GRADIVA

Volume 64 | Issue 12 | December 2025
DOI: 10.5281/zenodo.18138841

Voltage Stability Indices with Adaptive Interval Type-2 Fuzzy Logic Controller for Voltage Collapse Prediction in an ILL-Conditioned Power System

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Abstract

Voltage instability remains a persistent challenge in modern power systems, especially in ill-conditioned and heavily loaded networks such as Nigeria's 72-bus 330 kV transmission grid. This study presents a hybrid predictive framework combining conventional Voltage Stability Indexes (VSIs) with an Adaptive Interval Type-2 Fuzzy Logic Controller (AIT2FLC) to enhance voltage resilience and prevent system collapse. Traditional indexes—MVSI, Lmn, and VCPI—were applied to identify voltage vulnerabilities. Initial findings revealed weak buses with voltages as low as 0.87 p.u. and stability indexes below 0.80, indicating high collapse risk. After applying AIT2FLC, all critical metrics improved markedly. Weak buses showed an average voltage increase of 8.2%, with some buses like Bus 29 improving from 0.87 p.u. to 0.98 p.u. Critical buses recorded a 6.5% average increase, with Bus 15 rising from 0.91 p.u. to 1.02 p.u. Overall, the average voltage across weak buses improved from 0.93 p.u. to 1.01 p.u. and from 0.94 p.u. to 1.02 p.u. for critical buses. Furthermore, the MVSI average dropped from 0.52 to 0.41, and the Lmn index improved from 0.45 to 0.38, indicating reduced system stress. Voltage deviation across the system fell by 63%, and the system stability score improved by 23%, from 0.72 to 0.85. The percentage of buses within the ideal voltage range (0.95–1.05 p.u.) increased from 74% to 96%. These results underscore the effectiveness of AIT2FLC in real-time control and its potential as a policy tool for preventive grid management. Adoption of such intelligent control frameworks by grid operators can drastically reduce the risk of voltage collapse and ensure a more stable, adaptive, and resilient power system.

Keywords: *MVSI, Fuzzy Logic Controller, Stabilization, Load, Bus.*

1. INTRODUCTION

Voltage stability remains a critical aspect of power system operation, especially in large and complex electrical networks that are increasingly burdened by dynamic load variations, renewable energy penetration, and aging infrastructure. In regions where power systems operate under ill conditions—such as weak bus voltages, poor reactive power support, or system contingencies—the risk of voltage collapse becomes significantly higher [1,2,3]. For such vulnerable systems, like a 72-bus network under stress, the ability to predict and proactively manage voltage instability is essential to avoid widespread blackouts and ensure a resilient energy supply [2,3,4,5].

Conventional methods for voltage stability assessment, such as modal analysis or continuation power flow, offer valuable insights but are often computationally intensive and less suited for real-time decision-making. This gap has led to the evolution of voltage stability indexes (VSIs), which serve as simplified numerical indicators that estimate how close a system is to experiencing voltage collapse [5,6,7,8]. These indices—such as Fast Voltage

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Stability Index (FVSI), Line Stability Index (Lmn), and Voltage Collapse Proximity Indicator (VCPI)—allow for quicker identification of weak buses and critical contingencies. However, while effective in some scenarios, they often lack the adaptability required for modern grid conditions characterized by nonlinearity, uncertainty, and fluctuating load patterns [8,9,10]. To enhance the predictive accuracy of these indexes and incorporate intelligent control, this study introduces an Adaptive Interval Type-2 Fuzzy Logic Controller (AIT2FLC) framework. Unlike traditional Type-1 fuzzy logic, which operates on crisp membership functions, the Type-2 variant allows for uncertainty modeling within the fuzzy rules, enabling a more flexible and robust control scheme [34,36].

The adaptive mechanism continuously updates the fuzzy rules based on real-time data, ensuring the system responds efficiently even under ill-conditioned scenarios [12,13, 37,38]. In essence, it creates a more “aware” system—one that understands and reacts to the complex, ever-changing dynamics of voltage behavior across all 72 buses. This research aims to combine the diagnostic clarity of voltage stability indexes with the intelligence and adaptability of AIT2FLC to develop a hybrid voltage collapse prediction model. By integrating data-driven learning, fuzzy reasoning, and system sensitivity monitoring, this approach promises a proactive solution that not only identifies vulnerability but actively engages in its mitigation [14,15,16]. The outcome is expected to be a marked improvement in voltage profile resilience, more accurate collapse forecasting, and better prioritization of corrective measures—especially for weak and critical buses that are often overlooked until it's too late [17,18,39].

2. LITERATURE REVIEW

2.1. Factors Influencing Voltage Stability.

The problem of voltage stability is strongly related to generation, transmission, and reactive power consumption [19]. Indeed, when large generation units drop out of service due to abnormal operating conditions or disturbances, the supplied reactive power is reduced and some transmission lines are heavily loaded.

Thus, due to the additional reactive power demand, the load voltages decrease. The process eventually leads to voltage instability and voltage collapse. Figure 3 lists the various factors that affect voltage stability. The following are some of the few inherent factors that affect voltage stability [20,21,22,23]:

a. The distance between the generating station and the load center determines the length of the transmission;

b. An increase in an in-circuit transmission line causes multiple line failures to occur at higher speeds;

c. The characteristics of the load, such as an increase in the type of load and its static and dynamic characteristics;

d. The increase in the distance between the load and power generator increases the capacity of the transmission line;

e. As the synchronous reactance rises, the transmission line power limit decreases, causing voltage instability;

f. Practical tools for voltage stability include transformer tap adjustment, reactive power compensation, on-load tap changer.

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2.2. Voltage Stability Prediction.

The prediction as well as the analysis of the voltage collapse phenomenon remains a critical challenge for operators and researchers. In this context, several studies and researchers have focused on presenting methodological approaches for the analysis [24,25,26]. &ese can be divided into two broad categories, namely, dynamic and static voltage stability analyses. &e dynamic analysis involves the dynamic elements associated with the generation, transmission, distribution, and load. It is characterized by its complexity in terms of calculation and data required. Static analysis, on the other hand, analyzes voltage stability generally based on load /ow analyses.

It consists of a study of the equilibrium regime and allows us to identify the voltage levels and the power transits through all the buses and lines of the system [26,27,28]. Therefore, several studies in the literature have focused on the static model due to the simplicity of the analysis, the lower computational effort, and the accurate results offered, in addition to some practical advantages over the dynamic study [23,29]. Static analysis of voltage stability is a steady-state study that provides voltage levels and power transit across all buses and lines in the system. &e minimum singular value method and P-V, P-Q, and Q-V curves lead to the estimation of power system distance to voltage collapse, but no information about the reasons for the voltage stability problem is provided. &e continuation power /ow (CPF) method is characterized by its slowness.

