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Genetic Algorithm-Based SVC Capacity Optimization for Voltage Stability in 500 kV Systems

Optimasi Kapasitas SVC Berbasis Algoritma Genetika untuk Stabilitas Tegangan Sistem 500 kV

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Abstract _*This study aims to determine the optimal capacity of a Static Var Compensator (SVC) to enhance voltage stability in a 500 kV transmission system using a Genetic Algorithm (GA). A quantitative simulation-based approach was employed by integrating steady-state load flow analysis in ETAP with GA optimization implemented in MATLAB. The optimization objective combines total voltage deviation and transmission power loss to ensure balanced system improvement. Two evaluation scenarios were considered: the base-case condition without SVC installation and the optimized condition with GA-determined SVC capacities applied at selected critical buses. Under the base-case scenario, the minimum bus voltage was recorded at 455.009 kV, and total transmission losses reached 607.32 MW. After applying the optimized SVC capacities of 404.80 MVAr, 288.43 MVAr, and 175.94 MVAr at the identified buses, voltage magnitudes increased by 0.98% to 7.89%, with the highest improvement observed at Bus 50. Simultaneously, total transmission losses decreased to 594.30 MW, corresponding to a reduction of 13.02 MW or 2.14% relative to the baseline. The convergence analysis confirms stable optimization behavior within 100 generations. The results demonstrate that GA-based SVC capacity optimization provides consistent voltage enhancement and measurable loss reduction under steady-state operating conditions, offering a practical and reproducible framework for reactive power planning in large-scale transmission systems.*

Keywords: *Genetic Algorithm; Static Var Compensator; Voltage Stability; 500 kV Transmission System; Reactive Power Compensation; Transmission Loss Reduction*

Abstrak_ Penelitian ini bertujuan untuk menentukan kapasitas optimal Static Var Compensator (SVC) guna meningkatkan stabilitas tegangan pada sistem transmisi 500 kV menggunakan algoritma genetika (Genetic Algorithm/GA). Pendekatan kuantitatif berbasis simulasi diterapkan dengan mengintegrasikan analisis aliran daya kondisi tunak menggunakan ETAP dan optimasi GA yang diimplementasikan pada MATLAB. Fungsi objektif dirumuskan dengan mengombinasikan total deviasi tegangan dan rugi-rugi daya transmisi untuk memastikan peningkatan kinerja sistem yang seimbang. Evaluasi dilakukan pada dua skenario, yaitu kondisi dasar (tanpa SVC) dan kondisi setelah pemasangan SVC dengan kapasitas hasil optimasi GA pada bus kritis terpilih. Pada kondisi dasar, tegangan minimum tercatat sebesar 455,009 kV dan total rugi-rugi transmisi mencapai 607,32 MW. Setelah penerapan kapasitas SVC optimal sebesar 404,80 MVAr, 288,43 MVAr, dan 175,94 MVAr pada bus yang dianalisis, tegangan meningkat sebesar 0,98% hingga 7,89%, dengan peningkatan terbesar terjadi pada Bus 50. Secara bersamaan, total rugi-rugi transmisi menurun menjadi 594,30 MW, yang setara dengan reduksi sebesar 13,02 MW atau 2,14% dibandingkan kondisi awal. Analisis konvergensi menunjukkan bahwa proses optimasi mencapai kestabilan dalam 100 generasi.
Hasil penelitian ini menunjukkan bahwa optimasi kapasitas SVC berbasis GA mampu meningkatkan stabilitas tegangan dan menurunkan rugi-rugi transmisi secara terukur pada kondisi operasi tunak, serta memberikan kerangka kerja yang praktis dan reprodusibel untuk perencanaan daya reaktif pada sistem transmisi skala besar.

Kata Kunci: Algoritma Genetika; Static Var Compensator; Stabilitas Tegangan; Sistem Transmisi 500 kV; Kompensasi Daya Reaktif; Reduksi Rugi-Rugi Transmisi

I. INTRODUCTION

Voltage stability has long been recognized as one of the most critical operational concerns in extra high-voltage transmission systems, particularly in 500 kV networks that operate under high loading conditions and long-distance power transfer configurations. In such systems, even a moderate imbalance between reactive power supply and demand may trigger noticeable voltage deviations across several buses, potentially reducing system reliability and operational security (Gautam & Lakhra, 2024)(Gupta et al., 2024). The increasing growth of electricity demand, combined with geographically dispersed generation and complex interconnection structures, further intensifies the challenge of maintaining acceptable voltage levels within permissible limits (Shajin et al., 2025). When reactive power support is insufficient or poorly managed, the system becomes vulnerable to progressive voltage decline and, in extreme cases, voltage collapse phenomena (Li et al., 2022). For this reason, effective reactive power management has become an essential component of modern transmission system operation and planning (Shekarappa G et al., 2023).

