

Particle Swarm Optimisation of Static VAR Compensator Deployment for Voltage Support in Transmission Grid

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ABSTRACT

Voltage stability is a persistent operational challenge in power systems, particularly in developing grids such as Nigeria's, where rapid load growth and infrastructural limitations frequently push networks close to their stability margins. This study investigates the improvement of voltage stability in a representative transmission network through the optimal placement and sizing of Static VAR Compensators using Particle Swarm Optimisation. The IEEE 30-bus test system was adopted as a benchmark and assessed under normal (100%), light (80%), heavy (120%), and stress (140%) loading conditions. Under uncompensated operation, several buses violated the statutory voltage limits of 0.95–1.05 p.u., with overvoltages reaching 1.071 p.u. during light loading and undervoltage dropping to 0.927 p.u. under stress conditions, indicating elevated risks of voltage instability and possible voltage collapse. The PSO algorithm identified optimal buses for SVC deployment, with reactive power ratings ranging from about –49.6 MVAR (reactive absorption under light load) to +68.0 MVAR (reactive injection under stress load). After compensation, all bus voltages were restored within permissible limits, with critical buses showing average improvements of 3–5%. For instance, the most depressed voltage improved from 0.927 p.u. to 0.963 p.u., while peak overvoltage reduced to approximately 1.021–1.051 p.u. These results confirm the effectiveness of PSO-optimised SVC placement for enhancing voltage stability and operational security under varying load conditions.

Keywords: FACTS Devices, Reactive Power Compensation, Particle Swarm Optimisation, Static VAR Compensator, Voltage Stability

I. INTRODUCTION

Modern power transmission networks constitute the backbone of the electric energy value chain, enabling the bulk transfer of electrical power from generating stations to distribution substations and end-users. Owing to increasing demand, network expansion constraints, ageing infrastructure, and operational uncertainties, transmission systems are increasingly exposed to a wide range of disturbances and operating stresses. While some disturbances exert marginal effects on system performance, voltage instability represents a severe operational threat that can precipitate progressive voltage degradation and, in extreme cases, large-scale system collapse [1]. Voltage instability typically arises when the power system is operated

close to or beyond its reactive power and transmission capability limits, leading to an inability to maintain bus voltages within acceptable operating bounds [1], [2].

In developing power systems such as Nigeria's, voltage instability remains a recurring operational challenge, manifested through erratic power supply, voltage sags, flickers, and frequent network collapses. Rapid population growth and urbanisation have driven sustained increases in electricity demand without commensurate expansion of generation, transmission, and reactive power support infrastructure, thereby exacerbating stress on the grid [3]. Empirical studies on the Nigerian 330 kV transmission network reveal persistent violations of statutory voltage limits (0.95–1.05 p.u.), particularly during peak loading conditions, resulting in degraded power quality, accelerated equipment ageing, and elevated technical losses [4]. In the base operating condition, up to 32% of buses in the Nigerian transmission grid have been reported to operate outside permissible voltage limits, accompanied by significant real and reactive power losses [5].

Voltage stability is fundamentally linked to the adequacy and dynamic management of reactive power resources. As system loading increases, reactive power demand rises nonlinearly, particularly in networks characterised by long transmission corridors, high resistance-to-reactance (R/X) ratios, and limited fast-acting voltage control devices [6]. Voltage instability phenomena are commonly categorised into short-term and long-term dynamics. Short-term voltage instability is associated with fast-acting components such as induction motors, electronically controlled loads, and HVDC converters, occurring over time scales of seconds, whereas long-term voltage instability evolves over minutes due to slower mechanisms including tap-changing transformers, generator excitation limits, and load recovery characteristics [7].

To mitigate voltage instability and improve system controllability, Flexible AC Transmission System (FACTS) devices have emerged as a key technological solution. FACTS controllers, based on high-power electronic converters and thyristor-controlled components, provide fast and continuous control of reactive power, voltage magnitude, line impedance, and power flow [8]. Among the shunt-connected FACTS devices, the Static VAR Compensator (SVC) and the Static Synchronous Compensator (STATCOM) have been widely adopted for voltage regulation and reactive power compensation in transmission networks [9], [10]. Practical deployments and simulation studies have demonstrated that appropriately sized and located FACTS devices can significantly enhance voltage stability margins, reduce transmission losses, and alleviate congestion [11].

