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Optimization of Facts Controllers for Enhanced Voltage Stability in Smart Grids

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Abstract

The integration of FACTS (Flexible AC Transmission Systems) controllers in smart grids is pivotal for enhancing voltage stability, a crucial factor in maintaining the reliability and efficiency of modern power systems study optimizes Flexible AC Transmission Systems (FACTS) controllers such Static Var Compensators (SVC) and Thyristor Controlled Series Compensators to improve smart grid voltage stability. Reactive power shortages and power system overloads cause voltage stability difficulties. The suggested model uses the L-index method to assess power system voltage stability and optimizes FACTS device allocation, reactive power flow, and bus voltages to address these difficulties. It uses complex optimization algorithms, including an adaptive evolutionary algorithm (AEA), to prevent premature convergence and preserve global search capabilities. The Matpower package in MATLAB simulates IEEE 14 and 57 busbar systems to verify these optimization ideas. Voltage stability, reactive power losses, and L-index values improved significantly in experiments. In the IEEE 14 busbar system, the AEA reduced voltage variation by 90%, reactive power losses by 20%, and L-index by over 30%, outperforming typical evolutionary algorithms. In the IEEE 57 busbar system, it achieved comparable improvements. This study shows how optimized FACTS controllers maintain voltage stability, improving smart grid dependability and efficiency. The findings underscore the importance of strategic placement and tuning of FACTS devices in achieving optimal voltage stability, thereby contributing to the development of more reliable and sustainable power systems.

Keywords: Optimization, Controllers, Voltage Stability, Smart Grids, Static Var Compensators (SVC)

1.INTRODUCTION

The operation and stability of power systems are facing serious problems due to the growing demand for electricity and the integration of renewable energy sources. Voltage stability is one of the most important issues among these difficulties, especially in light of contemporary smart grids. Smart grids present a viable way to improve the sustainability, efficiency, and dependability of power transmission because they integrate cutting-edge communication and control technologies. However, because of their dynamic character and the erratic generation from renewable sources combined with changing loads, smart grids require creative solutions to keep voltage stability. Using Flexible AC Transmission Systems (FACTS) controllers has become a crucial tactic in this area

Static Var Compensators (SVC), Static Synchronous Compensators (STATCOM), and Unified Power Flow Controllers (UPFC) are examples of FACTS controllers that enhance power system controllability and offer dynamic voltage support. By enabling quick responses to voltage changes, these devices improve the grid's stability and dependability. Since FACTS controllers must be placed strategically and precisely tuned to function at their best, optimizing them is essential to maximizing their potential benefits. The objective is to guarantee that, in both regular and emergency situations, the power system functions within safe voltage limits.

This paper explores how to improve voltage stability in smart grids by optimizing FACTS controllers. Sophisticated models and algorithms are used in the optimization process, which takes into account a number of variables including load changes, the integration of renewable energy sources, and possible system emergencies. The study attempts to improve the efficiency of FACTS devices in managing voltage instability by improving their placement and settings. The study shows how enhanced FACTS controllers can enhance voltage regulation and overall grid resilience by using simulation tools to examine their performance in various scenarios.

2. REVIEW OF LITERATURE

Almohaimeed and Abdel-Akher (2020) investigate the power quality issues that arise due to the integration of wind power into electric grids. Their study emphasizes the intermittent and variable nature of wind energy, which can lead to voltage fluctuations, harmonics, and other power quality problems. The authors discuss various mitigation strategies, including the use of advanced control techniques and the deployment of FACTS devices, such as SVCs and STATCOMs, to enhance the stability and reliability of power grids. The research highlights the importance of addressing power quality issues to ensure the seamless integration of renewable energy sources into existing power systems. This work provides a foundational understanding of the challenges associated with wind power penetration and underscores the necessity for robust control mechanisms in maintaining grid stability

Ghaghishpour and Koochaki (2020) propose an intelligent method for assessing the online voltage stability margin using an optimized Adaptive Neuro-Fuzzy Inference System (ANFIS) combined with associated rules techniques. This approach leverages the strengths of both fuzzy logic and neural networks to provide real-time voltage stability assessment. The optimized ANFIS model is designed to handle the nonlinear characteristics of power systems and offers a high degree of accuracy in predicting voltage stability margins. The authors demonstrate the effectiveness of their method through extensive simulations, showing its capability to enhance the reliability and operational efficiency of power systems. This study contributes significantly to the field by presenting a practical tool for real-time stability monitoring, which is crucial for the dynamic management of modern power grids.