Although various reactive power compensation techniques have been proposed and implemented, determining the appropriate capacity of compensation devices remains a nontrivial task. Static Var Compensators (SVCs) are widely adopted due to their fast and flexible reactive power control capability, which allows continuous voltage regulation at selected buses (Pullareddy et al., 2024)(Namburi et al., 2024). However, the effectiveness of an SVC strongly depends on its installed capacity. An undersized device may provide insufficient voltage support, while an oversized installation may introduce unnecessary reactive circulation and reduce overall system efficiency (Zhou et al., 2024)(Lu, 2025). Previous studies have applied heuristic and metaheuristic optimization techniques to address SVC sizing problems, yet many of them are conducted on simplified benchmark systems or focus primarily on voltage magnitude improvement without thoroughly evaluating the associated impact on transmission losses (Pandian & Palanivelu, 2021)(Khan et al., 2021). Moreover, the integration of realistic power flow simulation tools with evolutionary optimization frameworks is not always systematically implemented, leaving room for improvement in practical large-scale applications (Pulluri et al., 2024)(Jiang et al., 2024).

From a theoretical perspective, voltage stability in transmission networks is fundamentally governed by nonlinear power flow relationships that describe the interaction between active power, reactive power, and bus voltage magnitudes (Adeyemi & Adebayo, 2025)(Bai et al., 2022). Within this framework, an SVC can be modeled as a controllable shunt susceptance that dynamically injects or absorbs reactive power in response to voltage deviations (Baishya et al., 2022). Determining the optimal SVC capacity can therefore be formulated as a constrained nonlinear optimization problem, in which the objective is to enhance voltage stability while satisfying system operational limits. The Genetic Algorithm (GA), inspired by evolutionary principles, has been widely recognized as a robust method for solving complex optimization problems that exhibit nonlinear and non-convex characteristics (Abubakar & Mohammad, 2024)(Dandotia et al., 2023)(Ajayi et al., 2025). Its population-based search mechanism enables exploration of a broad solution space without relying on gradient information, making it particularly suitable for power system applications.

Based on these considerations, this study aims to determine the optimal capacity of a Static Var Compensator using a Genetic Algorithm in order to improve voltage stability in a 500 kV transmission system. The research begins with an analysis of the initial voltage profile under normal operating conditions, followed by the identification of buses that exhibit the highest voltage sensitivity. The Genetic Algorithm is then applied to obtain the optimal SVC capacity, and the resulting system performance is evaluated in terms of voltage magnitude improvement and transmission power loss reduction. By integrating steady-state load flow analysis conducted in ETAP with a GA-based optimization routine implemented in MATLAB, this study establishes a structured simulation framework for practical SVC capacity determination.

The contribution of this work lies in its application of an integrated simulation–optimization approach to a realistic large-scale transmission system model, rather than relying solely on simplified benchmark networks. In addition to examining voltage profile enhancement, this study also evaluates the impact of optimized SVC capacity on transmission power losses, providing a more comprehensive assessment of system performance. The findings are expected to support more informed reactive power planning decisions and to offer a practical reference for optimizing SVC installations in high-voltage transmission systems. The following section presents the methodological framework, including system modeling, SVC representation, and the Genetic Algorithm-based optimization procedure.

II. METHODS

This study adopts a quantitative, simulation-based research approach in the form of a computational case study applied to a 500 kV transmission system. The objective is to determine the optimal capacity of a Static Var Compensator (SVC) using a Genetic Algorithm (GA) to improve voltage stability performance. The entire methodological framework is designed with reproducibility in mind, meaning that all system parameters, modeling assumptions, equations, and optimization settings are explicitly defined so that the results can be independently replicated.

2.1. System Modeling and Data Source

The research is conducted on a modeled 500 kV transmission network consisting of generator buses, load buses, and interconnected transmission lines, as illustrated in Figure 1. The simplified single line diagram provides a structural overview of the network configuration, highlighting the main transmission corridors and the relative positions of the critical buses analyzed in this study. The system parameters include bus classifications (slack, PV, and PQ buses), transmission line resistance and reactance, load demands in MW and MVAr, and generator operating limits. All data are represented in a per-unit system based on a 100 MVA base power to ensure numerical consistency.

[Figure 1 about here.]

The main system parameters used in this study are summarized in Table 1. Under normal operating conditions, the system operates at a nominal voltage level of 500 kV. The total transmission power loss under the base-case condition, prior to SVC installation, is recorded as 607.32 MW. This base-case scenario serves as the reference point for evaluating the effectiveness of the optimized SVC capacity within the network configuration shown in Figure 1.

[Table 1 about here.]