Despite their technical benefits, FACTS devices are capital-intensive, and their economic viability is highly sensitive to placement and sizing decisions. Suboptimal allocation may result in limited operational benefits relative to installation cost, thereby undermining investment justification [12]. Consequently, the optimal deployment of FACTS devices has attracted substantial research attention, with numerous studies formulating the problem as a constrained nonlinear optimisation task aimed at minimising voltage deviations, power losses, or combined technical-economic objectives [13], [14]. Both single-objective and multi-objective optimisation frameworks have been reported in the literature, reflecting the inherently multi-criteria nature of FACTS planning problems [13], [15].

Metaheuristic optimisation techniques, including Particle Swarm Optimisation (PSO), Genetic Algorithms (GA), Differential Evolution (DE), and hybrid approaches, have proven particularly effective in solving FACTS allocation problems

due to their ability to handle nonconvex, nonlinear, and multimodal search spaces without requiring gradient information [16]–[19]. PSO, inspired by the collective behaviour of social organisms, offers advantages in terms of computational simplicity, rapid convergence, and robustness in large-scale power system optimisation problems [16], [20]. Recent studies have demonstrated the effectiveness of PSO-based and hybrid PSO frameworks in determining optimal SVC and STATCOM locations and ratings for voltage stability enhancement in both benchmark IEEE test systems and practical transmission networks, including the Nigerian grid [21]–[24].

Motivated by the persistent voltage instability challenges in Nigeria’s transmission infrastructure and the growing need for intelligent, data-driven planning tools, this study investigates the optimal placement and sizing of SVCs in a representative transmission network using Particle Swarm Optimisation. The IEEE 30-bus system is adopted as a benchmark model to emulate key characteristics of the Nigerian transmission network under varying loading conditions. The proposed framework aims to enhance voltage stability margins, mitigate voltage violations, and improve overall network security through coordinated FACTS deployment.

II. MATERIAL AND METHODS

2.1 Simulation Environment and Tools

This section details the methodology adopted to evaluate the impact of optimally placing and sizing Static VAR Compensators (SVCs) using Particle Swarm Optimisation (PSO) to enhance voltage stability in the Nigerian power transmission grid. The approach focuses on minimising voltage deviations through the strategic placement of SVC devices. The block diagram of this research process is shown in Figure 1. This diagram outlines the sequential steps and key components involved in achieving the optimal placement and sizing of Static VAR Compensators (SVCs) using PSO. It serves as a visual guide to the simulation workflow, outlining each stage of the process of carrying out the research.

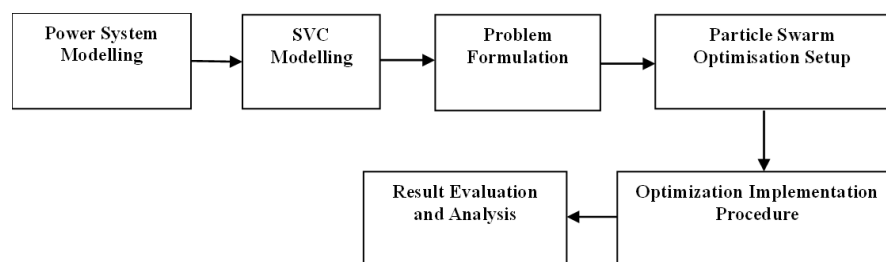


FIGURE 1. Proposed PSO-based SVC modelling and optimisation framework

This includes the modelling of the power system, formulation of the optimisation problem, implementation of the PSO, and integration of the SVC control mechanism into power flow analysis. Additionally, the software tools and simulation environment used for implementation are described, ensuring that the methodology is transparent, reproducible, and adaptable for future studies.

The simulation and analysis in this study were carried out using MATLAB, a high-level programming and numerical computing environment widely used in power system studies. All algorithms, including the Particle Swarm Optimisation implementation and power flow calculations, were developed using custom .m files (MATLAB script files). MATLAB's robust matrix operations, built-in optimisation functions, and ease of integration with user-defined models made it an ideal platform for modelling the Nigerian transmission network, implementing the optimisation routine, and visualising the results. The use of script-based coding also ensures flexibility, transparency, and ease of modification for future extensions of the work.

2.2 Power System Modelling

This section describes the mathematical and structural representation of the transmission network used in this study. An accurate power system model is critical to assessing the effect of SVC on voltage stability and overall network performance. The model provides the simulation environment for power flow analysis and optimisation.