Habib et al. (2022) focus on the enhancement of transient response, robustness, and stability of automatic voltage regulator (AVR) systems using an improved Whale Optimization Algorithm (WOA). The improved WOA is designed to optimize the parameters of the AVR system, thereby improving its performance. The study shows that the optimized AVR system exhibits superior transient response characteristics, enhanced robustness, and improved overall stability. The authors validate their findings through a series of simulations, comparing the performance of the improved WOA with other optimization techniques. The results indicate that the proposed method outperforms traditional algorithms, providing a more effective solution for voltage regulation in power systems. This research highlights the potential of advanced optimization algorithms in improving the performance of critical power system components, thereby contributing to the stability and reliability of the entire grid.

Hemeida, Rezk, and Hamada (2018) conducted a detailed comparative analysis of STATCOM and SVC-based fuzzy controllers for enhancing the stability of wind farms connected to multi-machine power systems. Their study focuses on the dynamic performance of these FACTS devices under various operating conditions. The researchers employed a fuzzy logic controller to manage the reactive power compensation provided by both STATCOM and SVC. Through extensive simulation studies, they demonstrated that the STATCOM-based fuzzy controller outperforms the SVC-based controller in terms of voltage stability, reactive power support, and overall system reliability. The findings of this study underscore the superior dynamic response and flexibility of STATCOM, making it a more effective solution for stability improvement in wind-integrated power systems.

3. FACTS DEVICES

When reactive power is insufficient or the power system is loaded, voltage stability becomes an issue. Reactive power generation, transmission, and demand can all be used to study voltage stability. The suggested model assesses the voltage stability in power systems by using the L-index method.

margin of collapse.

The index that indicates the closeness to the voltage collapse for a power system with n buses is defined as

$$L_j = \left| 1 - \sum_{i=1}^{n_G} C_{ji} \frac{V_i}{V_j} \right|$$

where Cji is the element of the matrix C, nG is the number of generation buses, Vi is the voltage in complex form of the i-th generation bus, and Vj is the voltage in complex form of the j-th load bus.

$$[C]=-[Y_{LL}]^{-1}[Y_{LG}]$$

The Ybus submatrix includes the matrices [YLL] and [YLG].

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix}$$

From 0, stable system, to 1, voltage collapse, is the range of this index Lj.

4. FACTS DEVICES

Reactive power flow, bus voltages, transmission line impedance, and power systems parameters are all controlled and adjusted under the umbrella of the Flexible AC Transmission System (FACTS) concept. Two FACTS devices that are utilized by the suggested method are presented in the ensuing subsections

4.1 Static var compensator.

The Static Var Compensator (SVC) has an adjustable reactance and is shunt linked to a bus One way to represent the reactive power provided by SVC in the j-th bus is using Equation (4).

$$Q_{SVC}=-B_{SVC}V_j^2$$

where BSVC is the SVC susceptance and Vj is the voltage magnitude at the j-th bus.

4.2. Thyristor controlled series compensator

To regulate the impedance of a transmission line, a Thyristor Controlled Series Compensator (TCSC) is linked in series with it. A capacitor bank and a thyristor-controlled reactor are used in tandem by TCSC. To ensure a certain amount of active power flow across the transmission line, the series reactance is automatically adjusted. The updated admittance matrix with a TCSC added is written as

$$\Delta y_{ij} = y_{ij}^{\text{mod}} - y_{ij} = (g_{ij}^{\text{mod}} + jb_{ij}^{\text{mod}}) - (g_{ij} + jb_{ij})$$

$$g_{ij} = -\frac{r_{ij}}{\sqrt{r_{ij}^2 + x_{ij}^2}}$$

$$b_{ij} = -\frac{x_{ij}}{\sqrt{r_{ij}^2 + x_{ij}^2}}$$

$$g_{ij}^{\text{mod}} = -\frac{r_{ij}}{\sqrt{r_{ij}^2 + (x_{ij} + x_{TCSC})^2}}$$

and

$$b_{ij}^{\text{mod}} = -\frac{x_{ij+x_{TCSC}}}{\sqrt{r_{ij}^2 + (x_{ij} + +x_{TCSC})^2}}$$

