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Improving Power Factor of a Distribution System Using Optimally Sited and Sized Capacitor Bank

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ABSTRACT
In distribution systems, the electrical loads are predominantly inductive, resulting in a poor power factor owing to higher reactive power. Hence, there is a requirement to adjust for the reactive power. The goal of this study was to increase the power factor, reduce power loss, and optimise the voltage profile of distribution systems using a modified IEEE 14-bus system as a case study by properly placing and sizing the capacitor bank using the Particle Swarm Optimisation (PSO) Algorithm. Modifying the inertia weight enhanced the PSO's performance in identifying the solution while reducing the computational cost. The approach was evaluated using a PSAT-modelled and simulated case study to assess the algorithm's overall performance and usefulness in identifying a solution. The simulation results revealed that the system loss was reduced by 3.7%, the voltage profile improved to 1.0 per unit, and net savings were maximised at $57,674.4.

Keywords: *power factor, capacitor bank, Multi-Objective Particle Swarm Optimisation (MOPSO), power loss*

1. INTRODUCTION

Electrical power systems play a major role in modern-day living. However, maintaining power quality, which is directly linked to power factor, is critical for the efficient operation of an electrical system. Power quality is a function of the efficiency of the electricity grids that supply power capable of operating electrical equipment needed for domestic and industrial use. Power quality is important while considering economic and technological benefits. Power factor is one of the major factors that affect the power quality of an electrical power system. A low power factor indicates poor power quality and a high-power factor yields good power quality. So, poor power quality causes equipment failure, downtime and high electricity bills, hence the need to improve the power factor. A low power factor has many disadvantages, such as increased line current, larger conductor size, high losses, and poor voltage levels. However, with a high-power factor, the generating station transfers more kWh to the power system. Therefore, improving the power factor will increase utility companies' profits (Michal *et al.*, 2022). Inductive loads such as refrigerators, air-conditioners, and fluorescent lighting are common in industrial and public buildings. Often, the operation of these inductive loads at a low power factor leads to power system distortion, resulting in wastages and a high cost of electricity (Kalhari *et al.,* 2022). Inductive loads, which constitute a distribution system, result in increased reactive and apparent power and consequently decrease the power factor and efficiency of the electrical system (Tiwan and Ghanmare, 2020). In Nigeria, there are three types of consumers: domestic, industrial, and commercial. Public buildings are classified as commercial consumers. Both public and industrial buildings have much inductive loads.

Inductive loads draw current with two major components. These are power-producing current and magnetising current. The magnetising current is required to maintain the electromagnetic field in the component that produces reactive power. The current drawn by inductive loads lags the applied voltage. Inductive loads consume reactive power but do not convert it to useful work. Reactive power is responsible for the decrease in the power factor of an electrical system (Wahab *et al.,* 2021). Power factor correction benefits consumers and electricity companies since consumers pay for maximum energy consumption in kVA and the unit consumed. With power factor improvement, the maximum demand in kVA will be reduced, resulting in annual savings. However, power factor improvement comes with an additional cost on consumers' annual net savings. From the utility side, a low power factor increases both investment and maintenance costs for the electric power distribution system. Optimal sizing and placement of capacitor banks in the electrical network are efficient techniques to improve the power factor, minimise losses, improve voltage profile, and ensure the release of power system capacity.

Erita *et al.* (2023) proposed Particle Swarm Optimisation (PSO) to determine the optimal location and size of the capacitor to reduce losses. The method was tested on an IEEE 34 bus radial distribution system, and the result showed a significant reduction in power losses by 20%. Mehrdad *et al.* (2021) used MOPSO Algorithm to locate and determine the distribution system's capacity of distributed generation sources and capacitor banks. A standard 33-bus system was used to conduct the study, and the results were compared with genetic and PSO Algorithms. It was found that the MOPSO Algorithm gave a more accurate outcome than ordinary PSO. Oladepo and Hasimah (2019) presented Adaptive Particle Swarm Optimisation (APSO) to address the challenges of simultaneous allocation of Capacitor banks and Distribution Generation in radial distribution systems to enhance voltage profile and reduce power losses. In his work, PSO was modified by replacing inertial weight in the velocity update equation. The method was tested on IEEE 69-bus, 33-bus and 30- bus test distribution system. The results showed reduction in power loss and enhanced voltage profile.