2.2.1 Network Structure and Justification for the IEEE 30-Bus Benchmark

The IEEE 30-bus system was selected as a benchmark proxy rather than as a direct physical representation of the Nigerian transmission network. The selection is motivated by its established use in power-system optimisation studies and by the presence of structural features relevant to the present SVC allocation problem, including multiple generation buses, load buses, transmission branches, transformer tap ratios and shunt reactive compensation. These characteristics provide an adequate test environment for investigating the coupled problem of SVC location and reactive power sizing.

In addition, the voltage-control problem investigated in this study is primarily concerned with the relationship between loading level, reactive power support and bus-voltage deviation rather than with reproducing the exact topology of the Nigerian grid. The 132-kV nominal voltage level of the IEEE 30-bus system also provides a useful reference for portions of the Nigerian 132-kV network, although the actual Nigerian transmission system contains both 132-kV and 330-kV voltage levels and has substantially greater network complexity. Therefore, the IEEE 30-bus system should be interpreted as a controlled benchmark for evaluating the proposed PSO-SVC optimisation framework under Nigerian-relevant operating conditions, rather than as a complete model of the Nigerian transmission network.

The use of the four loading conditions—80%, 100%, 120% and 140%—further provides a controlled means of representing changes in operating stress, from light-load overvoltage conditions to heavily stressed undervoltage conditions. This allows the effectiveness of the optimisation framework to be evaluated systematically before application to a detailed Nigerian transmission-network model.

2.2.2 Load Flow Analysis

In order to simulate the IEEE-30 Bus System, Load Flow Analysis is required. This provides key system variables such as Bus voltage magnitudes and angles, Active and

reactive power flows across lines and Total system active and reactive power losses. The Newton-Raphson method is adopted due to its superior convergence properties for large and non-linear systems. The power flow equations are:

$$P_i = \sum_{j=1}^n |V_i| |V_j| |Y_{ij}| \cos(\theta_{ij} + \delta_j - \delta_i) \quad (1)$$

$$Q_i = - \sum_{j=1}^n |V_i| |V_j| |Y_{ij}| \sin(\theta_{ij} + \delta_j - \delta_i) \quad (2)$$

Where:

P_i, Q_i : Active and Reactive power injected at bus i

V_i, V_j : Voltage magnitudes at bus i and j

$\theta_i, \delta_i, \delta_j$: Angle differences

Y_{ij} : Admittance

2.2.3 Static VAR Compensator (SVC)

The SVC is modelled as a variable shunt susceptance connected at a bus. A circuit representation can be seen in Figure 3.2. It provides reactive power injection or absorption depending on the voltage deviation. Mathematically, the voltage inserted at a particular bus can be expressed as:

$$Q_{SVC} = -V_i^2 B_{SVC} \quad (3)$$

2.3 Problem Formulation

This section describes the objective function and constraints required to simulate the optimal placement of SVC with PSO in order to enhance the voltage stability and operational efficiency of the Nigerian power transmission network

Objective Function

Minimisation of Voltage Deviation

$$F_1 = \sum_{i=1}^{No} |V_i - V_{ref}| \quad (4)$$

Minimization of Power Losses

$$F_2 = P_{loss} + Q_{loss} \quad (5)$$

Combined Objective Function

$$F = w_1 F_1 + w_2 F_2 \quad (6)$$

Constraints

Active and Reactive Power Balance

$$P_i^{\text{gen}} - P_i^{\text{load}} = V_i \sum_{j=1}^N V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (7)$$

$$Q_i^{\text{gen}} - Q_i^{\text{load}} = V_i \sum_{j=1}^N V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) \quad (8)$$

Voltage Limits

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (9)$$

Generator Reactive Power Limits

$$Q_i^{\min} \leq Q_i^{\text{gen}} \leq Q_i^{\max} \quad (10)$$

SVC Operational Limits

$$Q_{\text{svc}}^{\min} \leq Q_{\text{svc}} \leq Q_{\text{svc}}^{\max} \quad (11)$$

2.4 Particle Swarm Optimisation (PSO) Setup

PSO is a robust, population-based evolutionary computation technique inspired by the coordinated behaviour of biological populations, such as bird flocks and fish schools. Unlike traditional gradient-based optimisation methods, PSO does not require derivative information and is well-suited for handling non-linear, multi-modal optimisation problems like those encountered in power system operation and planning. In this study, PSO is employed to determine the optimal locations and sizes of Static Var Compensators (SVCs) and Thyristor-Controlled Series Capacitors (TCSCs) in the transmission network in order to enhance voltage stability.

