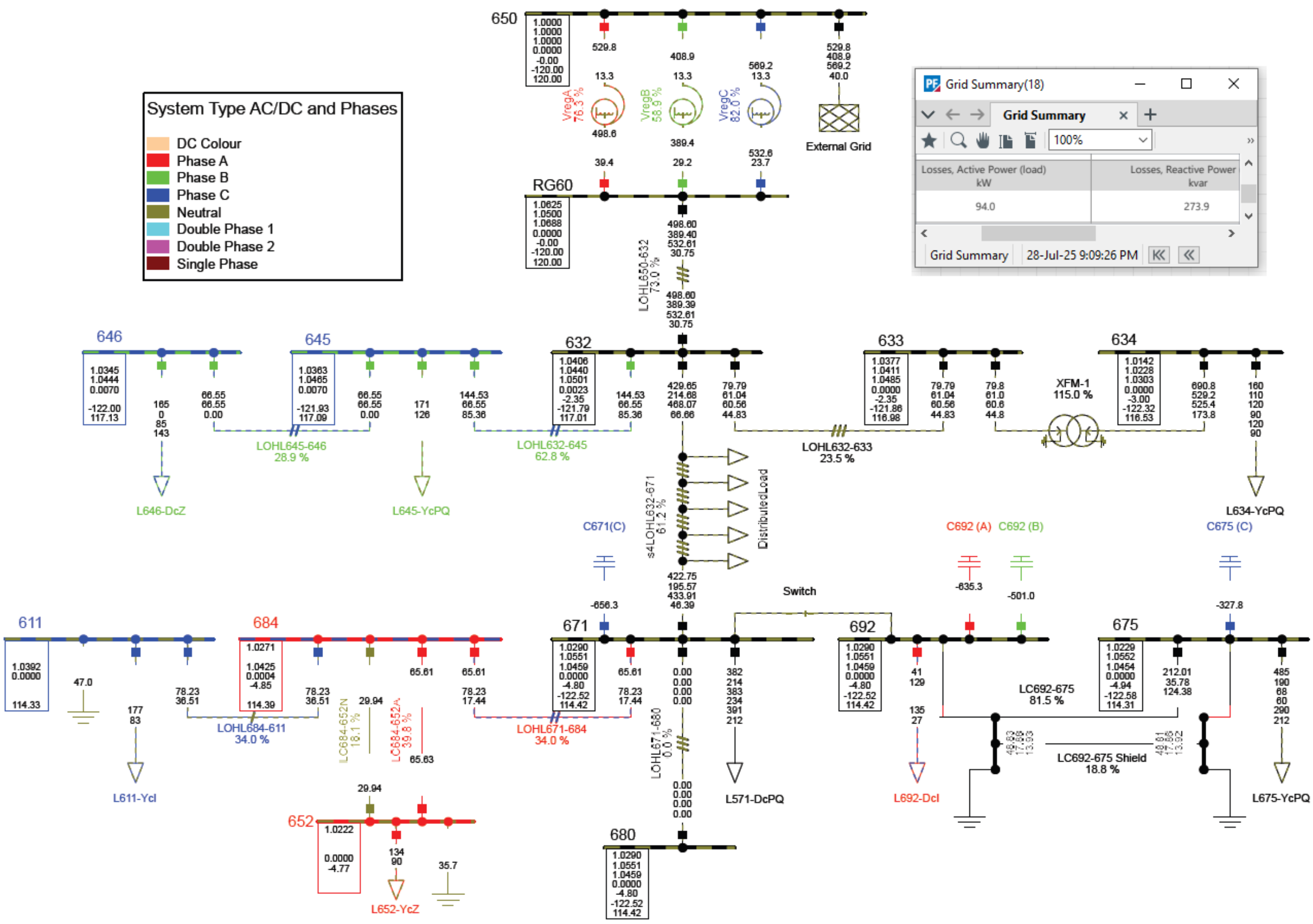


**Figure 3.** Simulation result obtained using DIgSILENT PowerFactory 2024 for the IEEE 13-bus test system with four installed CBs.

tuning approach, 10 independent optimization runs were conducted for each scenario involving one to four CBs. Two PSO variants were considered: the classic PSO with control parameters set as $w_0 = 0.9$, $w_1 = 0.4$,

