Voltage Stability in Power Systems using AI and Metaheuristic Algorithms: A Comprehensive Review

Peace Ifeoluwa, Ikuforiji
Department of Mathematics,
Kebbi State University of Science and Technology, Aliero, Nigeria

Ahmad Muhammad Gummi,
Department, Electrical and Electronics Engineering Usmanu Danfodiyo University Sokoto, Nigeria

Yabani Gelwasa Galadima
Department of Elect/Elect Engineering
Kebbi State University of Science and Technology, Aliero, Nigeria.

Mubarak Jibril Yeldu
Department of Computer Science
Abdullahi Fodio University of Science and Technology, Aliero, Nigeria.

Abstract
Voltage stability is referred to a fundamental requirement for stable and reliable operation of modern power systems, particularly under growing penetration of renewable energy sources, such like; distributed generation, and inverter-based technologies. This paper reviews recent advances of three years in voltage stability assessment and improvement, give emphasis to the integration of artificial intelligence (AI) techniques and metaheuristic optimization algorithms. It look at data-driven approaches for predictive modeling and real-time decision-making, together with optimization-based strategies for reactive power dispatch, flexible AC transmission system (FACTS) device placement, and distributed generation siting. In generalit used voltage stability indices, optimization objectives, and constraints are formalized, with add-ontables. Comparative analyses summarize the performance of AI models, metaheuristic methods, and hybrid frameworks. Key challenges are discussed, including generalization under topology changes, Measurementsparsity, renewable energy uncertainty, and the need for explainable decision support. Future directions highlight physics-informed AI, graph-based learning, robust optimization, and coordinated multi-agent control for sustainable and resilient voltage stability management.

Keywords
Voltage stability, Artificial intelligence, Met heuristics, Reactive power optimization, Power system resilience.

1. Introduction

Voltage stability refers to the ability of a power system to maintain acceptable voltage levels at all buses under normal operating conditions and following disturbances. This capability is increasingly challenged by the integration of renewable energy sources (RES), inverter-based resources (IBRs), and distributed generation (DG), which introduce low-inertia conditions, variable generation, and frequent topology changes [1], [2]. These factors can reduce voltage security margins and increase the risk of voltage collapse.

Conventional voltage stability assessment (VSA) techniques, such as continuation power flow (CPF), PV/QV curve analysis, and sensitivity-based indices, remain effective for offline planning studies but are computationally demanding for real-time operation[3], [4], [5], [6]. At the same time, preventive and corrective measures including reactive power support, optimal placement of FACTS devices, on-load tap changer (OLTC) coordination, and DG siting often require solving non-convex, multi-objective optimization problems [7]. Such problems are NP-hard, making exact solutions computationally infeasible for large-scale systems.

Metaheuristic optimization algorithms, including particle swarm optimization (PSO), grey wolf optimizer (GWO), differential evolution (DE), whale optimization algorithm (WOA), and their multi-objective variants, have been widely applied for reactive power dispatch, FACTS device placement, and DG siting [8], [9], [10]. These methods excel in handling mixed discrete–continuous variables and avoiding local optima.

In parallel, AI techniques including machine learning (ML), deep learning (DL), and reinforcement learning (RL) have been successfully deployed for data-driven VSA, critical bus detection, and stability margin prediction[8], [11], [12]. Recent hybrid approaches integrate AI with metaheuristics, enabling predictive and prescriptive voltage stability management under uncertainty[7], [12].

Research gap: While prior reviews have addressed AI-based VSA or metaheuristic-based voltage control [13], [14]separately, few have provided an integrated analysis of both domains within a unified framework, incorporating recent advances such as graph-based learning, physics-informed AI, and coordinated multi-agent RL control.

Contributions: This review

1. Consolidates recent three years developments in AI- and met heuristic-based voltage stability enhancement.
2. Provides unified mathematical formulations for stability indices, optimization objectives, and AI training processes.
3. Presents comparative tables summarizing datasets, algorithms, indices, test systems, and performance metrics.
4. Identifies open challenges and outlines a research roadmap for sustainable and resilient voltage stability management.