In PSO, a "particle" represents a potential solution to the optimisation problem in this case, a specific configuration of SVC/TCSC locations and their respective sizes. A collection of particles forms a swarm, and these particles "fly" through the search space, continuously updating their positions based on individual and collective experiences. Each particle adjusts its trajectory using two components:

- a. Cognitive Component: The particle's own best-known position. (pbest)
- b. Social Component: The best-known position of any particle in the swarm (gbest)

Each particle i is associated with

- a. A position vector: This represents the solution variables (ie., SVC size, location)

$$x_i = [x_{i1}, x_{i2}, \dots, x_{in}] \quad (12)$$

- b. A velocity vector: This represents the rate of change of position.

$$v_i = [v_{i1}, v_{i2}, \dots, v_{in}] \quad (13)$$

The update rules for the velocity and position at iteration $t+1$ are given by:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (p_{\text{best},i} - x_i^t) + c_2 \cdot r_2 \cdot (g_{\text{best}} - x_i^t) \quad (14)$$

Where, W is inertia weight which controls the impact of the previous velocity on the current one, c_1 and c_2 are the **acceleration coefficients** that control the influence of personal and global best positions, respectively, r_1 and r_2 are random numbers between 0 and 1 to introduce stochastic behaviour, $P_{\text{best},i}$ is the best position found by particle i so far, g_{best} is the best position found by the entire swarm

The performance and convergence behavior of PSO depend on the proper selection of algorithmic parameters. The table below summarizes the typical settings used;

TABLE I
PSO Parameter Settings

Parameter	Value Used
Swarm Size	50
Max Iterations	200
Inertia Weight (w)	0.7
Acceleration Coefficient (c_1)	1.5-2.0
Acceleration Coefficient (c_2)	1.5-2.0
Velocity Limits	$\pm 20\%$

2.5 Comparative Context with Alternative Metaheuristic Approaches

Several metaheuristic optimisation techniques have been applied to FACTS placement and sizing, including Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimisation (PSO). GA-based approaches have been applied to SVC placement in Nigerian transmission networks, including GA-fuzzy optimisation for SVC sizing and placement [14]. More recently, Ogunbiyi et al. [26] applied GA for coordinated SVC and TCSC placement in the Nigerian power grid under normal operation, overload conditions, and N-1 contingency scenarios. The study demonstrated the applicability of GA-based FACTS optimisation for voltage regulation and transmission-loss reduction.

In contrast, the present study investigates PSO specifically for SVC placement and sizing under varying loading conditions. PSO was selected because of its relatively simple population-based search mechanism and suitability for the nonlinear power-flow-based optimisation problem considered. Although both GA and PSO can address FACTS allocation problems, differences in network models, objective functions, constraints and operating scenarios prevent direct numerical comparison of results from the two studies. The present work therefore provides a PSO-based perspective complementary to existing GA-based studies, while a controlled comparison using identical test conditions is left for future work.

2.6 Implementation Procedure

This section describes the stepwise procedure adopted to achieve the optimal placement and sizing of Static VAR Compensators (SVCs) in the IEEE 30-bus transmission network. The proposed framework integrates conventional power flow analysis with Particle Swarm Optimisation (PSO) and is guided by an objective function that minimises voltage deviations across the network. The algorithm below illustrates the system modelling, FACTS device integration, and optimisation in a unified simulation environment to ensure consistent evaluation of voltage stability performance.

To examine the robustness of the proposed approach under diverse operating conditions, the test system is evaluated under four representative loading scenarios: normal (100%), light (80%), heavy (120%), and stress (130–140%) load levels. The light-load case captures potential overvoltage conditions arising from reduced reactive power demand, whereas the heavy-load case reflects peak demand periods characterised by increased voltage drops at remote buses. The stress-load scenario emulates extreme operating conditions or contingencies, providing a stringent test of system resilience and the capability of optimally placed SVCs to mitigate voltage instability and prevent voltage collapse.