Theophilus *et al.* (2019) analysed the technical and economic effects of properly placing fixed and switched capacitors on the distribution system using the PSO Algorithm. The search space for the location of the capacitor was reduced using the loss sensitivity index. The results indicated lower investment, improvement of voltage profile and significant reduction of power loss. Also, the two scenarios considered obtained a better-optimised system with considerable cost savings. Deependra *et al.* (2019) used loss sensitivity factors to locate the buses that require compensation and the particle swarm optimisation (PSO) Algorithm to determine the size of the capacitor. After the optimal location of the capacitor, the voltage level was improved above 0.9 p. u, and the power loss was reduced significantly.

This paper proposed Multiple-Objective Particle Swarm Optimisation algorithm (MOPSO), a computational technique to optimally site and size capacitor banks to improve the power factor, reduce power losses and enhanced the voltage profile on the IEEE 14 bus system. The MOPSO adopted has capacity to handle multi-objective problems, increase search space and improve performance.

Adaptive PSO (APSO) and adaptive velocity update relaxation PSO (AVURPSO), two of the latest PSO algorithm models, employed distinct techniques to enhance the system parameters (Ratnaweera *et al.*, 2004). As a result, the Multiple-Objective Particle Swarm Optimisation (MOPSO) Algorithm introduced in this work left both and created an altered process. In the primary PSO algorithm, the particles' velocities and locations are restricted by v maximum, minimum, x maximum, and minimum, respectively. Typically, v maximum and minimum are equivalent to x maximum and minimum. As a result, the primary PSO adds computational load to the process by validating the particle location at each iteration cycle and then implementing an appropriate position constraint measure to restrict or reject solutions as needed. The multi-objective Particle Swarm Optimisation technique can handle many objective functions, unlike PSO, which cannot handle multiple-objective problems (Kumar *et al.*, 2017). MOPSO increases search capability and improves performance (Venkatesan *et al.*, 2021). MOPSO employed the boundary velocity validity testing of the particles, following the AVURPSO postulates, without carefully examining the validity of locations in each iteration round (Zirkohi *et al.*, 2010).

$$v_i(It)=\chi\left(w\cdot v_i(It-1)+c_1\cdot rand_1\cdot(p_i-x_i(It-1))+c_2\cdot rand_2\cdot(p_g-x_i(It-1))\right) \quad (1)$$

$$x_i(It)=w\left(x_i(It-1)\right)+(1-w)\left(v_i(It)\right)$$

(2)

$$w=w_{\max}-\left(\Delta w_{\max\min}\frac{(It)}{MaxIt}\right) \quad (3)$$

Where: in (1), w_i is the position number between 0 and 1, c_1 and c_2 are the cognitive and social acceleration coefficient. $rand_1$ and $rand_2$ are two random with uniform distribution in the range (0, 1), p_i is the best position found by the particle while p_g is the global best position found by any particle.

Where: in (3), w linearly decreased after every iteration. w_{max} and w_{min} are selected between 0.4 and 0.88. The particle's velocity in (1) is controlled by w attached to it. Also, χ, a constriction factor is attached to the equation to ensure the velocity stays within the feasible solution. Instead of the momentum introduced in AVURPSO (Zirkohi *et al.*, 2010), MOPSO used the weight defined in (3), which makes the algorithm faster; the new position vector is the point on the line between the former position vector $x_i(It-1)$ and $v_i(It)$ the new velocity vector.

Adopting low values for c_1 and c_2 allows the particle to wander far from the target boundaries before being turned back. Otherwise, adopting high values results in a sudden movement toward or passes the target boundaries. Therefore, c_1 and c_2 are introduced (Zirkohi et al., 2010) as:

$$\begin{aligned} c_1 &= c_{1final}\left(\frac{It}{MaxIt}\right)+c_{1initial}\left(\frac{MaxIt-It}{MaxIt}\right) \\ c_2 &= c_{2final}\left(\frac{It}{MaxIt}\right)+c_{2initial}\left(\frac{MaxIt-It}{MaxIt}\right) \end{aligned} \quad (4)$$

$$\phi_i = c_{1i}+c_{2i} \text{ and } \phi_i \geq 2$$

$$\chi_i=\frac{2}{\left|2-\phi-\sqrt{\phi^2-4\phi}\right|} \quad (5)$$

Where: the initial guess of c_1 and c_2 are $c_{1initial}$ and $c_{2initial}$, and the final guess of c_1 and c_2 are c_{1final} and c_{2final} respectively. In a real sense, the best solutions are determined over the full range of search for c_1 changing from 1.5 to 0.5 and c_2 from 0.5 to 1.5 (Zirkohi *et al.*, 2010). With a substantial value of c_1 and a small value of c_2 at the commencement, particles can move about the search space instead of moving toward the particle best at that instance. A small value c_1 and a significant value c_2 allow the particles to converge to the global best in the latter part of the optimisation (Zirkohi *et al.*, 2010).