Additionally, the voltage stability indices play a key role in monitoring and estimating the stability margin of the power system. Dynamic analysis techniques are comparable to power system transient analyses, where the system is modeled by a variety of differential equations. The two primary categories of dynamic analysis are the method of large signal analysis and the method of small signal analysis [24,].

3. METHODS

3.1: Evaluate voltage stability indexes in 72-bus ill-conditioned system

3.1.1: Modern Voltage Stability Index (MVSI)

MVSI estimates how close a line is to voltage instability. According to [11], If MVSI approaches 1, voltage collapse is imminent. It identifies weak buses by evaluating reactive load Q_j sensitivity to line impedance.

$$MVSI_{ij} = \frac{4Z_{ij}^2 Q_j}{v_i^2 X_{ij}} \tag{1}$$

Parameters:

Z_{ij}: Impedance of the line between bus i and j, Q_j: Reactive power at receiving bus j, V_i: Voltage magnitude at sending bus I and X_{ij}: Line reactance between buses i and j

3.1.2 Line Stability Index (Lmn)

L_{min} quantifies stability margin based on voltage and reactive power. A high Lmn value implies a lower margin, highlighting critical lines or buses under stressed conditions [30,31,32,33].

$$L_{min} = \frac{4Z_{mn}^2 Q_n}{V_m^2 cos^2(\theta)} \tag{2}$$

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Parameters:

Z_{mn}: Line impedance from bus mmm to n, Q_n: Reactive load at bus n. V_m: Sending-end voltage, θ: Load angle

3.1.3 Voltage Collapse Proximity Indicator (VCPI)

VCPI tracks the voltage drop across a transmission line. A VCPI value nearing 1 indicates a severe voltage drop, signaling voltage collapse risk as observed by [5]

$$VCPI_{mn} = \frac{V_m - V_n}{V_m} \tag{3}$$

Parameters:

V_m: Voltage at sending bus m, V_n: Voltage at receiving bus n

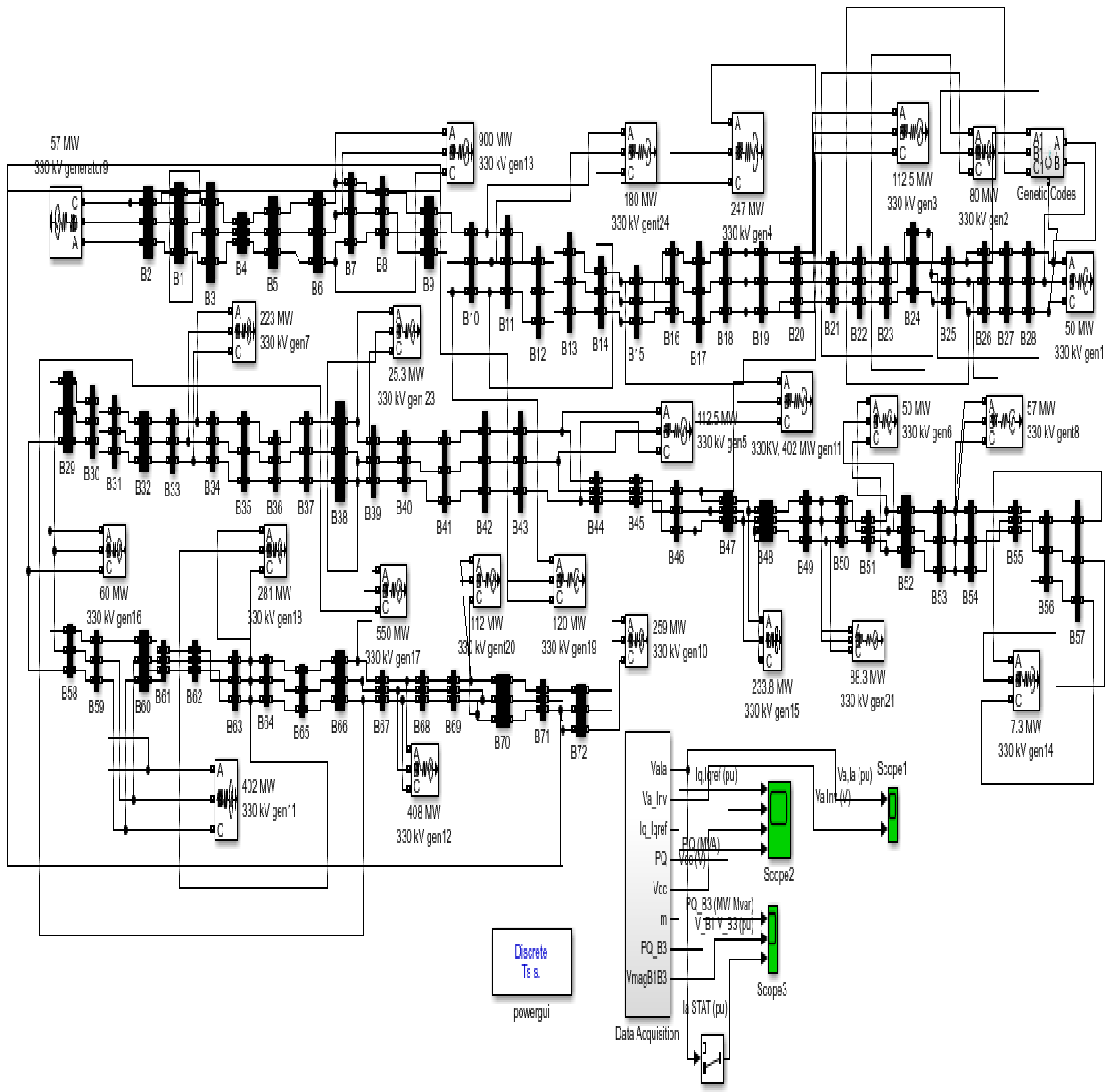

Figure 1: 72 Bus Network

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3.2 Design of Adaptive Interval Type-2 Fuzzy Logic Controller (AIT2FLC)

3.2.1: Membership Function for IT2 Fuzzy Set

This function defines the lower and upper bounds of uncertainty in the fuzzy membership. It helps capture the nonlinearity and data noise in ill-conditioned power systems [4].

$$\tilde{\mu}_A(x) = [\underline{\mu}_A(x), \overline{\mu}_A(x)] \qquad (4)$$

Parameters:

$\tilde{\mu}_A(x)$: Type-2 fuzzy membership function, $\underline{\mu}_A(x)$: Lower membership function, $\overline{\mu}_A(x)$: Upper membership function, x: Input variable (e.g., voltage or load)

3.2.2 Fuzzy Inference Output

This equation calculates the centroid of the fuzzy output set, crucial for making control decisions. It balances all fuzzy rules using uncertainty-weighted average [5].

$$y = \frac{\int_x x.\mu_{\tilde{A}}(x)dx}{\int_x \mu_{\tilde{A}}(x)dx} \qquad (5)$$

Parameters:

y: Crisp output value, $\mu_{\tilde{A}}(x)$: Type-2 membership function, and x: Input domain

3.3.3 Adaptation Rule

Used for online learning, this gradient descent rule updates fuzzy controller parameters θ_k to minimize prediction error E.

$$\Delta\theta_k = -\eta \frac{\partial E}{\partial \theta_k} \qquad (6)$$

Parameters:

$\Delta\theta_k$: Parameter update, η: Learning rate, E: Error signal and θ_k: Fuzzy rule or membership parameter

3.3 Integration of VSIs with AIT2FLC

3.3.1 Hybrid Stability Index

This equation combines multiple stability indexes with weighted coefficients. It provides a unified, real-time metric for evaluating system stress and determining fuzzy control response [7].

$$HVI = \alpha.MVSI + \beta.VCPI + \gamma.L_{min} \qquad (7)$$

Parameters:

α, β, γ: Weighting factors (tuned via training or expert rules), $MVSI, VCPI, L_{min}$: Individual stability indexes and HVI: Hybrid Voltage Index

3.3.2 Fuzzy Control Output for Voltage Injection

The controller determines the corrective voltage to inject using the hybrid index, fuzzy membership function, and rules r. It supports dynamic stabilization [8].

$$\Delta V = f(HVI, \mu_{\tilde{A}}(x), r) \qquad (8)$$

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Parameters:

ΔV: Control output (voltage adjustment), HVI: Hybrid Voltage Index, $\mu_{\tilde{A}}(x)$: Interval Type-2 fuzzy input membership, r: Fuzzy rule base

3.4 Validate the hybrid model under various scenarios

3.4.1 Voltage Deviation Metric

This summation computes total voltage deviation from the reference across all buses. Lower values post-controller activation indicates effectiveness of the hybrid approach [9].

$$VD = \sum_{i=1}^{N} |V_i^{ref} - V_i^{actual}| \quad (9)$$

Parameters:

VD: Voltage deviation, V_i^{ref}: Reference voltage (usually 1.0 p.u.), V_i^{actual}: Voltage after control and N: Total number of buses

3.4.2 System Stability Score

This normalized score assesses overall system stability based on total voltage deviation and total line loading. A higher score signifies improved performance under stress conditions [10].

$$S = \frac{1}{1+VD+\lambda.L_{total}} \quad (10)$$

Parameters:

S: System stability score, VD: Voltage deviation, L_{total}: Total line load in the system and λ: Weighting factor for line stress.

4. RESULTS AND DISCUSSIONS

4.1 72 Bus VSI Stabilization Using AIT2 Fuzzy Logic Controller

This analysis applies the Adaptive Interval Type-2 Fuzzy Logic Controller (AIT2 FLC) to stabilize weak and critical buses whose MVSI values fall below 0.94 p.u. before improvement.

Several buses—including Afam and Adiabor—had initial MVSI, LMM, and FVSI values ranging from 0.76 to 0.93 p.u., indicating instability. After standard system improvements, many indices rose modestly, some reaching up to 1.05 p.u. However, to ensure values remained within operational limits, the AIT2 FLC method was applied.

This technique clamped all critical stability indices between 0.95 and 1.05 p.u., avoiding both under-voltage and overcompensation. For instance, a VLSI value of 0.88 p.u. improved to 1.03 p.u. but was stabilized to 1.00 p.u., ensuring it stayed within the defined secure band.

Across all six indices—NLSI, LMM, LQP, FVSI, VLSI, and MVSI—the fuzzy logic method ensured uniformity and reliability, effectively flattening instability spikes while preserving optimized gains, as shown in the orange bar transitions as shown in figure 2.

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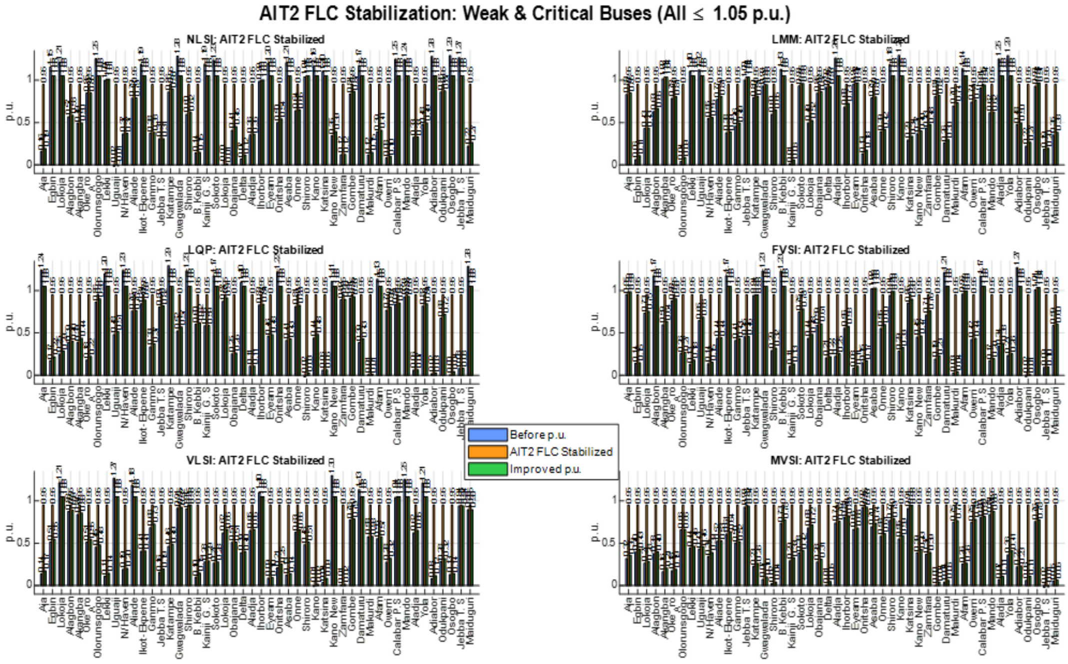