2. Fundamentals of Voltage Stability

2.1 Power Flow Equations

For an n-bus power system, the complex power injection at bus ii is given by:

$$S_i=P_i+jQ_i=V_i \sum_{k=1}^{n} V_k \left(G_{IK} - jB_{ik}\right)e^{j(\theta_i-\theta_k)} \quad 2.1$$

WhereV_i and $\theta_i$are the voltage magnitude, and angle at busi,$G_{ik}B_{ik}$ are conductance and susceptance between buses i and k

2.2 Voltage Stability Indices

(a) L-IndexPartition buses into generator (G) and load (L) sets. From the admittance matrix:

$$F = Y_{LL}^{-1}Y_{LG}, L_i = 1-\sum_{g\epsilon G} F_{ig}\frac{V_g}{V_i} \quad 2.2$$

(b) The venin-Based Margin

$$\mu = 1 - \frac{|Zth}{Z_l} \quad 2.3$$

(c) PV-QV Curve Analysis

From CPF results, the nose point in PV curves and the lowest point in QV curves indicate voltage stability margins (VSM).

2. 3 Classical Stability Enhancement

Traditional methods include installing shunt capacitors, adjusting transformer taps, and re-dispatching reactive power generation [24]. While effective in steady conditions, these approaches are limited under fast-changing operational scenarios caused by RES variability.

3. Problem Formulations

Voltage stability enhancement and assessment tasks can be formulated into

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three main computational frameworks: (i) data-driven voltage stability assessment (VSA), (ii) optimization-based control for preventive and corrective actions, and (iii) reinforcement learning (RL)-based coordinated control.

3.1 Data-Driven Voltage Stability Assessment

In a data-driven setting, the objective is to train a model f_θ that maps real-time system measurements x to either a classification label y (secure/insecure) or a continuous voltage stability margin mm.

Let $x \in R^d$ represent feature vectors comprising bus voltages, phase angles, active/reactive power injections, line flows, and network topology indicators, often derived from PMU data streams. The general learning objective is:

$$\min_\theta E_{(x,y)} \; [P(f_\theta(x), y)] + \Omega(\theta) \qquad 3.1$$

Where $P(\cdot)$ is the loss function (cross-entropy for classification, mean squared error for regression), and $\Omega(\theta)$ is a regularization term to improve generalization.

Example targets:

i. Classification: $y \in \{Secure, Insecure\}$
ii. Regression: $m = VSM,\ L - index,\ |Z_{th}|/|Z_L|$
iii. Training datasets are generated from time-domain simulations or continuation power flow (CPF) under varying operating conditions and contingencies.

3.2 Optimal Reactive Power Dispatch (ORPD)

Reactive power dispatch seeks optimal generator voltage set-points, transformer tap settings, and reactive compensation to minimize system losses, voltage deviations, and instability risk[6], [13], [15]. The multi-objective formulation is:

$$\min_u w1PP(u) + w_2 \sum_{i-1}^{N} |V_i(u) - V_i^{ref}| + w_{23} \sum_{i-1}^{N} = \max(0, Li(u) - \tau) \qquad 3.2$$

Where:

1. u is the control vector (reactive outputs, tap positions, capacitor sizes),
2. P_P is total active power loss,
3. V_i^{ref} is the reference voltage for bus ii,
4. Li(u) is the L-index,
5. τ is the allowable stability threshold,
6. $w_1, w_2 w_3$ are weighting factors.

Constraints:

$$V_{min}^{I} \le V_i \le V_{max}^{i} \quad \forall_i$$

$$V_g^{min} \le V_g \le V_g^{max}, \forall_g$$

AC power flow equations satisfied

3.3 FACTS/DG Placement and Sizing

Placement and sizing of FACTS devices (STATCOM, SVC, TCSC, UPFC) and DG units can be modeled as a Mixed-Integer Nonlinear Programming (MINLP) problem[6], [13], [15]:

$$\min_{z,s} w1PP(z, s) + w_2 VD(z, s) + w_3 Cost(z, s) + w_4 VSI\_risk \qquad 3.3$$

Subject to:

i. Voltage limits: $V_{min}^{I} \le V_i \le V_{max}^{i}$
ii. Thermal limits: $|S_{ij}| \le S_{max}^{ij}$
iii. Stability constraints: $L_i \le \tau$ for all buses.

Here:

i. $z \in \{0,1\}^n$ are binary decision variables for device placement,
ii. S represents ncontinuous sizing variables.

3.4 Reinforcement Learning for Volt/VAR Control

The voltage control problem can be cast as a Markov Decision Process (MDP) with:

i. State space SS: Bus voltages, angles, reactive power flows, and device statuses.

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ii. Action space AA: Reactive power injections, tap changes, FACTS set-points.

iii. Reward RR:

$$R_t = -\alpha \sum_i | V_i - V_i^{ref} | - \beta \, tap\_wear - \gamma \, instability\_risk \quad 3.4$$

➢ Transition dynamics: Governed by AC power flow and grid operational physics.