The fitness function of this research is based on a modified and expanded multi-objective ideology (Del Valle *et al.*, 2006) of three normalised objectives. The constituents of our objectives are to address the optimal installation and the sizing of Capacitor banks in a coordinated manner to enhance the power factor. The location of capacitor banks in the configuration of power systems is addressed by formulating an objective function optimised using MOPSO for the placements and sizing of the Capacitor bank.

The optimal placement and sizing of the Capacitor bank is a problem described as a multi-objective minimisation problem in this research work:

$$Min\ F = \{F_1, F_2, F_3\} \tag{6}$$

The fitness functions F_1, F_2 and F_3 are defined and used in optimisation. The objectives, if treated independently, could lead to conflict. In order to avoid any conflict, the three objectives are described in the same mathematical function by being normalised comparatively with the base case (the system without any controller) and connecting them with weights to be evaluated using the rank exponent model. The fitness function of this problem is fully defined in (7).

$$Min\ F = \alpha F_1 + \beta F_2 + \eta F_3 \tag{7}$$

Where:

$$F_1 = k_p P_{loss},\ F_2 = \sum_{i=1}^{nc} k_{c_i} Q_{c_i}\ and\ F_3 = \Delta V_d / \Delta V_{base}$$

Where, Kp is the annual cost per unit of the active power loss (\$/ kW /year),

P_{loss} is the total network active power loss (kW),

K_{ci} is the annual cost per unit of the reactive power injected (\$/kVAr /year),

Q_{ci} is the active power injected at bus i (kVAr)

nc is the total number of the shunt capacitor to be installed,

ΔV_d is the sum of the voltage deviation

ΔVbase is the base case of the sum of voltage Deviation.

The objectives *F* considered are prioritised based on weights set by a direct weight elicitation technique called rank exponent, described by (8) (Buede, 2009):

$$w_i = \frac{(K - r_i + 1)^z}{\sum_{j=1}^{K}(K - r_j + 1)^z} \tag{8}$$

Where the i^{th} objective rank is r_i and $i = 1, 2..., K$, r_j ranges from $j-K$, and K is the total number of objectives. The normalised approximation ratio scale weight of i^{th} objective is w_i; z is an approximate quantity of the weight distribution. The bigger the z, the more prominent the fraction of the most ranked objective to the smallest (Buede, 2009). With the three independent objectives in *F* having three weights, the total sum of the weights is unity.

Equation (7) is subject to:

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{9}$$

$$0 \le P_{loss} \le P_{loss,base} \tag{10}$$

$$Q_{ci}^{\min} \le V_i \le Q_{ci}^{\max} \tag{11}$$

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_b} V_j [G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)] = 0 \tag{12}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N_b} V_j [G_{ij}\sin(\delta_i - \delta_j) + B_{ij}\cos(\delta_i - \delta_j)] = 0 \tag{13}$$

The sum of voltage deviation is defined as:

$$\Delta V = \sqrt{\sum_{i=1}^{b}(1 - V_i)^2} \tag{14}$$

where b is the number of the network buses and V_i is the voltage at bus I. The total power loss in a power system is given as:

$$P_{loss} = \sum_{n=1}^{b_r} I_n^2 R_n = \sum_{i=1}^{b}\sum_{\substack{j=1\\ i\neq j}}^{b}\left[V_i^2 + V_j^2 - 2V_iV_j\cos\left(\delta_i - \delta_j\right)Y_{ii}\cos\varphi_{ij}\right] \quad (15)$$

where br, and b, are the numbers of lines and buses, respectively; R_n is the resistance of line n; I_n is the current through-line n; V_i and δ_i are the magnitude and angle of voltage at the i^{th} bus, respectively; Y_{ij} and φ_{ij} are the magnitudes and angle of the line admittance between bus i^{th} and bus j^{th}, respectively.