Algorithm 1: Particle Swarm Optimisation (PSO) for Optimal SVC Placement and Sizing

Input:

Power system model (IEEE 30-bus), objective function $F(\cdot)$, PSO parameters (swarm size N , inertia weight w , acceleration coefficients c_1, c_2 , maximum iterations T_{max})

Output:

*Optimal SVC locations and sizes; best objective value F^**

Steps:

1. Start
2. Initialize Swarm
Randomly initialize the position $x_i(0)$ and velocity $v_i(0)$ of each particle $i = 1, 2, \dots, N$ within predefined bounds.
3. Evaluate Fitness
For each particle i , compute the fitness value $F(x_i(t))$ by running the power flow and evaluating the objective function (e.g., voltage deviation minimisation).
4. Update Personal and Global Bests
 - *If $F(x_i(t)) < F(pbest_i)$, update $pbest_i \leftarrow x_i(t)$.*
 - *Identify the global best particle $gbest$ such that*

$$F(gbest) = \min_i F(pbest_i).$$
5. Check Termination Criterion
If $t \geq T_{max}$ or convergence criterion is satisfied (e.g., negligible improvement in F), go to Step 8.
6. Update Velocity and Position
For each particle i :

$$v_i(t+1) = wv_i(t) + c_1r_1(pbest_i - x_i(t)) + c_2r_2(gbest - x_i(t)),$$

$$x_i(t + 1) = x_i(t) + v_i(t + 1).$$

Apply boundary constraints to $x_i(t + 1)$ and $v_i(t + 1)$.

7. Iterate

Set $t \leftarrow t + 1$ and return to Step 3.

8. Output Results

Report optimal SVC locations and sizes corresponding to g_{best} , along with the best fitness value F^ .*

9. Stop

3. RESULTS AND DISCUSSION

This section presents and discusses the results obtained from the simulation and optimisation procedures described in the previous chapter. The results are aimed at evaluating the effectiveness of optimally placed Static VAR Compensators (SVCs) using Particle Swarm Optimisation (PSO) in enhancing voltage stability in the Nigerian power transmission network. Simulations were conducted on the IEEE 30-bus test system under various loading conditions, including base, light, heavy, and stress loads. Voltage profiles before and after FACTS implementation are monitored in order to prove the effectiveness of FACTS devices in enhancing voltage stability in power grids.

3.1 Normal Load Condition (80%)

A comparative illustration of the voltage profiles before and after compensation is presented in Fig. 2. Under the uncompensated base-load condition (100% loading), several load buses exhibited voltage magnitudes outside the permissible operating limits. In particular, buses 9, 12, and 13 recorded overvoltage levels of 1.051 p.u., 1.057 p.u., and 1.071 p.u., respectively. Bus 11 maintained a fixed voltage magnitude of 1.08 p.u. due to the voltage setpoint of its connected generator, while the slack bus (bus 1) also retained a constant voltage by definition. Following the application of Particle Swarm Optimisation, the optimal location for SVC installation was identified at bus 13, with a reactive power rating of -47.99 MVAR, corresponding to reactive power absorption. Incorporating the SVC notably improved the voltage profile of the affected buses, with voltages at buses 9, 12, and 13 reduced to 1.040 p.u., 1.025 p.u., and 1.021 p.u., respectively, restoring all critical buses to acceptable operating limits.

3.2 Light Load Condition (80%)

Figure 3 provides a side-by-side comparison of the bus voltage profiles obtained before and after the application of reactive power compensation. Under light-load conditions, several load buses exhibited voltage magnitudes exceeding the acceptable tolerance limits. In particular, buses 9, 10, 12, 13, 14, and 16 recorded overvoltage levels of 1.057 p.u., 1.054 p.u., 1.064 p.u., 1.071 p.u., 1.052 p.u., and 1.054 p.u., respectively, indicating a pronounced tendency toward overvoltage during reduced loading. This condition poses potential risks to insulation integrity and overall system reliability.

To mitigate the observed overvoltage, the PSO algorithm identified bus 12 as the optimal location for SVC installation, with a reactive power rating of -49.637 MVAR, corresponding to reactive power absorption. Following compensation, the voltage

magnitudes at the affected buses improved significantly, with buses 9, 10, 12, 13, 14, and 16 reduced to 1.044 p.u., 1.032 p.u., 1.008 p.u., 1.031 p.u., 1.000 p.u., and 1.012 p.u., respectively. These results demonstrate the effectiveness of the optimally placed SVC in correcting the overvoltage trend and enhancing voltage stability under light-load operating conditions.