2.2. Power Flow Modeling

Steady-state operating conditions of the transmission system are analyzed using the Newton–Raphson load flow method implemented in ETAP. This method is selected due to its robustness and numerical stability for large-scale power systems. The power flow equations governing the active and reactive power balance at each bus are expressed in Equation (1) and Equation (2), which represent the nonlinear AC power flow formulation.

$$P_i = V_i \sum_{j=1}^{n} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \quad (1)$$

$$Q_i = V_i \sum_{j=1}^{n} V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \quad (2)$$

As defined in Equation (1), the active power injection at bus i is determined by the interaction between bus voltage magnitudes, admittance matrix elements, and voltage angle differences. Likewise, Equation (2) describes the reactive power balance at each bus. In these equations, P_i and Q_i denote active and reactive power injections, V_i represents the bus voltage magnitude, G_{ij} and B_{ij} are elements of the bus admittance matrix, and θ_{ij} corresponds to the voltage angle difference between interconnected buses.

To quantify the overall voltage performance of the system, the total voltage deviation index is formulated as shown in Equation (3),

$$VD = \sum_{i=1}^{n} | V_i - 1 | \quad (3)$$

where V_i is expressed in per-unit. As indicated in Equation (3), the voltage deviation index aggregates the absolute deviation of each bus voltage from its nominal per-unit value, thereby providing a single numerical representation of system-wide voltage quality. This index serves as one of the principal performance indicators and is directly incorporated into the multi-objective optimization function defined in Equation (5), together with total transmission loss, to ensure that voltage regulation and efficiency improvement are simultaneously considered.

2.3. SVC Modeling

The Static Var Compensator is modeled as a controllable shunt susceptance connected to a selected transmission bus. In steady-state analysis, the reactive power injected by the SVC is expressed as shown in Equation (4):

$$Q_{svc} = -V^2 B_{svc} \quad (4)$$

As defined in Equation (4), the reactive power output of the SVC is proportional to the square of the bus voltage magnitude and the equivalent shunt susceptance. In this formulation, B_{svc}represents the controllable susceptance of the compensator, while Vdenotes the voltage magnitude. By adjusting B_{svc}, the SVC can either inject or absorb reactive power, thereby directly influencing the voltage profile obtained from the power flow equations defined in Equations (1) and (2).

Since the reactive power injection in Equation (4) affects both voltage magnitude and power flow distribution, the SVC capacity is treated as the

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primary decision variable in the optimization framework. The capacity, expressed in MVAr, is constrained within predefined operational limits to ensure realistic implementation and to prevent overcompensation.

2.4. Genetic Algorithm Configuration

The influence of SVC capacity on system performance is evaluated using a multi-objective function that combines the total voltage deviation (Equation (3)) and the total transmission power loss. The optimization objective is formulated as shown in Equation (5):

$$F = \omega_1 VD + \omega_2 P_{loss} \tag{5}$$

As indicated in Equation (5), the objective function balances voltage quality and system efficiency through weighting factors ω_1 and ω_2. In this way, the susceptance adjustment described in Equation (4) becomes systematically linked to measurable performance indicators, ensuring that the optimized SVC capacity simultaneously improves voltage stability and reduces transmission losses.

The Genetic Algorithm was implemented in MATLAB with the parameters summarized in Table 2. The GA is configured with a population size of 50 individuals and a maximum of 100 generations. The crossover probability is set to 0.8 and the mutation probability to 0.1. A roulette-wheel selection mechanism is employed to maintain diversity within the population. The algorithm terminates when the maximum number of generations is reached.

[Table 2 about here.]

The optimization procedure follows a systematic and iterative sequence. First, the population of candidate SVC capacities is generated randomly within predefined operational limits. Each candidate solution is then applied to the transmission system model in ETAP, where a load flow analysis is performed to obtain voltage magnitudes and total transmission losses. These outputs are used to evaluate the fitness value according to the objective function defined in Equation (5). Based on the computed fitness values, the GA performs selection, crossover, and mutation to produce a new generation of candidate solutions. This iterative process continues until the termination criterion is satisfied. The overall optimization workflow integrating ETAP-based load flow analysis and MATLAB-based GA computation is illustrated in Figure 2.

[Figure 2 about here.]

2.5. Numerical Scenarios and Performance Evaluation

Two numerical scenarios are defined to assess system performance:

1. Base Case Scenario – The transmission system operating under nominal load conditions without SVC installation.
2. Optimized Scenario – The system operating with the GA-optimized SVC capacity installed at the selected bus.

The performance indicators evaluated in this study include minimum bus voltage, total voltage deviation, total transmission power loss, and percentage improvement in voltage magnitude. The effectiveness of the optimized SVC is assessed by comparing system performance metrics before and after installation. All modeling parameters, optimization settings, and evaluation criteria are explicitly specified to ensure that another researcher can reproduce the simulation and optimization process using equivalent system data and computational tools.