The particle is defined as a vector that contains the first location (bus number) of the capacitor and the second location (size determinant) of the Capacitor bank, as shown in (16).

$$x_i = \left[V_i \quad \lambda_i \quad \kappa_i\right] \quad (16)$$

Where: V_i : is the voltage level of the capacitor bank

λ_i : is the location (bus number) of the capacitor bank

k_i : is the Capacitor bank size

All the components of the particle vector (voltage, bus number and their sizes) are real numbers, hence $x_i \in \Re^2$, where $i = 1, 2, ..., n$.

Regarding the features of the power system and the desired voltage profile, several constraints to the problem need to be addressed. Each constraint signifies a limit in the exploration space; consequently, the PSO algorithm is programmed so that the particles can only move over their feasible region. In the procedure, whenever a particle's new position includes a bus with a generator or without load, the site changes to the geographically neighbouring load bus. If λ_i is out of the range, the values are shuffled, i.e., the particle moves to a randomly chosen bus. Also, the Capacitor bank unit κ_i's size is restricted by (17) applied to the particles. If the maximum limits are exceeded, then the particles get reshuffled.

$$150 \le \lambda_i \le 1,200\, k\,\text{var} \quad (17)$$

The equation defines the desired voltage profile restriction required (18) as:

$$0.90 \le V_i \le 1.10 \quad (18)$$

An individual solution which does not satisfy the above restrictions is considered infeasible; thus, its fitness function value is set to infinity:

$$\begin{aligned}\lambda_i^{\min} \le \lambda_i \le \lambda_i^{\max} \\ \kappa_i^{\min} \le \kappa_i \le \kappa_i^{\max}\end{aligned} \quad (19)$$

2. METHODOLOGY

Optimal sizing and placement of a capacitor bank is one of the most efficient methods to reduce reactive current, reduce losses, correct power factors, and enhance voltage profiles. In this section, the Multiple-Objective Particle Swarm Optimisation (MOPSO) technique was adopted to determine the optimal sizing and placement of the capacitor bank.

Particle Swarm Optimisation (PSO) is a computational technique inspired by the social behaviour of bird flocking and fish schooling, and it was developed by Eberhart and Kennedy in 1995. PSO involves a population of particles that moves through solution space to obtain optimal solutions based on their own experiences and those of their neighbours. In PSO, the 'best' values are followed as each particle is updated. Pbest, the first value, is the best solution achieved, while Gbest, the global best, represents the best value achieved by any of the particles. The particle speed and location are determined by PSO (Egeruo and Ipinnimo, 2022). PSO solves single-objective optimisation problems. However, many PSO algorithm versions have been developed, including Multiple-Objective Particle Swarm Optimisation (MOPSO). MOPSO uses a single mutation operator that chooses the population's member and changes the dimension's value to a number value range, which is valid. MOPSO selects Pbest and Gbest best on a specific mechanism. Since all dominant responses are superior, it cannot select a particular pbest and gbest as the best solution. Pbest is updated only when a new particle dominates its previous value. In each iteration, gbest is selected among the dominant responses in the archive. In multiple-objective problems, many objective functions are optimised simultaneously.

In such a case, the problem always has more than one solution. In order to determine the optimal placement and sizing of the capacitor bank in this study, the MOPSO algorithm was used to carry out the following in the electrical network with the aims of minimising losses, enhancing the voltage profile, and reducing the cost (Mehrdad *et al.*, 2021).

2.1. Modelling and Simulation of the case study network.

In this section, the electrical network of the IEEE14-bus system was modelled and simulated in the Power System Analysis Toolbox (PSAT 2.1.11) using the Newton-Raphson power flow algorithm. The network data was used to analyse and assess this research work. Figure 1 shows the model of IEEE14-bus system.