5. AUTOMATIC ALLOCATION OF FACTS DEVICES

In order to improve the voltage stability of power systems, this research study looks at three indicators: reactive power losses, voltage deviation, and L-index. These indicators are used by the suggested optimization strategy to represent three objective functions. Equation (12) is the first objective function, which makes use of Lindex.

$$F_1(X) = \min(\max(L))$$

where the L-index is represented by L ę [0;1] and the vector of choice variables by X. Stability is shown by L = 0, while the proximity to voltage breakdown is indicated by LȊ1.
Equation (13) represents the second goal function, which makes use of the voltage deviation.

$$F_2(X)=\sqrt{\sum_{i=1}^{N_L}(V_i-1)^2}$$

where NL is the number of load buses and Vi is the voltage magnitude of the i-th load bus in pu. The popularity of optimization algorithms derived from biological activity has increased recently due to the superiority of these solutions, their simplicity of use, and their adaptability to changes in the objective function.

The optimization techniques employed in the experimental investigation are shown in the next subsections.

5.1 Adaptive Evolutionary Algorithm

One of the most well-known techniques for evolutionary computation is the evolutionary algorithm, which is a potent search and optimization process. Preserving diversity in an evolutionary algorithm is crucial in order to prevent premature convergence. Reducing the discrepancy between population diversity and a reference value is the goal of diversity control. The suggested approach regulates population diversity using an adaptive evolutionary algorithm (AEA), preventing early convergence and preserving the global search.

5.2 Decision Variable Coding

The voltage magnitude of the generator buses, the bank of shunt capacitors, the transformer tap settings, the location and reactive power injection of the TCSC and SVC devices, and other factors combine to generate the individual of the population, which codes the vector of choice variable X.

5.3 Variation Operators

Crossover and mutation are the two common EA variation operators used in this work. As seen in Fig. 1, there is a random cut point for the two parents, P1 and P2, during the crossover process. The mingled portions of the two parents produce the descendants, D1 and D2 in Figure 1.

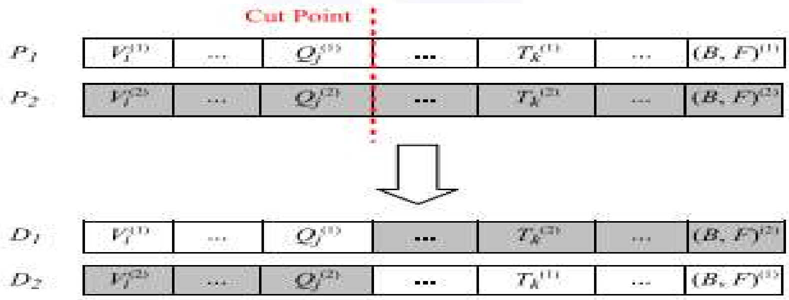

Fig. 1. One-point crossover'

Following the crossover, the mutation is a random alteration of the genes (decision variables) based on a probability pm ȩ. The elements of the vector of choice variables, X, are where the mutation is carried out in the suggested model. The FACTS devices have different locations and inject reactive electricity. A descendent before and after mutation, for instance, is depicted in Fig. 2, where r ȩ is a random variable with uniform distribution. If r pm for every gene, the gene is changed.

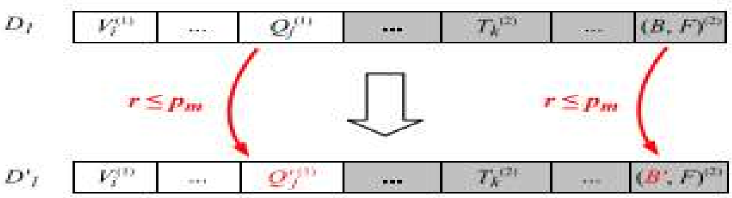

Fig.2. Mutation of the descendent after crossover

5.4. Diversity Control

The degree to which people differ from one another is measured by the population variety. Preventing early convergence to a local optimum and taking into account many niches for the solution of multimodal problems are two ways that controlling an EA's population diversity, or reducing its loss, may aid the evolutionary process.