**Table 7.** Performance comparison of classic and Taguchi-tuned PSO across capacitor configurations.

| Case | Method | $F$min | $F$mean | $F$max | STD |
|---|---|---|---|---|---|
| 1 CB | Taguchi-based PSO | 18973.19 | 18973.19 | 18973.19 | 0 |
| | Classic PSO | 18973.19 | 18973.19 | 18973.19 | 0 |
| 2 CBs | Taguchi-based PSO | 17617.45 | 17617.45 | 17617.45 | 0 |
| | Classic PSO | 17617.45 | 17746.25 | 17657.66 | 61.15 |
| 3 CBs | Taguchi-based PSO | 16342.16 | 16319.35 | 16485.69 | 57.10 |
| | Classic PSO | 16343.49 | 16543.65 | 16820.64 | 149.34 |
| 4 CBs | Taguchi-based PSO | 16226.16 | 16410.78 | 16524.73 | 65.04 |
| | Classic PSO | 16388.74 | 16754.88 | 17152.87 | 299.34 |

$c_1 = 2$, $c_2 = 2$, $N = 30$, and $t_{\max} = 100$; and the Taguchi-optimized PSO with parameters $w_0 = 0.5$, $w_1 = 0.3$, $c_1 = 2.5$, $c_2 = 1.5$, $N = 30$, and $t_{\max} = 100$. The comparative results, including the minimum, mean, and maximum objective function values, as well as the standard deviation (STD) for each case, are summarized in Table 7.

As presented in Table 7, the Taguchi-tuned PSO consistently outperformed the classic configuration in terms of minimum, average, and maximum objective values. Furthermore, the significantly lower standard deviation achieved by the Taguchi-based approach demonstrates improved robustness and convergence stability across repeated runs. This performance enhancement is particularly evident in the four-CB scenario, where the STD dropped from 299.34 to 65.04, indicating a more reliable and consistent optimization process. It is worth noting that in the scenario involving the installation of a single CB, both the classic and Taguchi-tuned PSO algorithms converged to the same optimal solution across all runs, yielding identical values for the minimum, mean, and maximum objective function, as well as a standard deviation of zero. This outcome indicates that the optimization problem in this case was relatively simple, such that both algorithms were equally effective in identifying the global optimum.

The convergence profiles of the classic PSO and Taguchi-based PSO algorithms obtained from 10 independent runs for cases involving one to four CBs are presented in Figure 2. These results, which visually confirm the quantitative data in Table 7, indicate that the proposed Taguchi-tuned PSO algorithm generally converges to the optimal solution in fewer iterations and exhibits a more stable convergence behavior compared to the classic PSO algorithm.

Figure 3 presents the results obtained using the DIgSILENT PowerFactory 2024 software [12] for the scenario involving four installed CBs. The active and reactive power losses recorded were 94 kW and 273.9 kVAr, respectively, which closely align with the values obtained using the proposed Taguchi-tuned PSO-based optimization approach (93.71 kW and 273.48 kVAr). This strong agreement confirms the accuracy of the BFS power flow method applied within the optimization framework.

## 6 Conclusion

The main conclusions of this study can be summarized as follows:

- A robust and systematic optimization framework for CB placement and sizing in unbalanced DSs was developed using the PSO algorithm tuned via the Taguchi method. The approach successfully integrates sensitivity to parameter settings with robustness against stochastic behavior.
- The Taguchi method, applied with an L25 orthogonal array, proved effective in identifying optimal PSO parameter combinations ($w_0 = 0.5$, $w_1 = 0.3$, $c_1 = 2.5$, $c_2 = 1.5$, $N = 30$). This tuning led to significantly improved convergence behavior, lower average objective function values, and reduced variability compared to conventional PSO configurations.
- Simulation results on the IEEE 13-bus test system demonstrated that optimal placement and sizing of up to four CBs enhanced voltage regulation, reduced active and reactive power losses (by as much as 39.45 kW and 117.93 kVAr), and yielded substantial cost savings (up to 6,144.55 $).
- The results obtained using the BFS method within the proposed framework closely matched those from DIgSILENT PowerFactory simulations, confirming the accuracy and reliability of the adopted power flow technique.

Overall, the presented approach demonstrates the benefits of hybrid metaheuristic-statistical tuning methods for solving practical power system optimization problems. Future work may extend the methodology to include harmonic mitigation, probabilistic load modeling, and multi-objective formulations.

## Data Availability Statement

Data will be made available on request.

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## Conflicts of Interest

The authors declare no conflicts of interest.

## Ethical Approval and Consent to Participate

Not applicable.