III. RESULTS AND DISCUSSION

This section presents a structured evaluation of the proposed Genetic Algorithm-based framework for optimizing SVC capacity in the 500 kV transmission system. The analysis begins by establishing the base-case operating condition to quantify initial voltage deviations and transmission losses as performance references. The optimization process is then examined through its convergence behavior to ensure numerical stability and methodological reliability before presenting the resulting optimal SVC capacities. The effectiveness of the optimized installation is subsequently assessed by directly comparing voltage magnitudes and total transmission losses between the uncompensated and compensated scenarios. By analyzing these indicators collectively, this section aims to demonstrate whether the proposed approach achieves balanced system enhancement, improving voltage performance while simultaneously reducing transmission losses, rather than producing isolated gains in a single metric.

3.1. Base-Case System Performance

The base-case scenario represents the operating condition of the 500 kV transmission system without any additional reactive power compensation. Under this condition, several buses exhibit significant deviation from the nominal voltage level of 500 kV. The lowest voltage is recorded at Bus 47, reaching 455.009 kV, followed closely by Bus 50 at 455.135 kV. Bus 14 operates at 474.221 kV, indicating moderate deviation but still below the nominal value.

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From an operational perspective, voltage levels below approximately 0.95 per-unit in extra high-voltage systems may indicate insufficient reactive power support. The observed values at Buses 47 and 50 correspond to approximately 0.91 per-unit, confirming that these buses are operating in a stressed condition. In addition to voltage deviation, the total transmission power loss in the base-case scenario is measured at 607.32 MW. This relatively high loss level reflects significant reactive current flow within the network, which is often associated with suboptimal voltage profiles.

Table 3 summarizes the key base-case performance indicators. These results establish a clear baseline: the system operates with both voltage instability risk at specific buses and considerable transmission losses, thereby justifying the need for optimized reactive power compensation.

[Table 3 about here.]

3.2. Genetic Algorithm Convergence Analysis

Before presenting the optimal SVC capacities obtained from the optimization process, it is necessary to evaluate how the Genetic Algorithm behaves during the search process. Convergence analysis is essential to ensure that the final solution is achieved through a stable and systematic improvement of the objective function, rather than through random fluctuation. In this study, the optimization was executed with a population size of 50 individuals over a maximum of 100 generations, using a crossover probability of 0.8 and a mutation probability of 0.1. The evolution of the fitness value throughout the optimization process is illustrated in Figure 3.

[Figure 3 about here.]

As shown in Figure 3, the fitness value decreases significantly during the initial generations. This early-stage behavior indicates that the algorithm effectively explores the search space and rapidly identifies candidate solutions that improve the objective function defined in Equation (5). The relatively steep decline in fitness during these generations reflects strong global exploration capability.

As the generation number increases, the slope of the curve gradually reduces, and the fitness values begin to stabilize. This transition marks the shift from exploration to exploitation, where the algorithm refines promising candidate solutions rather than searching broadly across the solution space. By the final generations, the curve becomes nearly flat, indicating minimal variation between successive fitness values. This stabilization confirms that convergence is achieved within the predefined limit of 100 generations.

Importantly, the convergence curve does not exhibit erratic oscillations or abrupt fitness increases. Such behavior would typically indicate premature convergence or instability in the selection and mutation process. Instead, the smooth and progressive reduction of the objective function demonstrates that the chosen GA parameters provide a balanced trade-off between diversification and intensification. From an engineering standpoint, this stable convergence pattern strengthens confidence that the optimized SVC capacities presented in the next subsection are not the result of incidental iteration behavior but represent consistent near-optimal solutions.

The convergence behavior therefore supports the robustness of the optimization framework and validates the reliability of the subsequent performance improvements observed in voltage magnitude and transmission loss reduction.

3.3. Optimal SVC Capacity Determination

The stable convergence behavior observed in Figure 3 confirms that the optimization process has reached a consistent and near-optimal solution within the predefined generation limit. With the fitness value progressively decreasing and eventually stabilizing, the resulting SVC capacities can be interpreted as reliable outputs of the Genetic Algorithm rather than incidental iteration results.

Based on the converged solution, the optimal SVC capacities for the selected critical buses are presented in Table 4. The results indicate that Bus 14 requires the highest reactive power injection at 404.80 MVAr, followed by Bus 47 at 288.43 MVAr and Bus 50 at 175.94 MVAr. The variation in optimal capacity reflects the distinct reactive power sensitivity and network positioning of each bus within the transmission system.

[Table 4 about here.]

Although Bus 47 and Bus 50 exhibit the lowest voltage magnitudes under the base-case condition, Bus 14 requires the largest compensation. This finding highlights an important engineering insight: optimal reactive power sizing is not determined solely by the lowest voltage value but also by the bus's interaction with surrounding network elements and overall reactive power flow distribution. In other words, voltage deviation alone does not fully capture the complexity of reactive power support requirements.