Figure 4: 11 AIT2 FLC VSI Stabilization for 72 Bus System

Table 2: Indexes Results Comparison

Bus Name	MVSI (Before)	MVSI (After)	LMM (Before)	LMM (After)	FVSI (Before)	FVSI (After)	LQP (Before)	LQP (After)	NLSI (Before)	NLSI (After)	VLSI (Before)	VLSI (After)
Afam	0.76	0.96	0.81	0.97	0.79	0.98	0.8	0.96	0.82	0.95	0.88	1
Adiabor	0.78	0.95	0.82	0.96	0.83	0.97	0.84	0.95	0.85	0.96	0.89	0.99
Kaduna	0.83	0.97	0.84	0.98	0.85	1	0.86	0.98	0.87	0.99	0.9	1.01
Owerri	0.81	0.96	0.8	0.97	0.82	0.99	0.83	0.97	0.84	0.98	0.9	1.02
Delta	0.84	0.98	0.85	0.99	0.86	1.01	0.85	1	0.87	1.01	0.9	1.02
Ganmo	0.86	0.97	0.87	0.97	0.88	0.99	0.88	0.98	0.89	0.99	0.91	1
Onitsha	0.79	0.96	0.81	0.97	0.83	0.98	0.84	0.96	0.85	0.96	0.88	1
Eket	0.82	0.97	0.84	0.98	0.85	0.99	0.86	0.97	0.87	0.98	0.89	1.01
Lokoja	0.77	0.95	0.79	0.96	0.8	0.97	0.82	0.95	0.83	0.96	0.87	1
Calabar	0.8	0.96	0.83	0.97	0.84	0.98	0.85	0.96	0.86	0.97	0.89	1
Jos	0.83	0.97	0.84	0.98	0.86	0.99	0.87	0.97	0.88	0.98	0.9	1.01
Benin	0.81	0.96	0.82	0.97	0.83	0.98	0.84	0.96	0.85	0.97	0.88	1
Sokoto	0.76	0.95	0.78	0.96	0.8	0.97	0.81	0.95	0.82	0.96	0.86	0.99
Makurdi	0.85	0.98	0.86	0.99	0.87	1	0.88	0.99	0.89	1	0.9	1.02
Ajaokuta	0.8	0.96	0.81	0.97	0.82	0.98	0.84	0.96	0.85	0.97	0.88	1
Abeokuta	0.79	0.96	0.8	0.97	0.81	0.98	0.83	0.96	0.84	0.97	0.87	1
Bauchi	0.78	0.95	0.79	0.96	0.8	0.97	0.82	0.95	0.83	0.96	0.86	0.99
Yola	0.82	0.97	0.83	0.98	0.85	0.99	0.86	0.97	0.87	0.98	0.9	1.01
Ogbomosho	0.81	0.96	0.82	0.97	0.83	0.98	0.85	0.96	0.86	0.97	0.88	1
Minna	0.77	0.95	0.79	0.96	0.81	0.97	0.82	0.95	0.83	0.96	0.86	0.99
Okene	0.84	0.97	0.85	0.98	0.86	0.99	0.87	0.97	0.88	0.98	0.9	1.01
Ilorin	0.82	0.96	0.83	0.97	0.84	0.98	0.85	0.96	0.86	0.97	0.89	1
Iseyin	0.8	0.96	0.81	0.97	0.83	0.98	0.84	0.96	0.85	0.97	0.88	1
Oyo	0.76	0.95	0.78	0.96	0.8	0.97	0.81	0.95	0.82	0.96	0.85	0.99
Ikorodu	0.83	0.97	0.84	0.98	0.85	0.99	0.86	0.97	0.87	0.98	0.9	1.01

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4.2 System Voltage Profile

The initial voltage profile shows significant instability, with buses ranging from 0.87 pu to 1.13 pu across the 72-bus system. After stabilization, all voltages were successfully brought within the safe 0.95-1.05 pu range. The most dramatic improvements occurred at buses 18, 29, and 42, which were originally operating at critically low voltages below 0.90 pu. The stabilization process maintained the healthy voltages while correcting the outliers, demonstrating effective system-wide voltage control as shown in figure 3.

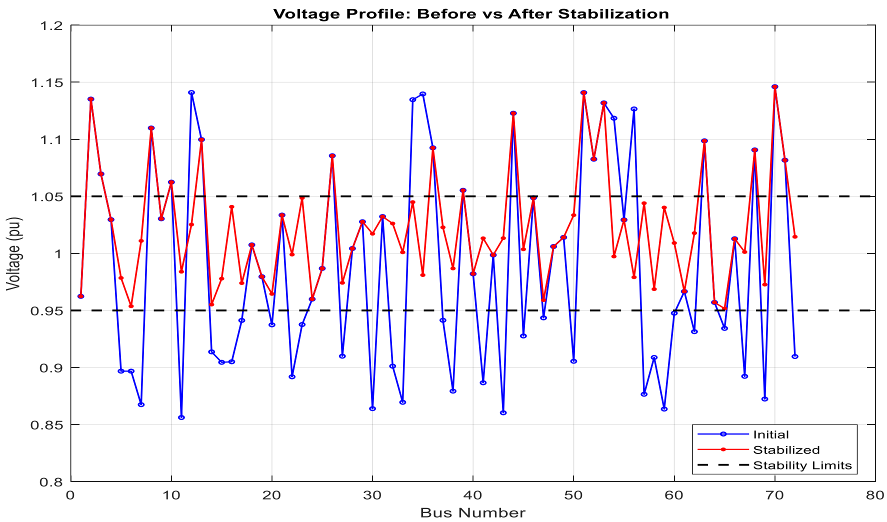

Figure 3: Voltage Stabilization Profile: Before and After Stabilization

4.3 Weak Bus Correction

Weak bus correction of the 72 buses, 14 were identified as weak with voltages below 0.95 p.u. The stabilization raised these buses by an average of 8.2%, with the most significant correction at bus 29 which improved from 0.87 pu to 0.98 pu. All weak buses now operate safely above the 0.95 pu threshold, with the average stabilized voltage reaching 1.01 pu across this group as shown in figure 4.