The RL agent seeks:

$$\pi * = \arg\min_{\pi} E[\sum_{t-0}^{\infty} \gamma t R_t \quad 3.5$$

Where π is the control policy and γ\gamma is the discount factor.

Safety constraints can be integrated via physics-informed critics or shielding layers that override unsafe actions.

4. AI-Based Voltage Stability Assessment of three year advancements

Artificial intelligence (AI) techniques have emerged as powerful tools for data-driven voltage stability assessment (VSA), enabling fast, adaptive, and scalable prediction of system stability margins under varying operating conditions[4], [5], [15], [15]. These methods exploit the increasing availability of phasor measurement unit (PMU) data, supervisory control and data acquisition (SCADA) signals, and real-time grid telemetry.

4.1 Feature Engineering and Input Representation

AI-based VSA models rely on well-designed input features that capture both steady-state and dynamic characteristics of the power system:

1. Steady-state features: Voltage magnitudes (|V|), phase angles (θ\theta), active/reactive power injections (P,QP, Q), and line flows (S_{ij})
2. Dynamic features: Frequency, rate of change of frequency (ROCOF), and voltage rate-of-change.
3. Topological encodings: Adjacency matrices of bus–line connectivity for graph-based models.
4. Time-series windows: Sequential PMU data for temporal learning in LSTM/CNN models.

Feature vectors are typically normalized and augmented with topology indicators for out-of-topology (OOT) robustness.

4.2 Model Families

(a) Tree-Based Models:

Ensemble methods such as XGBoost and Random Forests achieve high accuracy for classification and regression tasks with interpretable feature importance metrics[16].

(b) Sequence Models:

Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) capture temporal dependencies in PMU streams, enabling short-term VSA (ST-VSA) under dynamic events[16].

(c) Graph Neural Networks (GNNs):

Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), and Spatio-Temporal Graph Attention Networks (ST-GAT) directly model the grid topology, improving generalization to unseen network configurations [7], [17], [18].

(d) Neuro-Fuzzy Systems:

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) provide interpretable, rule-based predictions and are effective in small-data scenarios[3], [18], [19].

4.3 Model Training and Evaluation

Given a dataset$D = \{(xi, yi)\}_{i=1}^{N}$ training involves minimizing:

$$\min_{\theta} \frac{1}{N} \sum i = 1NP(f\theta(xi), yi) + \lambda|\theta|22 \, {}^{2}_{2} \quad 4.1$$

With cross-validation over different loading conditions, contingencies, and RES variability scenarios.

Evaluation metrics include accuracy, F1-score, Brier score for classification, and mean absolute error (MAE) or root mean square error (RMSE) for regression.

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4.4 Reported Advances (2022–2025)

Table 1 AI Models for Voltage Stability Assessment

Year	Model Type	Features	Target	Test System(s)	Highlights
2025	ST-GAT [31]	Graph + temporal PMU	VSM, secure/insecure	IEEE-118, real grid	Topology-aware; high OOT generalization
2025	Regression Trees [33]	Snapshots	VSM under RES variability	IEEE-39	Fast inference; robust to noise
2024	XGBoost [28]	Snapshot + topology	L-index regression	IEEE-118	Interpretable feature importance
2024	CNN-LSTM Hybrid [29]	PMU sequences	ST-VSA	IEEE-300	Learns spatial & temporal patterns
2024	GCN [30]	Graph structure	Security status	IEEE-118	Strong OOT performance
2023	ANFIS [32]	Engineered VSI	Predictive VSI	IEEE-57	Small-data effectiveness
2023	Transfer Learning DL [34]	PMU sequences	Security classification	Real grid	Reduces data requirement
2022	Thevenin-ML Hybrid [35]	PMU + Zthcalc	Online VSM	IEEE-14	Combines physics & ML

4.5 Hybrid AI Approaches

Recent work emphasizes physics-informed AI that embeds power system equations into the learning process, improving interpretability and reducing reliance on large labeled datasets. Other trends include multi-task learning, where a single model jointly predicts VSM, L-index, and critical buses[19], and explainable AI (XAI) tools such as SHAP values for operator trust.

4.6 Deployment Considerations

AI models for VSA must be:

1. Fastinference within milliseconds to meet operational timelines.
2. Robusttolerant to PMU failures or bad data.
3. Generalizableperform well under topology changes and new operating points.
4. Explainableprovide reasoning for predictions to support control room decision-making.

5. Metaheuristic Optimization for Voltage Stability Enhancement of the three years advancements

Metaheuristic optimization algorithms have been extensively applied to preventive and corrective voltage stability enhancement problems, including Optimal Reactive Power Dispatch (ORPD), FACTS device placement/sizing[13], and Distributed Generation (DG) siting. Their main advantage lies in handling non-convex, multi-objective, and mixed-variable optimization problems that arise in large-scale grids.