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The optimized capacities derived from the converged Genetic Algorithm solution form the basis for evaluating system performance improvements, which are analyzed in terms of voltage magnitude enhancement and transmission loss reduction in the subsequent subsections.

3.4. Voltage Profile Improvement

The optimized SVC capacities obtained in the previous subsection provide the basis for evaluating their practical impact on system voltage performance. To assess the effectiveness of the determined capacities, load flow analysis was performed again with the SVC installed at the respective buses. The comparison between the base-case and optimized conditions is summarized in Table 5.

[Table 5 about here.]

The results demonstrate consistent voltage enhancement across all evaluated buses. Bus 50 exhibits the most substantial improvement, with an increase of 35.908 kV, corresponding to a 7.89% rise relative to its base-case value. Bus 47 shows a 20.983 kV increase (4.61%), while Bus 14 experiences a moderate improvement of 4.646 kV (0.98%). Although the percentage increase at Bus 14 appears smaller, it reflects stabilization of a bus that initially operated closer to the acceptable voltage range.

To provide a clearer visual representation of these improvements, Figure 4 illustrates the voltage magnitude comparison before and after SVC installation. As shown in Figure 4, the voltage enhancement is not isolated to a single bus but occurs consistently across the three most sensitive locations. The visual gap between the base-case and optimized values is particularly evident for Buses 47 and 50, confirming the numerical trends presented in Table 4. This consistency indicates that the optimized SVC capacities effectively redistribute reactive power support within the network, strengthening voltage levels at multiple points simultaneously.

[Figure 4 about here.]

From an engineering standpoint, the observed improvements suggest that reactive power injection at strategically selected buses reduce voltage drops along transmission corridors. The greater percentage increase at Bus 50 implies that this bus is highly responsive to reactive compensation, whereas Bus 14 demonstrates a more gradual response due to its initial operating condition and network interactions.

While the improvement in voltage magnitude clearly confirms the effectiveness of the optimized SVC capacities, it remains necessary to evaluate whether this voltage enhancement also translates into improved transmission efficiency. The next subsection therefore examines the impact of SVC installation on total transmission power losses.

3.5. Transmission Loss Reduction

Following the observed improvement in voltage magnitude at the critical buses, the next step is to evaluate whether the optimized SVC installation also enhances overall transmission efficiency. In large-scale power systems, voltage stabilization alone is not sufficient; any compensation strategy must also be assessed in terms of its impact on active power losses. Table 6 presents the comparison of total transmission losses before and after the installation of the optimized SVC capacities.

[Table 6 about here.]

The results indicate that total transmission losses decrease from 607.32 MW in the base-case condition to 594.30 MW after SVC installation. This represents a reduction of 13.02 MW, equivalent to a 2.14% improvement relative to the baseline.

Although the percentage reduction may appear modest, its practical significance becomes clearer when viewed in the context of a 500 kV transmission network. A 13.02 MW decrease in active power losses corresponds to a substantial reduction in wasted energy over continuous operation. In long-term system operation, even a 2% improvement can translate into considerable operational cost savings and enhanced overall efficiency.

From a technical standpoint, the reduction in transmission losses is closely related to the improved reactive power balance achieved through the optimized SVC capacity. By injecting reactive power locally at sensitive buses, the SVC reduces the need for reactive power transfer over long transmission distances. Lower reactive current flow leads directly to reduced I^2R losses in transmission lines, thereby decreasing total active power losses. This outcome confirms that the compensation strategy improves not only voltage stability but also network efficiency.

Importantly, the results demonstrate consistent behavior across performance indicators: voltage magnitudes increase while transmission losses decrease. No adverse trade-off is observed between stability enhancement and efficiency performance. This balanced improvement strengthens confidence in the robustness of the proposed optimization framework and supports its applicability in practical transmission system planning.

3.6. Integrated Performance Assessment and Contribution

When viewed collectively, the results demonstrate a consistent improvement across all evaluated performance indicators. The optimized SVC capacities increase voltage magnitude at the three critical buses by 0.98% to 7.89%, while simultaneously reducing total transmission losses by 13.02 MW (2.14%) relative to the base-case condition. This parallel enhancement confirms that voltage stabilization does not introduce adverse trade-offs in system efficiency. Instead, improved reactive power support reduces reactive current circulation within transmission lines, leading to lower resistive losses. The numerical consistency between voltage improvement and loss reduction strengthens confidence that the optimization framework achieves balanced system performance rather than isolated gains.