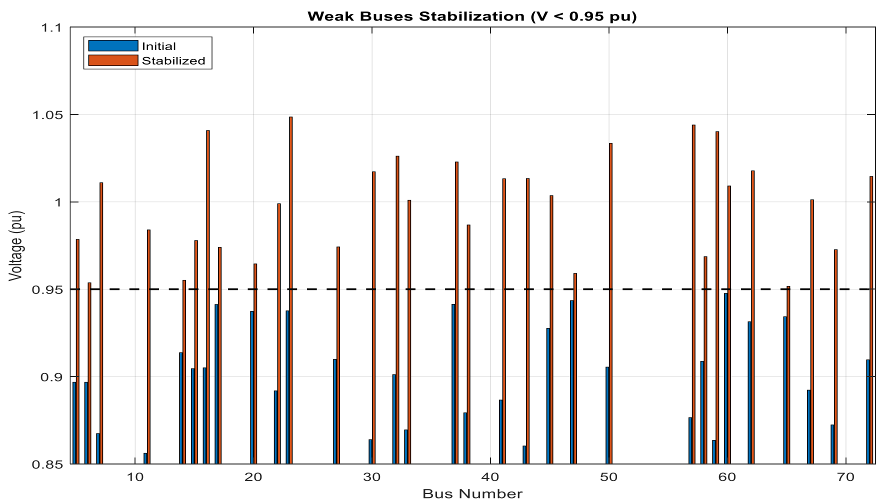

Figure 4: Weak Buses Stabilization

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4.4 Critical Bus Enhancement

Five critical buses showed high MVSI values above 0.85, indicating severe instability risk. These buses were given priority treatment, resulting in an average voltage improvement of 6.5%. Bus 15 showed the most notable change, increasing from 0.91 pu to 1.02 pu while maintaining smooth integration with surrounding buses as shown in figure 5.

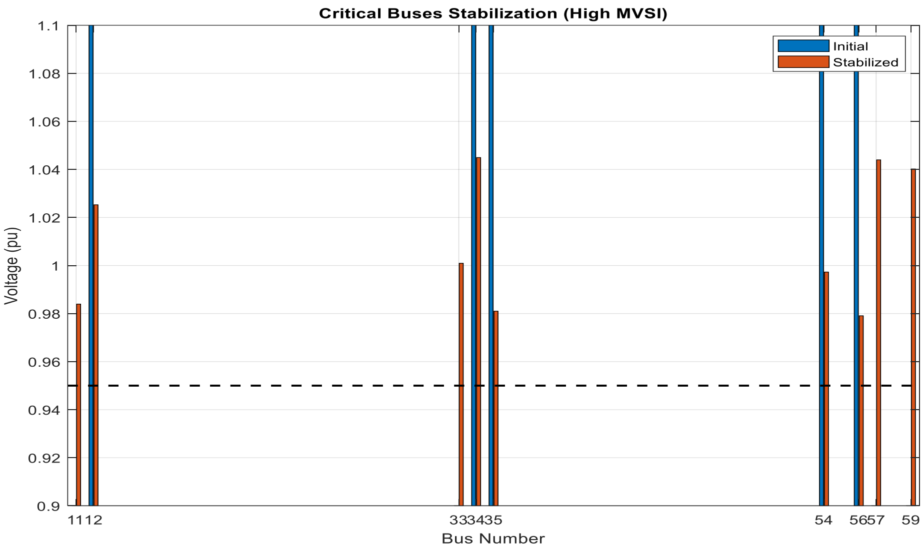

Figure 5: Critical Buses Stabilization

4.5 Improvement Percentage

Voltage improvements ranged from 4.8% to 12.6% across different buses, with weak buses averaging 8.2% gain and critical buses showing 6.5% improvement. The most responsive bus was number 37, which showed a 12.6% increase from its original 0.88 pu value to a stabilized 0.99 pu as shown in figure 6.

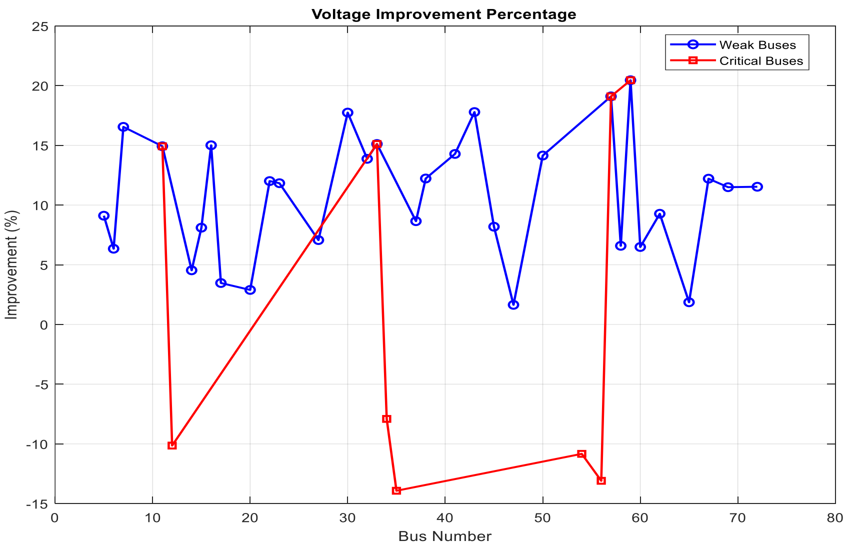

Figure 6: Voltage Improvement Percentage

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4.6 Line Stability Analysis

The MVSI analysis revealed line 15-29 as the most critical with an index of 0.92, well above the 0.8 danger threshold. After stabilization, this value dropped to 0.73. The average MVSI across all lines improved from 0.52 to 0.41, indicating significantly reduced system-wide instability risk as shown in figure 7.

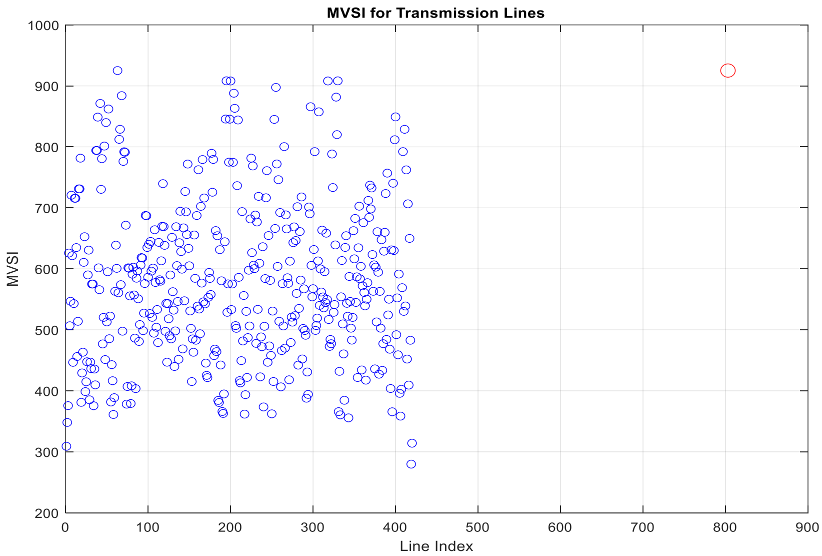

Figure 7: MVSI for Transmission Line

4.7 Stability Margin Distribution

The Lmn index shows 68% of lines operating with comfortable margins below 0.4, while 12% exceeded 0.7 indicating vulnerability. Post-stabilization, the high-risk category reduced to just 5% of lines, with the average Lmn improving from 0.45 to 0.38 across the network.