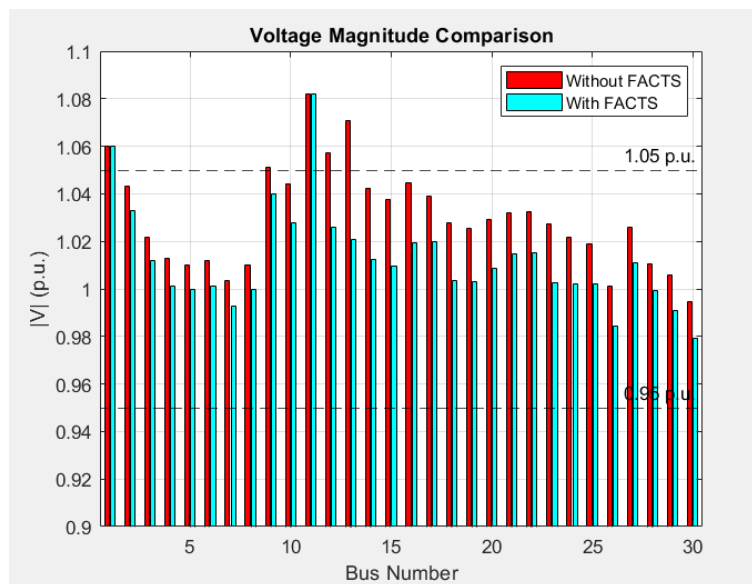


FIGURE 2. Voltage Magnitude with and without FACTS for normal loading conditions

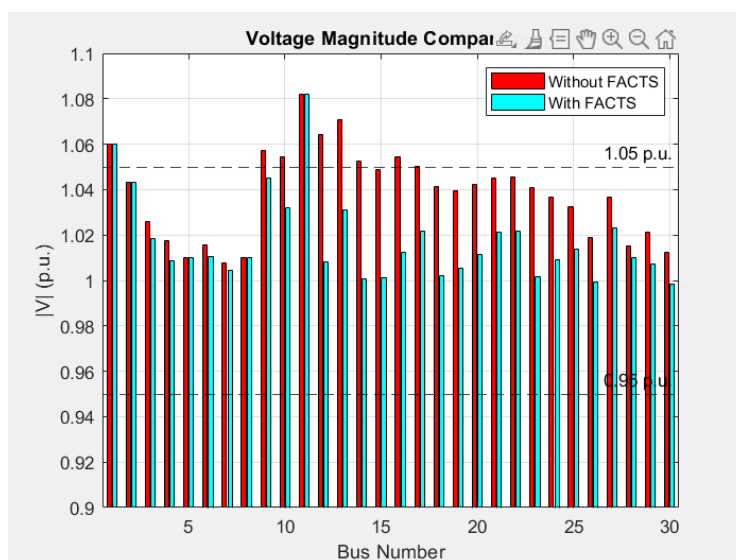


FIGURE 3. Voltage profile with and without facts in light load conditions

3.3 Heavy Load Condition (120%)

Figure 4 illustrates the voltage profiles of the network under heavy-load operation before and after compensation. During this operating condition, increased demand resulted in noticeable voltage drops across several buses, with buses 26 and 30

approaching or falling close to the lower permissible voltage limit. To address this undervoltage tendency, the PSO algorithm selected bus 30 as the optimal location for SVC installation, with a reactive power injection of 4.08 MVAR. The deployed SVC provided the required reactive support, leading to appreciable improvements in the voltage magnitudes at the most affected buses. In particular, buses that were previously operating near the lower tolerance threshold exhibited voltage recovery into the acceptable range. These results underscore the effectiveness of SVC-based compensation in mitigating voltage instability during peak loading conditions.