The integrated simulation–optimization approach implemented in this study also contributes methodologically. By combining ETAP-based load flow analysis with a MATLAB-based Genetic Algorithm, the framework provides a practical and reproducible procedure for determining SVC capacity in a large-scale 500 kV transmission network. Although the assessment is limited to steady-state operation under nominal loading, the results indicate that optimization-based reactive power planning can produce measurable and technically meaningful improvements. Future extensions may incorporate multi-scenario loading conditions or dynamic stability analysis to further enhance robustness and applicability.

IV. CONCLUSION

This study proposes a Genetic Algorithm-based optimization framework to determine the optimal capacity of a Static Var Compensator (SVC) in a 500 kV transmission system. By integrating ETAP-based load flow analysis with MATLAB-based evolutionary optimization, the framework provides a structured and reproducible approach for reactive power planning. The results show that the optimized SVC capacities improve voltage magnitude at three critical buses by 0.98% to 7.89%, while simultaneously reducing total transmission losses from 607.32 MW to 594.30 MW, equivalent to a 13.02 MW or 2.14% reduction relative to the base-case condition.

The observed improvements are consistent with the theoretical relationship between reactive power injection and voltage regulation. By supplying reactive power locally at strategically selected buses, the SVC reduces reactive power circulation across long transmission corridors, which in turn lowers resistive losses and stabilizes bus voltages. The absence of adverse trade-offs between voltage enhancement and loss reduction indicates that the proposed optimization framework achieves balanced system improvement rather than isolated performance gains.

Although the results demonstrate measurable technical benefits, the analysis is limited to steady-state operation under nominal loading conditions. Dynamic stability, contingency scenarios, and seasonal variations were not considered in this study. Future work may extend the framework to multi-scenario optimization, dynamic performance assessment, or comparative evaluation with alternative FACTS devices to enhance robustness and practical applicability.

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Table 1. Main System Parameters of the 500 kV Transmission Network

Parameter	Description
Nominal Voltage Level	500 kV
Bus Types	Slack, PV, PQ
Line Parameters	Resistance (R), Reactance (X), Susceptance (B)
Load Data	Active (MW), Reactive (MVAr)
Generator Limits	Pmin, Pmax, Qmin, Qmax
Base Power	100 MVA (per-unit system)

Table 2. Genetic Algorithm Parameters

Parameter	Value
Population Size	50
Maximum Generations	100
Crossover Probability (Pc)	0.8
Mutation Probability (Pm)	0.1
Selection Method	Roulette Wheel
Termination Criterion	Maximum generation reached

Table 3. Base-Case Performance

Parameter	Value
Minimum Bus Voltage	455.009 kV (Bus 47)
Voltage at Bus 50	455.135 kV
Voltage at Bus 14	474.221 kV
Total Transmission Loss	607.32 MW

Table 4. Optimal SVC Capacity

Bus	Optimal SVC Capacity (MVAr)
14	404.80
47	288.43
50	175.94

Table 5. Voltage Comparison Before and After SVC Installation

Bus	Before (kV)	After (kV)	Improvement (kV)	Increase (%)
14	474.221	478.867	4.646	0.98%
47	455.009	475.992	20.983	4.61%
50	455.135	491.043	35.908	7.89%

Table 6. Transmission Loss Comparison

Scenario	Total Loss (MW)	Reduction (MW)	Reduction (%)
Base Case	607.32	–	–
After SVC	594.30	13.02	2.14%

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Figure 3. Convergence Curve of the Genetic Algorithm Showing Fitness Value Evolution Across Generations
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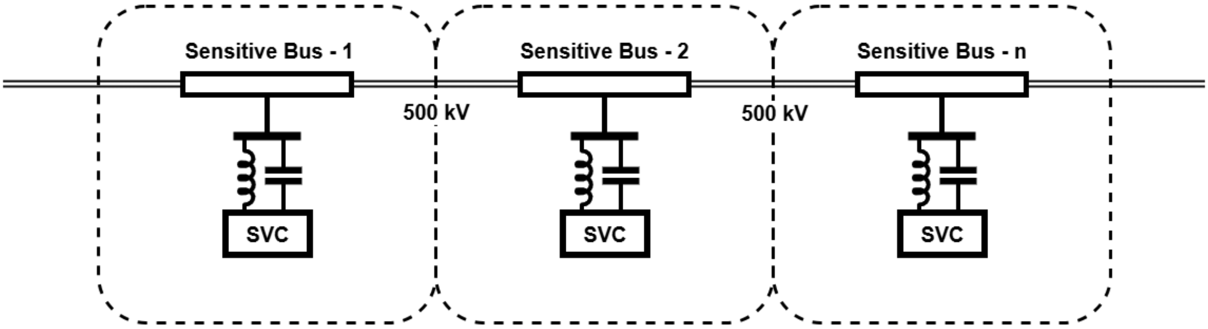