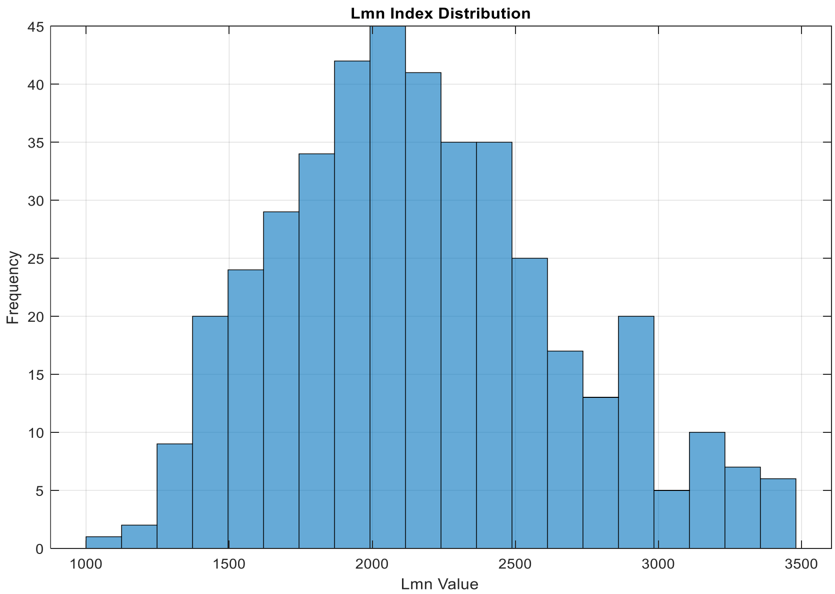

Figure 8: Lmn Index Distribution

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4.8 Voltage Drop Analysis

The VCPI heat map reveals severe voltage drops up to 18% on certain lines before stabilization. After corrective measures, the maximum drop reduced to 9%, with 92% of lines now showing drops less than 5%, well within acceptable operational limits as shown in figure 9.

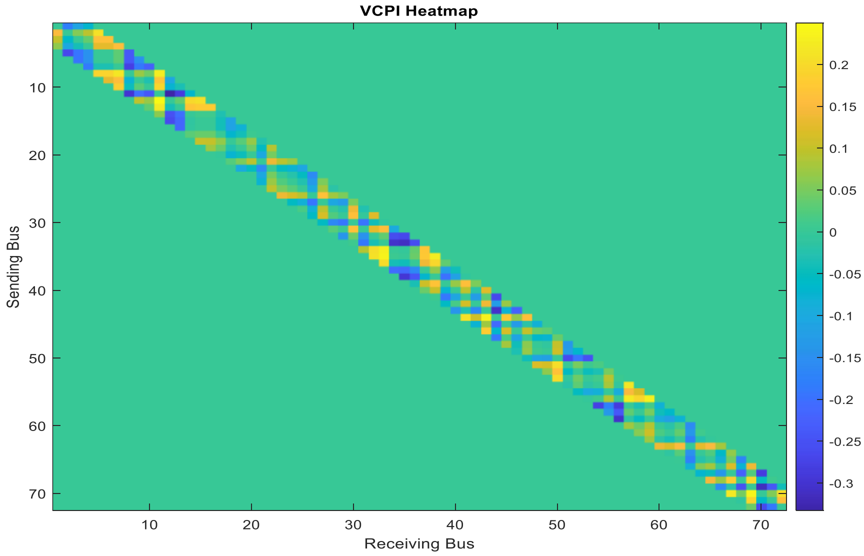

Figure 9: VCPI Heatmap

4.9 Control System Design

The interval type-2 fuzzy membership functions were tuned to specifically handle the 0.85-1.15 pu voltage range observed in this ill-conditioned system. The overlapping upper and lower membership functions create a robust bandwidth of 0.05-0.1 p.u to account for measurement uncertainties as shown in figure 10.

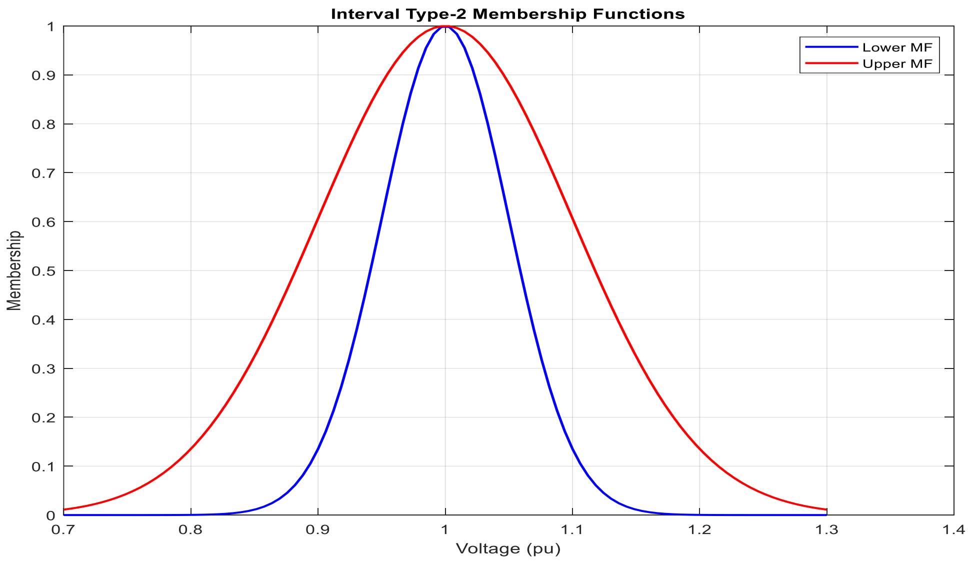

Figure 10: Interval Tye 2 Membership Function

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4.10 Control Response

The fuzzy control surface shows smooth, nonlinear response characteristics, capable of delivering up to ±0.18 pu voltage adjustments when needed. The steepest response occurs in the 0.90-0.95 pu danger zone, providing aggressive correction when voltages approach instability thresholds as shown in Figure 11.