In this work, the following formula is used to compute population diversity at the k-th generation:

$$\Gamma(k)=1-\sum_{i=1}^{n_s}\rho_i^2$$

where pi is the occurrence rate of the i-th allele and ns is the total number of alleles. An interval between each choice variable's inferior and superior bounds is called an allele.

When there is a difference in the population's (G) and reference's (Gr) diversities, diversity control is carried out by adjusting the mutation rate (pm). To eliminate this discrepancy, the mutation rate is modified as follows:

$$\rho_m(k+1)=\rho_m(k)+\eta(\Gamma_r-\Gamma(k))$$

where Ș is a constant.

6. EXPERIMENTAL STUDIES

The standard IEEE 14 and 57 busbar power systems were used to test the suggested methodology. The techniques were applied to power system simulations using the Matpower package and the MATLAB environment.

The SVC devices were not installed at the generation buses or anywhere a compensator of any kind, such as a reactive or synchronous one, is present. There was no installation of TCSC devices in between processing buses.

Two more probabilistic optimization techniques, simulated annealing (SA) and particle swarm optimization (PSO), are employed in the trials to validate the suggested approach. A swarm of possible solution particles searches the search space for the global optimal solution in a PSO process. Each particle's speed in the subsequent iteration of their journey using discrete-time iterations is determined by calculating its previous rate, optimal particle position, and optimal swarm position. In combinatorial optimization, Simulated Annealing (SA) simulates the physical annealing process. The goal of simulated annealing is to solve a difficult issue by locating its optimal state, or lowest possible energy.

The first population consisted of 100 randomly selected individuals. The algorithms underwent 1,000 generations or iterations. Empirical methods were utilized to determine the optimal parameters for the EA, PSO, and SA algorithms. EA employed a crossover rate of 60%, a mutation rate of 5%, and a tournament for selection. Initial speed is given for 10% of the particle's initial root position. PSO used initial and final inertia coefficients equal to 0.9 and 0.4, respectively, and C1 = 3:5 and C2 = 0:5. SA used Ĳ = 0:2, ƻ = 0:9, the perturbation of each point is made with a probability of 50%, changing the decision variables with a maximum of 10% of their range. The temperature change occurred only if 50 perturbations did not result in 10 improvements in the objective function. The experiments using the standard (non-adaptive) and adaptive evolutionary algorithms are shown in the subsections that follow.

6.1 Experiments with Standard EA

The IEEE 14 busbar system findings are displayed in Table I. Regarding the L-index-based goal functions, the outcomes from all approaches were comparable. In terms of voltage deviation-based goal functions, the suggested approach performed better than the alternatives. Both PSO and the suggested technique outperformed SA and produced similar results for the objective functions based on MVAR losses. Overall, the suggested EA-based method decreased voltage variation by 90%, reactive power losses by 20%, and L-index by more than 30%.

Table 1: Results for IEEE 14 busbar system

OBJ. FUNCTIONS	INITIAL	EA	PSO	SA
L-index	0.0768	0.0523	0.0523	0.0572
Voltage Deviation	0.1424	0.0067	0.0083	0.0236
MVAR losses	54.54	42.26	42.86	46.93

The IEEE 57 busbar system findings are displayed in Table 2. The suggested EA-based method decreased voltage deviation and L-index by more than 50%. Due to their larger dimensions compared to the IEEE 14 busbar system, the population-based approaches, EA and PSO, demonstrated a definite advantage over SA in the IEEE 57 busbar system.