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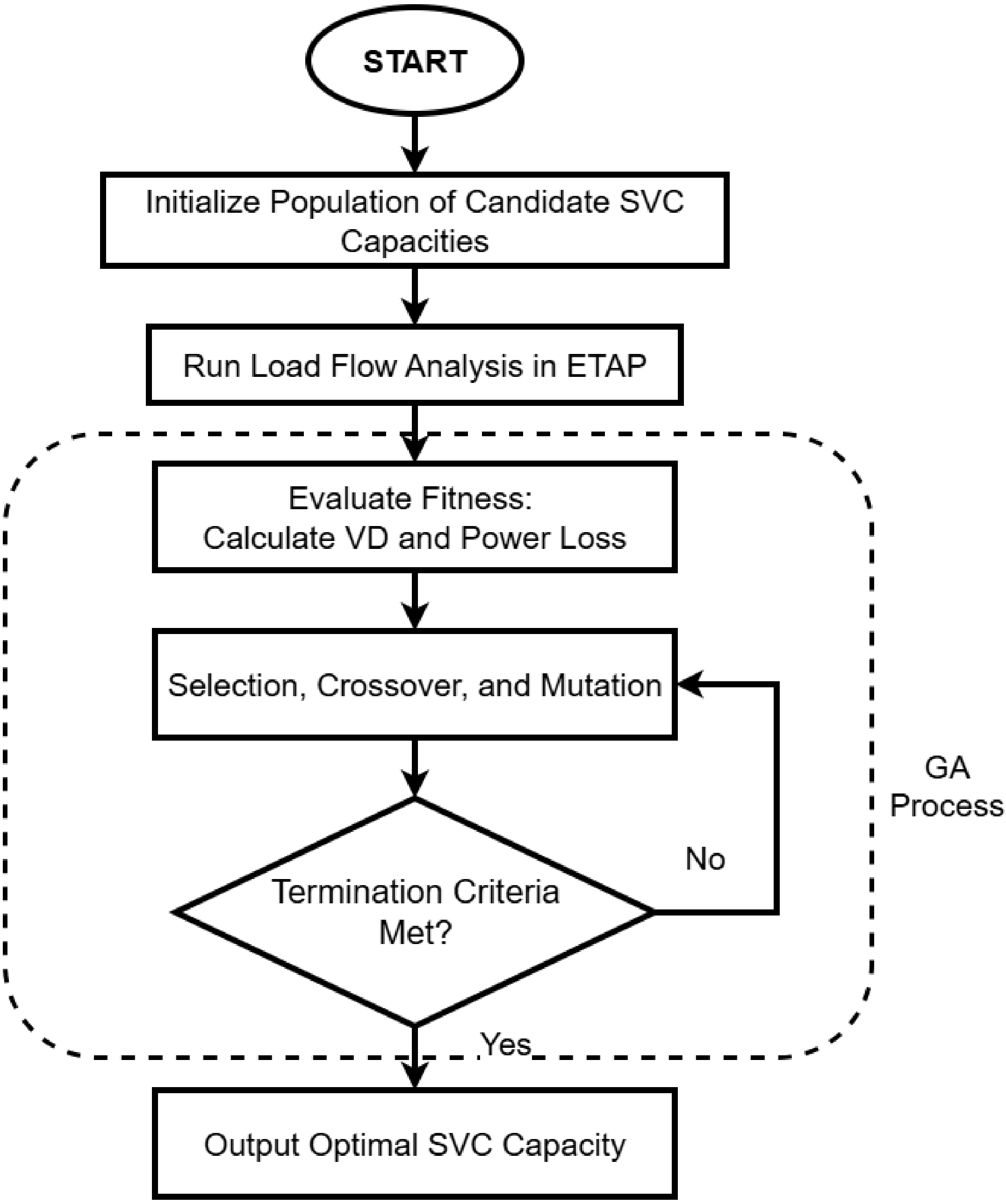