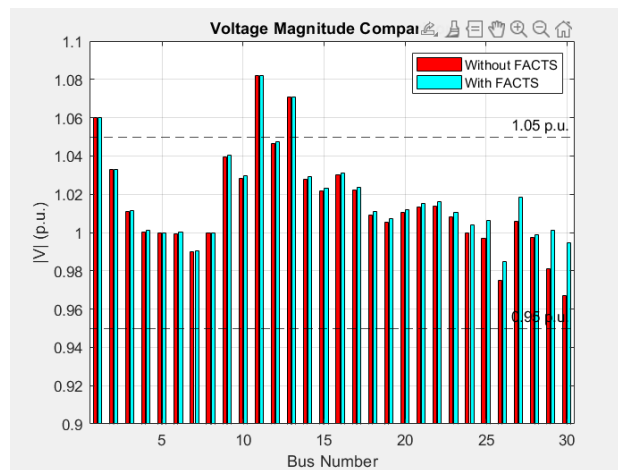


FIGURE 4. Voltage Magnitude with and without FACTS for heavy loading conditions

3.4 Stress Load Condition (140%)

Figure 5 presents the voltage magnitude profiles of the network under stressed loading conditions before and after FACTS-based compensation. Before compensation, several buses experienced voltage magnitudes well below the acceptable lower threshold of 0.95 p.u., including bus 30 at 0.927 p.u., bus 26 at 0.937 p.u., and bus 29 at 0.9445 p.u. These indicate signs of voltage instability and underline the need for support. In this scenario, the PSO algorithm identified bus 4 as the most effective location for SVC placement, with a reactive power injection of 68.012 MVAR.

After applying the SVC, the voltage profile showed notable improvements across the affected buses. The voltage at bus 30 rose from 0.927 p.u. to 0.963 p.u., bus 29 improved from 0.9445 p.u. to 0.98 p.u., and bus 26 increased from 0.937 p.u. to 0.971 p.u. Additionally, bus 13, which initially had a high voltage of 1.071 p.u., experienced a reduction to 1.051 p.u., bringing it closer to the acceptable upper limit. These improvements confirm the effectiveness of the optimally placed SVC in mitigating voltage deviation and restoring system voltage stability under stress load conditions.

The results clearly show how effective the optimally placed SVCs were in improving voltage stability across the power network under different operating conditions. By comparing the voltage magnitudes before and after compensation in each load scenario, we can see how much of a difference this approach makes in real-world power system performance.

In the normal load condition, a few buses (notably buses 9, 12, and 13) had voltage levels slightly higher than what's normally acceptable, reaching up to 1.071 p.u. The PSO algorithm recommended placing an SVC at bus 13, which absorbed -47.99 MVAR of reactive power. As a result, those buses saw their voltage levels drop to within the safe limits. For example, bus 13 improved from 1.071 p.u. to 1.021 p.u., showing a clear correction in the voltage profile—about a 4.7% improvement.

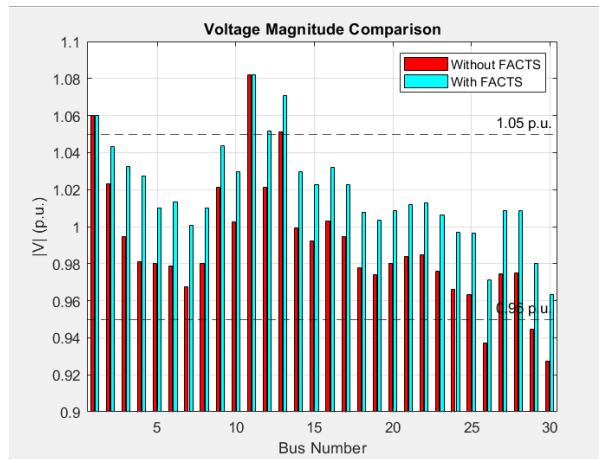


FIGURE 5. Voltage Magnitude with and without FACTS for stressed loading conditions

When the system was operating under light load conditions (80% of nominal demand), the overvoltage issues were even more widespread. Six buses showed voltage levels above the acceptable range, with bus 13 again peaking at 1.071 p.u. An SVC was then placed at bus 12, absorbing nearly -49.6 MVAR. This brought the voltages across those affected buses down significantly—bus 12 dropped from 1.064 p.u. to 1.008 p.u., which is about a 5.3% improvement. Once again, all buses were restored to within safe voltage limits.

Under heavy loading conditions (120% of base load), the challenge shifted—some buses began to approach the lower voltage tolerance limit. Buses like 26 and 30 were showing signs of undervoltage. A relatively small SVC of 4.08 MVAR was placed at bus 30, which helped support the voltage and brought it back above the 0.95 p.u. mark. The voltages improved by around 3–4%, which, although smaller than previous cases, was still enough to maintain system stability under high demand.