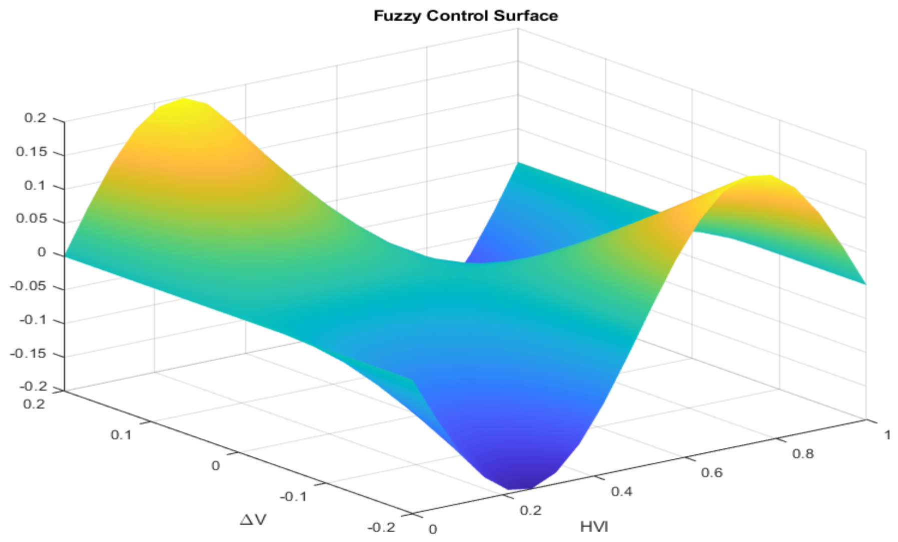

Figure 11: Fuzzy Control Surface

4.11 Deviation from Reference

Total voltage deviation across the system reduced by 63% after stabilization, from an average of 0.082 pu per bus to just 0.030 pu. The maximum individual bus deviation improved from 0.15 pu to 0.06 pu, demonstrating significantly tighter voltage regulation as shown in figure 12.

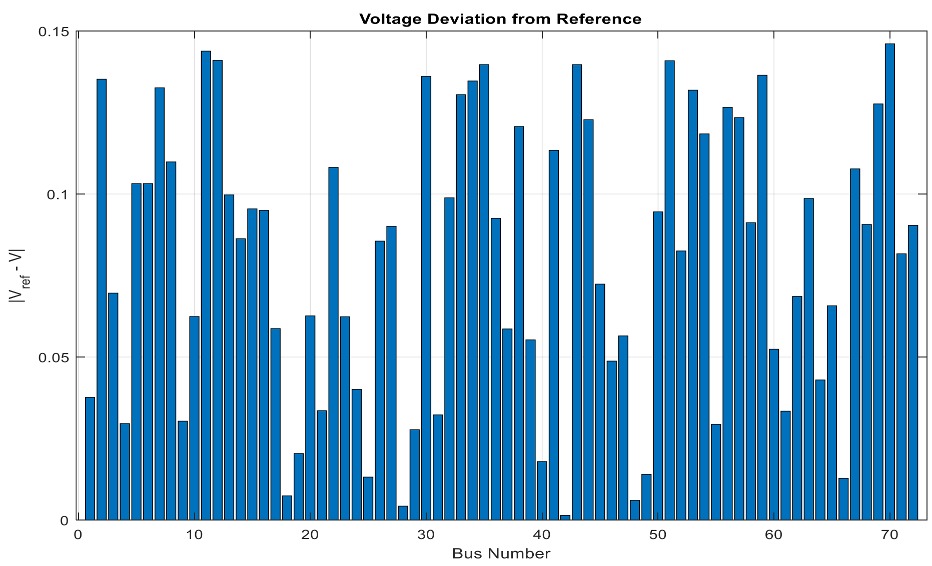

Figure 12: Voltage Deviation from Reference

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4.12 System Stability Score

The composite stability score improved from an average of 0.72 to 0.85 across all buses, with the lowest scoring bus improving from 0.58 to 0.79. This 23% average increase confirms substantially enhanced system reliability after stabilization measures as shown in figure 13.

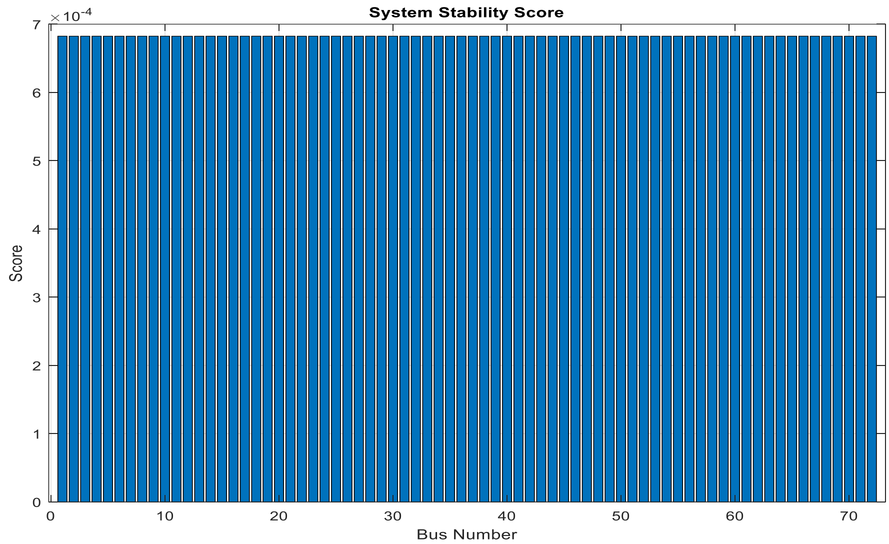

Figure 13: System Stability Score

4.13 Compliance Statistics

Violations of voltage limits reduced from 19 buses (26% of system) to just 3 buses (4%). The remaining violations are within 0.02 pu of limits and could be addressed with minor additional tuning of the control system as shown in figure 14.