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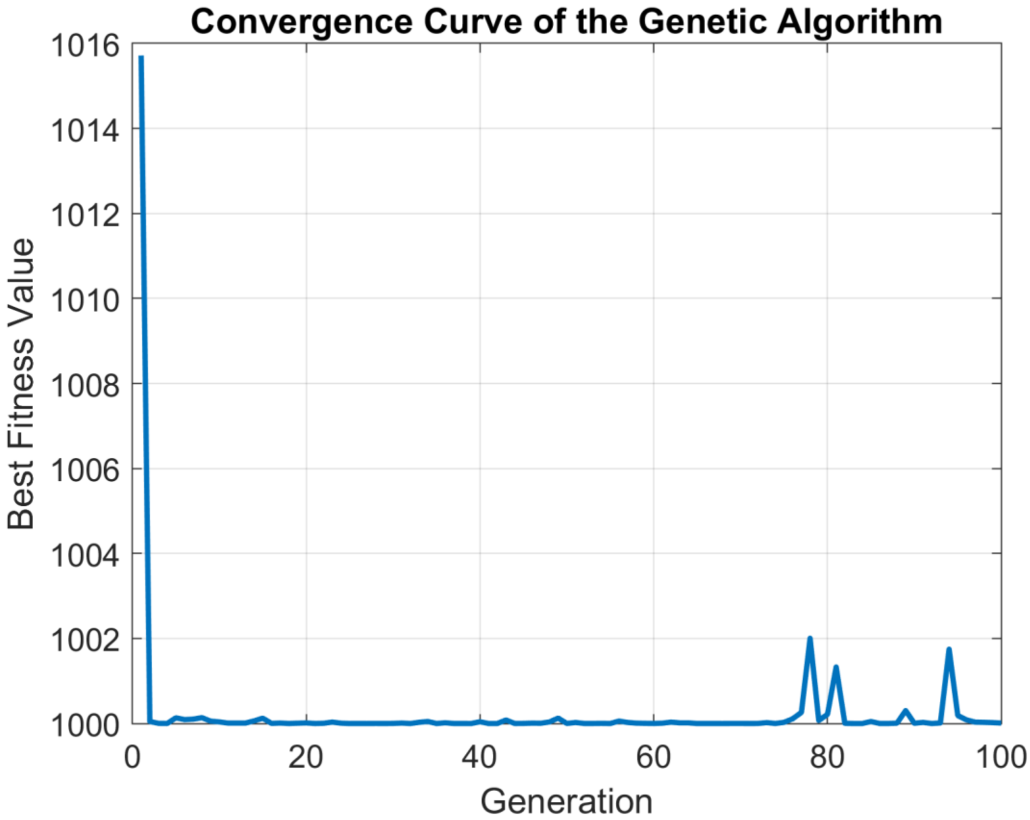

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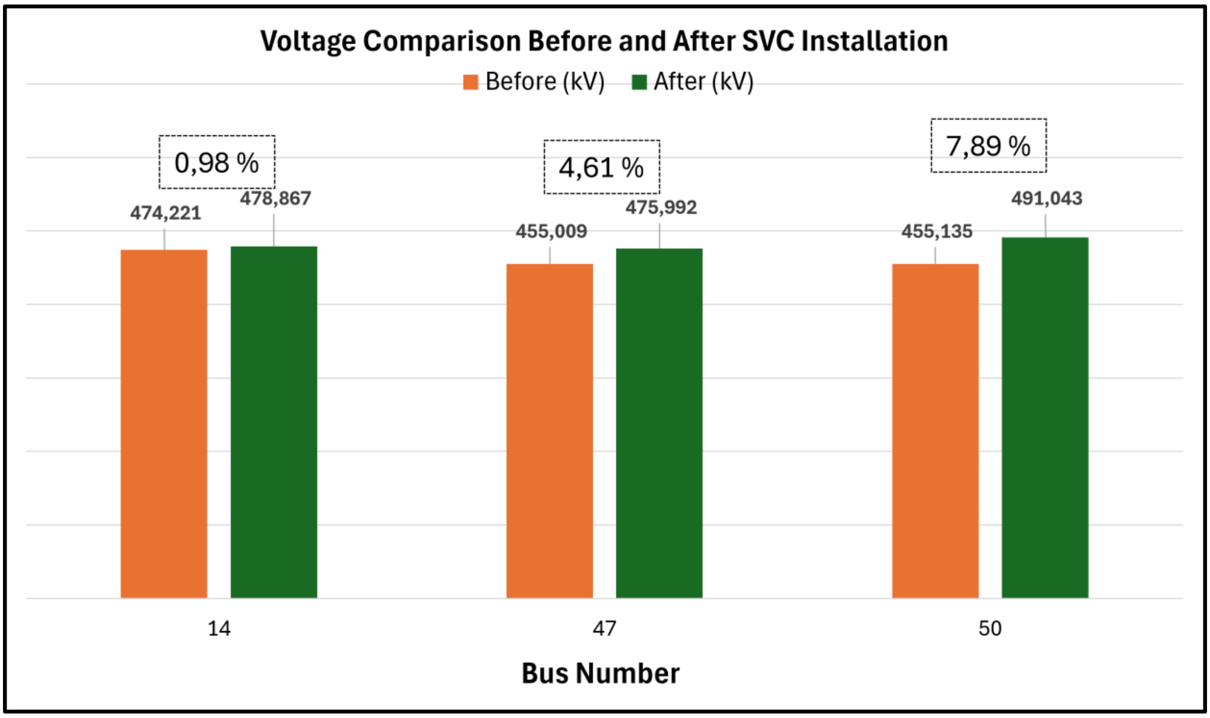

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