5.1 Algorithm Families

1. Particle Swarm Optimization (PSO). Widely used for ORPD due to fast convergence and simple implementation[20]. Variants include Lévy-flight PSO, which enhances global search ability[21].

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2. Grey Wolf Optimizer (GWO). Effective for DG/FACTS placement, known for its exploration–exploitation balance[22].
3. Differential Evolution (DE). Robust for mixed-variable FACTS placement problems[21][23].
4. Whale Optimization Algorithm (WOA). Efficient in capacitor placement, handling discrete and continuous variables simultaneously[24].
5. Multi-Objective PSO (MOPSO). Generates Pareto fronts for conflicting objectives like loss minimization, voltage profile improvement, and cost reduction[21].
6. Hybrid Approaches. Combine metaheuristics with sensitivity analysis, machine learning surrogates, or mathematical relaxations for faster convergence[25].

5.2 Generic Metaheuristic Workflow for Voltage Stability Enhancement

The general metaheuristic optimization process can be summarized as:

i. Problem Encoding: Represent decision variables (e.g., device placement, reactive set-points) as a candidate solution vector.
ii. Objective Function Evaluation:

$$F(x) = w_1 P_P(x) + w_2\ VD(x) + w_3\ VSI\_risk(x) + w_4\ Cost(x) \quad (5.1)$$

Constraint Handling: Penalty functions for voltage and thermal violations:

$$Penalty = \sum_i \max(0, V_i - V_i^{max}) + \sum_i \max(0, V_i^{min} - V_i) \quad (5.2)$$

Population Initialization: Randomly generate candidate solutions within operational limits.

i. Search Process: Apply algorithm-specific operators (e.g., velocity updates in PSO, encircling prey in WOA).
ii. Termination: Stop when convergence criteria or iteration limit is met.
iii. Best Solution Selection: Identify set-points/placements with best trade-offs.

5.3 Reported Advances (2022–2025)

Table 2 Metaheuristic Algorithms for Voltage Stability Enhancement

Year	Algorithm	Application	Decision Variables	Test System(s)	Highlights
2025	Lévy-PSO [40]	ORPD	Generator Q-setpoints, taps, caps	IEEE-57, 118	Escapes local optima; faster convergence
2025	MOPSO [44]	DG + capacitor siting	Locations, sizes	IEEE-33	Pareto fronts for loss, VD, cost
2025	Hybrid GWO–DE [45]	STATCOM/TCSC siting	Bus locations, device ratings	IEEE-118	Combines exploration & exploitation
2024	WOA [43]	Capacitor placement	Sizes, switching states	IEEE-33, 69	Handles discrete/continuous
2024	MGWO [41]	DG/FACTS placement	Discrete sites + sizes	IEEE-57	Good trade-off solutions
2024	DE [42]	FACTS siting &	Placement	IEEE-39	Robust performance

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		sizing	vector, capacities		
2023	PSO [39]	ORPD	Q-setpoints, tap positions	IEEE-30, 57	Fast convergence, simple tuning
2023	Hybrid ML–MOPSO [46]	ORPD + VSI improvement	Q-setpoints	IEEE-118	Surrogate model speeds convergence
2022	Sensitivity–PSO [47]	STATCOM placement	Bus index, MVAR size	IEEE-57	Reduced search space

5.4 Multi-Objective Optimization Considerations

Voltage stability enhancement problems often have conflicting objectives, such as:

i. Loss minimization vs Cost minimization
ii. Voltage deviation reduction vs Device utilization
iii. Stability margin maximization vs Reactive power reserve preservation

Multi-objective algorithms like MOPSO, NSGA-II, and MOEA/D generate Pareto-optimal solutions, enabling operators to choose set-points according to preferences and operational constraints.

5.5 Integration with AI

Recent work combines metaheuristics with AI-based predictive models to accelerate optimization by avoiding repeated full power flow calculations. Surrogate-assisted metaheuristics use trained models (e.g., XGBoost, ANN) to approximate objective functions, achieving up to 70% reduction in computation time in large-scale systems.

6. Comparative Analysis

This section synthesizes findings from Sections 4 and 5, enabling a direct comparison of artificial intelligence (AI) techniques and metaheuristic optimization algorithms applied to voltage stability assessment and enhancement between 2022 and 2025.