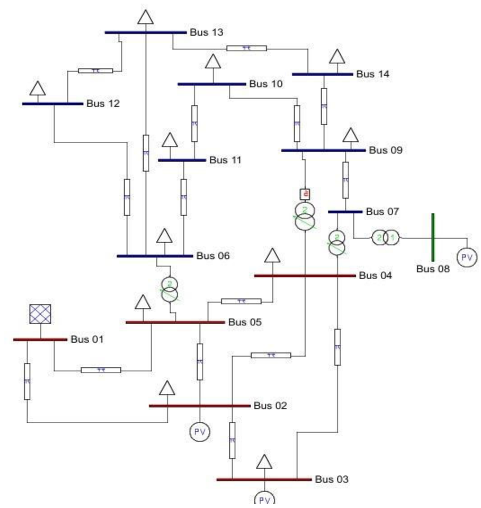

Figure 1: PSAT Model of 14-bus system**.**

The model was simulated to determine real and reactive power flow in all network branches, active and reactive power losses, and the magnitude and angle of the bus voltages in the network.

2.2. Multi-Objective Particle Swarm Optimisation Algorithm

The flowchart of the MOPSO operations is presented in Fig 2, summarising the proposed concept's complete procedure.

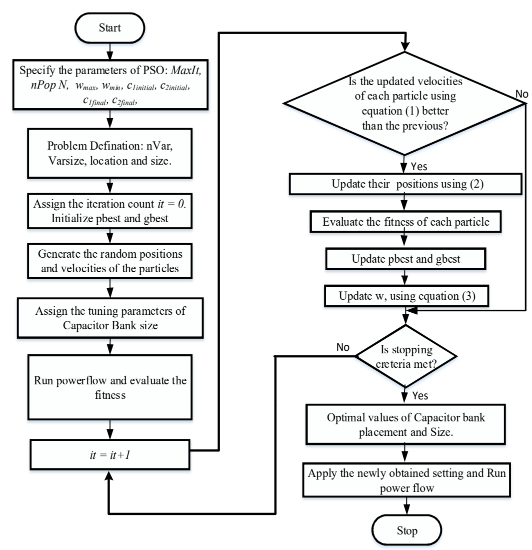

Figure 2: Flowchart of MOPSO

3. RESULTS AND DISCUSSIONS

The devised MOPSO method was put into action with the help of MATLAB, and it was evaluated on the IEEE 14-bus system. Both the position of the capacitor bank and its size were ideal, with Bus 9 and 1109kVAr being the best values, respectively. Following the addition of the adjustment, the minimum voltage at Bus 9 increased from 0.83 to 1.0. Before arriving at the figure for the yearly loss cost that was less expensive, many iterations were carried out. According to the simulation findings, the ideal option is the one with the lowest yearly loss cost value. The MOPSO optimisation results of the IEEE 14-bus system are summarised in Table 1, which includes both the results before and after rectification.

Convergence of the PSO occurred with the minimal cost of power loss, which was $359.13. This exemplifies the significance of achieving the highest possible global optimisation. Additionally, the convergence of MOPSO is shown in Figure 3.

Table 1: A summary of simulation results of the MOPSO Algorithm.

	Power loss (kW)	Voltage profile	Power factor	Net Saving
Before correction	174.8	0.83	0.82	-
After correction	168.3	1.0	0.95	$57,674.4

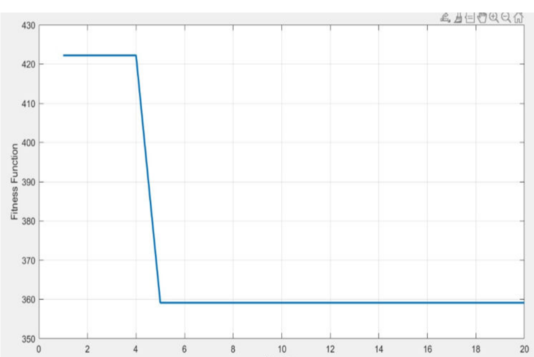

Figure 3. Convergence of MPSO

4. CONCLUSION

Power factor is improved by optimising capacitor bank size and placement utilising the Multiple-Objective Particle Swarm Optimisation (MOPSO) Algorithm. The IEEE 14-bus electrical network was designed and simulated using PSAT. According to the assessment, a more optimum system with superior technical and economic performance was suggested. The simulation indicates that appropriate capacitor bank size and location decrease system losses, power factor, voltage profile, and yearly system cost. After improving electrical system efficiency, the yearly power cost was lowered by $57,674.4. The Multiple-Objective Particle Swarm Optimisation (MOPSO) Algorithm may optimise the power factor by using suitably sized and arranged capacitor banks more efficiently and effectively.

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