Table 2: Results for IEEE 57 busbar system

OBJ. FUNCTIONS	INITIAL	EA	PSO	SA
L-index	0.3099	0.1497	0.1561	0.1722
Voltage Deviation	0.2043	0.0906	0.1471	0.1873
MVAR Losses	121.67	75.60	87.23	114.05

6.2 Experiments with Adaptive EA

Based on diversity control, case studies utilizing the adaptive evolutionary algorithm (AEA) have pm(0) = 0:05, \ = 0:2, ns = 50, đr = 0:55 for the IEEE 14 busbar system, and īr = 0:65 for the IEEE 57 busbar system.

The best individual for voltage deviation at the load buses in IEEE 14 busbar systems and during the evolutionary process, respectively, for EA and AEA, is shown in Figure 3. From the start of the evolutionary process, AEA performed better than EA, and by the end, AEA was 50% more fit than EA.

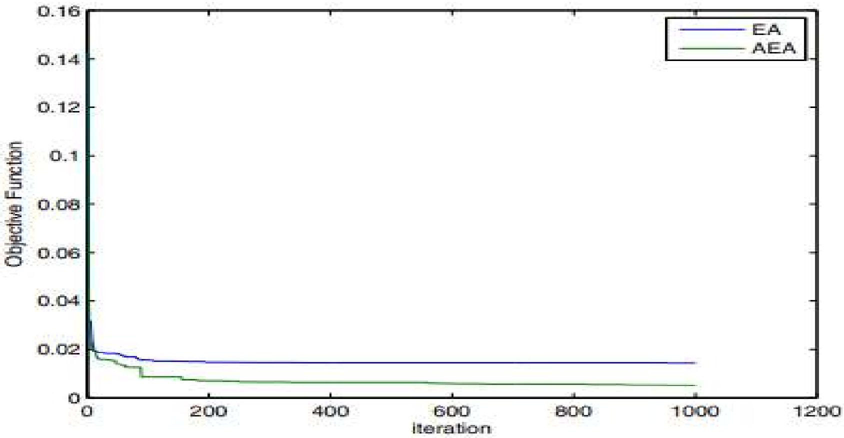

Figure 3: Voltage deviation in the IEEE 14 busbar system's evolutionary process for the EA and AEA

The best candidate for voltage deviation at the load buses in IEEE 57 busbar systems and during the evolutionary process is shown in Figure 4 for AEA and EA, respectively. For instance, Figure 4 from the IEEE 14 experiment demonstrates that AEA performed better than EA and that the former achieved a final fitness that was 60% higher than the latter. Furthermore, AEA consistently reduced the fittest individual, whereas EA accomplished that across a number of generations. By and large, AEA outperformed EA in terms of average voltage deviations at load buses.