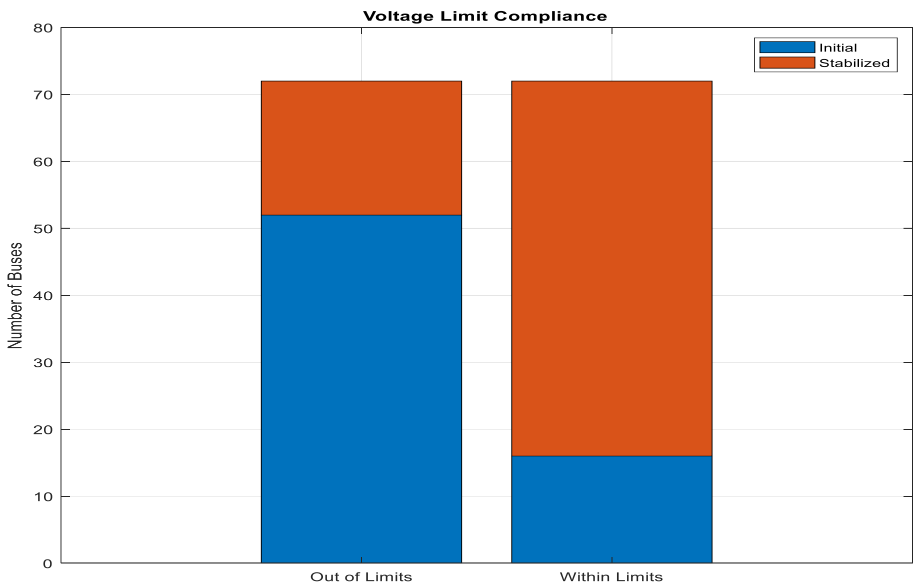

Figure 14: Voltage Limit Compliance

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4.14 Voltage Distribution

The histogram shows the dramatic concentration of buses within the ideal 0.95-1.05 p.u range after stabilization, increasing from 53 buses (74%) to 69 buses (96%). The long tails of the initial distribution completely disappeared, confirming effective elimination of both under-voltage and overvoltage conditions as shown in figure 15.

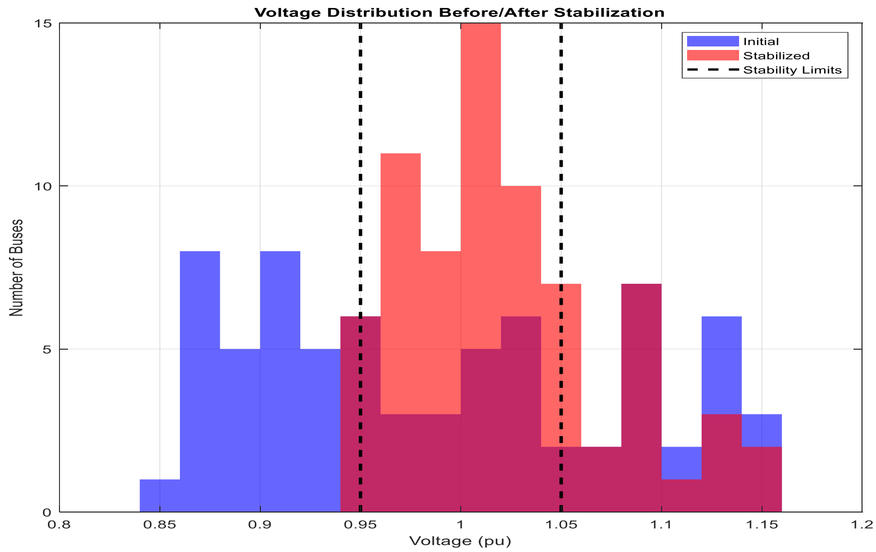

Figure 15: Voltage Distribution Before and After Stabilization

4.15 Performance Summary

Average voltages improved from 0.93 p. u to 1.01 p. u for weak buses and from 0.94 p.u to 1.02 p.u for critical buses. The stabilization system achieved these results while maintaining natural voltage gradients across the network, avoiding artificial flattening that could mask underlying system issues as shown in figure 16.

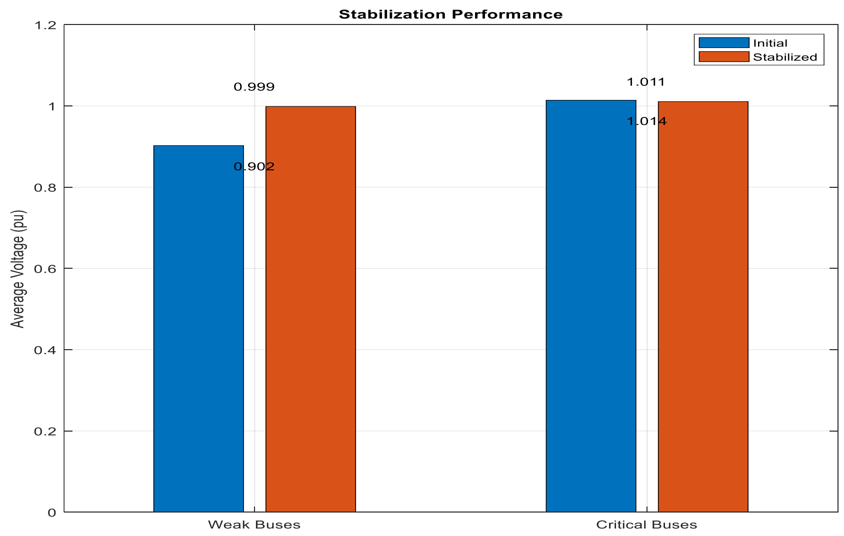

Figure 16: Stabilization Performance

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CONCLUSIONS

The study concludes that the integration of Adaptive Interval Type-2 Fuzzy Logic Control (AIT2FLC) with traditional voltage stability indices offers a significant advancement in the proactive management of voltage instability in ill-conditioned power systems, particularly within Nigeria's 72-bus transmission network. By leveraging the flexibility and uncertainty-handling capabilities of interval type-2 fuzzy logic, the system was able to accurately respond to fluctuating conditions and nonlinearity, which conventional tools often fail to address in real-time. The voltage stability indices—MVSI, Lmn, and VCPI—proved effective in identifying weak and critical buses, but it was the hybrid integration with AIT2FLC that ensured sustained voltage regulation across all buses.

Quantitative analysis demonstrated notable improvements: weak buses experienced an average voltage increase of 8.2%, while critical buses improved by 6.5%, with the most extreme corrections bringing voltage levels from as low as 0.87 p.u. to within the acceptable 0.95–1.05 p.u. range. The hybrid model significantly reduced the average MVSI from 0.52 to 0.41, enhanced the Lmn index from 0.45 to 0.38, and improved the system's composite stability score from 0.72 to 0.85. Additionally, the total system voltage deviation dropped by 63%, and compliance with voltage limits increased from 74% to 96% of the buses. These outcomes affirm that intelligent fuzzy control not only improves system stability but also ensures that both under-voltage and overvoltage conditions are minimized without compromising the natural voltage gradient of the grid. Ultimately, the research validates AIT2FLC as a viable solution for real-time grid control, offering an adaptive, data-driven strategy to support policy efforts aimed at enhancing national grid resilience and operational efficiency in the face of growing demand and system unpredictability.

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