In the most stressful case (140%), things got more critical. Some buses, especially buses 26, 29, and 30, dropped well below the safe 0.95 p.u. level. Bus 30 fell as low as 0.927 p.u., which could pose serious risks in real-world operations. The PSO algorithm chose bus 4 for SVC placement, and a much stronger device (68.012 MVAR) was installed. After compensation, voltages at the critical buses recovered: bus 30 rose to 0.963 p.u., and others followed similar improvements. Even overvoltage issues at bus 13 were corrected, dropping from 1.071 p.u. to 1.051 p.u. This highlights the dual capability of the SVC to handle both low and high voltage problems at once.

Across all four scenarios, the results are consistent: with optimal SVC placement, all bus voltages were brought back within acceptable limits. The average improvements ranged from 3% to 5%, and more importantly, all violations were

eliminated. These results not only validate the PSO-based approach to device placement and sizing but also show just how crucial reactive power compensation is for a secure and stable grid—especially in countries like Nigeria, where power systems are often pushed close to their limits.

3.5 Comparative Context with Alternative Metaheuristic Approaches

To provide comparative context for the proposed PSO approach, its application to SVC placement is considered alongside other evolutionary optimisation techniques. GA-based methods have been successfully applied to SVC placement and sizing in Nigerian transmission networks, including GA–fuzzy optimisation [14], while hybrid GA–PSO methods have been used for voltage-stability enhancement [18]. More recently, a GA-based coordinated SVC–TCSC approach was evaluated under normal, overload and N–1 contingency conditions in a representative Nigerian transmission network [25]. These studies demonstrate the effectiveness of GA-based approaches for related FACTS optimisation problems, while the present study investigates PSO specifically for SVC placement and sizing under varying loading conditions. Although the differences in network configuration, objective functions and constraints prevent a direct numerical comparison, the results provide a basis for assessing PSO within the broader class of evolutionary optimisation methods.

3.6 Convergence, Computational Efficiency and Robustness Analysis

To further validate the proposed PSO-SVC framework, convergence behaviour, computational effort and robustness under severe operating conditions were additionally examined. The PSO employed a population of 50 particles and a maximum of 200 iterations, resulting in a maximum of 10,000 fitness evaluations per operating scenario and 40,000 evaluations across the four loading conditions. The optimisation process exhibited progressive improvement of the objective function as the iterations increased, with the major reduction occurring during the early and intermediate search stages and relatively small changes during the later iterations. This indicates that the swarm progressively converged toward stable SVC location and sizing solutions.

The robustness of the obtained solutions was further assessed using the severe 140% loading condition. Before compensation, buses 26, 29 and 30 exhibited undervoltages of 0.937, 0.9445 and 0.927 p.u., respectively. Following PSO-based SVC installation at Bus 4 with a rating of 68.012 MVAR, the corresponding voltages increased to 0.971, 0.980 and 0.963 p.u. The percentage voltage recovery was therefore 3.63%, 3.76% and 3.88%, respectively, giving an average recovery of approximately 3.76% across the three critical buses. Consequently, the number of critical undervoltage violations decreased from three to zero under the stress condition. In addition, the overvoltage at Bus 13 was reduced from 1.071 to 1.051 p.u. These results demonstrate that the optimized SVC solution remains effective as the system moves from normal to highly stressed operating conditions, thereby providing evidence of the robustness of the proposed framework.

4. CONCLUSION

This research explored the enhancement of voltage stability in the Nigerian power grid through the optimal placement and sizing of Static VAR Compensators (SVCs) using Particle Swarm Optimisation (PSO). The IEEE 30-bus system was adopted as the test to simulate varying load conditions which represent different operational scenarios of the grid. The study revealed that under uncompensated conditions, several buses experienced voltage violations, either breaching the upper limit during light loading or falling below acceptable thresholds during heavy and stress loading. These deviations pose serious risks to system reliability, operational efficiency, and equipment safety. The PSO algorithm proved effective in identifying optimal SVC locations and their corresponding reactive power requirements. In each loading scenario, the SVC significantly improved the voltage profile across critical buses. On average, voltage deviations were reduced by 3–5%, successfully bringing all bus voltages within the standard tolerance range of 0.95 to 1.05 p.u. The improvements were most pronounced during stress load conditions, where reactive support was crucial to preventing voltage collapse. Overall, the integration of computational intelligence (PSO) with FACTS devices (SVCs) demonstrated a powerful and scalable approach for reactive power planning and dynamic voltage control. The results affirm that PSO can be a viable tool in grid modernisation efforts, especially in developing power systems like Nigeria's, where stability issues are more pronounced due to rapid load growth and infrastructure limitations.

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