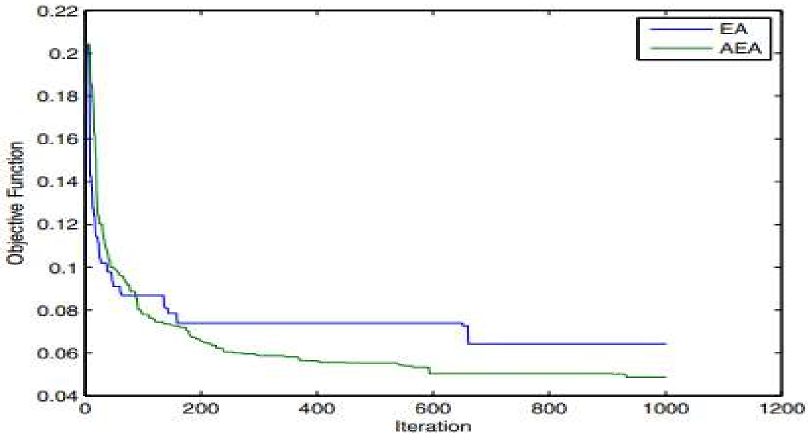

Figure 4: Evolutionary procedure in IEEE 57 busbar system using AEA and EA

7. CONCLUSION

This study shows how crucial it is to improve voltage stability in smart grids by using optimal Flexible AC Transmission Systems (FACTS) controllers, such as Static Var Compensators (SVC) and Thyristor Controlled Series Compensators (TCSC). Through the examination of reactive power deficits and power system overloads, the study demonstrates how useful the L-index approach is for evaluating voltage stability and FACTS device placement. The incorporation of sophisticated optimization methods, specifically the adaptive evolutionary algorithm (AEA), is essential for averting premature convergence and maintaining the capacity for global search. The Matpower package in MATLAB was utilized to simulate IEEE 14 and 57 busbar systems, and the findings produced from the simulations validated notable enhancements in L-index values, reactive power losses, and voltage stability. In particular, in the IEEE 14 busbar system, the AEA decreased voltage variation by 90%, reactive power losses by 20%, and L-index by over 30%. In the IEEE 57 busbar system, similar improvements were made. These results highlight how crucial it is to carefully position and adjust FACTS devices in order to preserve voltage stability, which improves the dependability and effectiveness of smart grids.

REFERENCES

1. Almohaimeed, S. A., & Abdel-Akher, M. (2020). Power quality issues and mitigation for electric grids with wind power penetration. Applied Sciences, 10(24), 8852.
2. Ghaghishpour, A., & Koochaki, A. (2020). An intelligent method for online voltage stability margin assessment using optimized ANFIS and associated rules technique. ISA transactions, 102, 91-104.
3. Habib, S., Abbas, G., Jumani, T. A., Bhutto, A. A., Mirsaeidi, S., & Ahmed, E. M. (2022). Improved whale optimization algorithm for transient response, robustness, and stability enhancement of an automatic voltage regulator system. Energies, 15(14), 5037.
4. Hemeida, M. G., Rezk, H., & Hamada, M. M. (2018). A comprehensive comparison of STATCOM versus SVC-based fuzzy controller for stability improvement of wind farm connected to multi-machine power system. Electrical Engineering, 100, 935-951.
5. Iqbal, J., Baig, M. N., Rashid, Z., Amjad, M., & Arfeen, Z. A. (2022). Voltage correction by a closed-form bus power factor tuning approach using non-orthogonal inverter current generation from STATCOM. Electrical Engineering, 1-12.
6. Jumani, T. A., Mustafa, M. W., Alghamdi, A. S., Rasid, M. M., Alamgir, A., & Awan, A. B. (2020). Swarm intelligence-based optimization techniques for dynamic response and power quality enhancement of AC microgrids: A comprehensive review. IEEE Access, 8, 75986-76001.
7. Liu, Q., Li, Y., Hu, S., & Luo, L. (2019). A transformer integrated filtering system for power quality improvement of industrial DC supply system. IEEE Transactions on Industrial Electronics, 67(5), 3329-3339.
8. Nair, D. R., Nair, M. G., & Thakur, T. (2022). A smart microgrid system with artificial intelligence for power-sharing and power quality improvement. Energies, 15(15), 5409.
9. OYIOGU, D., OGBOH, D., & NWOYE, G. (2021). Voltage Stability Improvement in Power System Using STATCOM and SVC.
10. Paredes, L. A., Molina, M. G., & Serrano, B. R. (2023). Enhancing dynamic voltage stability in resilient microgrids using FACTS devices. IEEE Access.
11. Park, B., & Olama, M. M. (2020). A model-free voltage control approach to mitigate motor stalling and FIDVR for smart grids. IEEE Transactions on Smart Grid, 12(1), 67-78.
12. Reddy, C. R., Goud, B. S., Aymen, F., Rao, G. S., & Bortoni, E. C. (2021). Power quality improvement in HRES grid connected system with FOPID based atom search optimization technique. Energies, 14(18), 5812.
13. Tephiruk, N., Kanokbannakorn, W., Kerdphol, T., Mitani, Y., & Hongesombut, K. (2018). Fuzzy logic control of a battery energy storage system for stability improvement in an islanded microgrid. Sustainability, 10(5), 1645.
14. Zargar, B., Wang, T., Pitz, M., Bachmann, R., Maschmann, M., Bintoudi, A., ... & Ioannidis, D. (2021). Power quality improvement in distribution grids via real-time smart exploitation of electric vehicles. Energies, 14(12), 3533.
15. Zhou, L., Swain, A., & Ukil, A. (2019). Reinforcement learning controllers for enhancement of low voltage ride through capability in hybrid power systems. IEEE Transactions on Industrial Informatics, 16(8), 5023-5031.