## References

[1] Aman, M. M., Jasmon, G. B., Bakar, A. H. A., Mokhlis, H., & Karimi, M. (2014). Optimum shunt capacitor placement in distribution system—A review and comparative study. *Renewable and Sustainable Energy Reviews, 30*, 429-439. [CrossRef]

[2] Mostafa, S. M. G., Shingh, J. G., & Haque, H. E. (2020). An extensive literature review and new proposal on optimal capacitor placement in distribution systems. *Journal of Engineering Advancements, 1*(04), 150-169. [CrossRef]

[3] Ahmadi Kamarposhti, M., Ghandour, R., Abdel-Aty, M., Hafez, M., Alfiras, M., Alkhazaleh, S., ... & Solyman, A. (2025). Optimizing capacitor bank placement in distribution networks using a multi-objective particle swarm optimization approach for energy efficiency and cost reduction. *Scientific Reports, 15*(1), 12332. [CrossRef]

[4] Mondal, S., & De, M. (2023). Optimal capacitor placement for unbalanced distribution system using graph theory. *IETE Journal of Research, 69*(9), 6512-6519. [CrossRef]

[5] De Araujo, L. R., Penido, D. R. R., Carneiro, S., & Pereira, J. L. R. (2018). Optimal unbalanced capacitor placement in distribution systems for voltage control and energy losses minimization. *Electric Power Systems Research, 154*, 110-121. [CrossRef]

[6] Asabere, P., Sekyere, F., Ayambire, P., & Ofosu, W. K. (2025). Optimal capacitor bank placement and sizing using particle swarm optimization for power loss minimization in distribution network. *Journal of Engineering Research, 13*(2), 1307-1315. [CrossRef]

[7] Wang, H., Geng, Q., & Qiao, Z. (2014, April). Parameter tuning of particle swarm optimization by using Taguchi method and its application to motor design. In *2014 4th IEEE international conference on information science and technology* (pp. 722-726). IEEE. [CrossRef]

[8] Dehnad, K. (1989). *Quality control, robust design, and the Taguchi method* (1st ed.). Wadsworth & Brooks/Cole Advanced Books & Software.

[9] IEEE Power & Energy Society. (n.d.). *IEEE PES Test Feeder*. Retrieved from https://cmte.ieee.org/pes-testfeeders/resources/

[10] Sahoo, S., Dalei, R. K., Rath, S. K., & Sahu, U. K. (2023). Selection of PSO parameters based on Taguchi design–ANOVA–ANN methodology for missile gliding trajectory optimization. *Cognitive Robotics, 3*, 158-172. [CrossRef]

[11] Minitab LLC. (2007). *Minitab Statistical Software* (Release 15) [Computer software].

[12] DIgSILENT GmbH. (2024). *DIgSILENT PowerFactory 2024 User Manual*. Gomaringen, Germany.

[13] Cheng, C. S., & Shirmohammadi, D. (1995). A three-phase power flow method for real-time distribution system analysis. *IEEE Transactions on Power Systems, 10*(2), 671-679. [CrossRef]

[14] Baghzouz, Y., & Ertem, S. (1990). Shunt capacitor sizing for radial distribution feeders with distorted substation voltages. *IEEE Transactions on Power Delivery, 5*(2), 650-657. [CrossRef]

[15] Milovanović, M., Radosavljević, J., & Perović, B. (2021). Optimal placement and sizing of shunt capacitors in distorted distribution systems using a hybrid algorithm. *Serbian Journal of Electrical Engineering, 18*(1), 115-135. [CrossRef]

[16] Milovanović, M., Radosavljević, J., & Perović, B. (2019). A backward/forward sweep power flow method for harmonic polluted radial distribution systems with distributed generation units. *International Transactions on Electrical Energy Systems, 30*(5), e12310. [CrossRef]

[17] Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of the IEEE International Conference on Neural Networks* (Vol. 4, pp. 1942-1948). [CrossRef]

[18] Marini, F., & Walczak, B. (2015). Particle swarm optimization (PSO): A tutorial. *Chemometrics and Intelligent Laboratory Systems, 149*, 153-165. [CrossRef]

[19] Clerc, M. (2006). *Particle swarm optimization*. Wiley-ISTE.

[20] Yang, C., Gao, W., Liu, N., & Song, C. (2015). Low-discrepancy sequence initialized particle swarm optimization algorithm with high-order nonlinear time-varying inertia weight. *Applied Soft Computing, 29*, 386-394. [CrossRef]

[21] Eberhart, R. C., & Shi, Y. (2001, May). Tracking and optimizing dynamic systems with particle swarms. In *Proceedings of the 2001 congress on evolutionary computation* (*IEEE Cat. No. 01TH8546*) (Vol. 1, pp. 94-100). IEEE. [CrossRef]

[22] Montgomery, D. C. (2013). *Design and analysis of experiments* (8th ed.). John Wiley & Sons.

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