6.1 AI vs. Metaheuristic Capabilities

Aspect	AI-Based VSA	Metaheuristic Optimization
Objective	Predict voltage stability status/margin (classification/regression)	Optimize control variables for enhanced stability
Input Data	PMU streams, SCADA data, network topology	Network models, load/generation data, device constraints
Output	Security status, VSM, L-index, critical bus ranking	Optimal set-points, device placement/sizing
Speed	Milliseconds inference (once trained)	Iterative search (seconds–minutes)
Adaptability	Adapts to new data via retraining	Adapts via re-optimization
Explainability	Varies (tree-based = high, deep learning = low unless XAI applied)	Moderate (decision variables explicit; trade-offs visualized)
Scalability	Scales with data availability; needs retraining for topology shifts	Scales with computation; hybridization can reduce complexity

6.2 **Summary of AI-Based Approaches (2022–2025)**

Year	Model	Features	Target	Test Systems	Accuracy / RMSE	Key Benefit
2025	ST-GAT [31]	Graph + PMU time	VSM, security	IEEE-118, real	Acc. > 97%	High generalization

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		series	status	grid		under topology change
2025	Regression Trees [33]	Snapshots	VSM	IEEE-39	RMSE < 0.02	Robust to noise
2024	CNN-LSTM [29]	PMU sequences	ST-VSA	IEEE-300	Acc. ≈ 96%	Captures spatial & temporal patterns
2024	XGBoost [28]	Snapshot + topology	L-index	IEEE-118	MAE < 0.015	Interpretable
2024	GCN [30]	Graph structure	Security status	IEEE-118	Acc. ≈ 95%	Topology-aware learning
2023	ANFIS [32]	Engineered VSI	Predictive VSI	IEEE-57	RMSE < 0.01	Interpretable rules
2023	Transfer Learning [34]	PMU sequences	Security class	Real grid	Acc. > 94%	Reduces data need
2022	Hybrid Thevenin-ML [35]	PMU + Zth	Online VSM	IEEE-14	MAE < 0.02	Physics-informed accuracy

6.3 Summary of Metaheuristic Approaches (2022–2025)

Year	Algorithm	Application	Decision Variables	Test Systems	Key Performance
2025	Lévy-PSO [40]	ORPD	Q-setpoints, taps, caps	IEEE-57, 118	Converges 20% faster; escapes local optima
2025	MOPSO [44]	DG + capacitor	Locations, sizes	IEEE-33	Balanced loss & VD
2025	Hybrid GWO–DE [45]	STATCOM/TCSC	Bus loc., ratings	IEEE-118	Improved convergence stability
2024	WOA [43]	Capacitor placement	Sizes, states	IEEE-33, 69	Handles discrete & continuous
2024	MGWO [41]	DG/FACTS placement	Sites + sizes	IEEE-57	Competitive Pareto fronts
2024	DE [42]	FACTS sizing	Placement, capacities	IEEE-39	Strong robustness
2023	PSO [39]	ORPD	Q-setpoints, taps	IEEE-30, 57	Simple, fast
2023	ML–MOPSO [46]	ORPD + VSI	Q-setpoints	IEEE-118	70% faster via surrogate
2022	Sensitivity–PSO [47]	STATCOM	Bus index, size	IEEE-57	Reduced search space

6.4 Performance Insights

i. AI Models excel in fast stability prediction, especially for online applications where millisecond-level decision-making is required[9].

ii. Metaheuristics are essential when optimal control actions need to be computed from scratch, especially for device placement and multi-objective optimization[23].

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iii. Hybrid AI–Metaheuristic Frameworks (e.g., ML-assisted MOPSO) combine predictive speed with optimization capability, reducing computation time without compromising solution quality[8].

7. Challenges and Future Research

Despite significant advances in AI- and metaheuristic-based voltage stability enhancement between 2022 and2025, several challenges remain before widespread deployment in real-world systems.

7.1 Topology Shift and Model Generalization

AI-based VSA models can suffer performance degradation when grid topology changes due to maintenance, expansion, or contingencies. Graph-based learning and domain adaptation techniques [9], [25]are promising, but practical frameworks for online adaptation without full retraining are still emerging.

7.2 Measurement Sparsity and PMU Deployment

PMUs provide high-quality synchrophasor data, but their deployment is limited by cost. Solutions include virtual PMUs, compressive sensing, and active sensing strategies[6], [9], [11], [22] to reconstruct missing measurements.

7.3 Renewable Energy Uncertainty

Variability and forecast errors in renewable generation cause dynamic voltage stability challenges. Robust optimization, stochastic programming, and chance-constrained reinforcement learning, are key to managing uncertainty while maintaining operational security [26].

7.4 Explainability and Operator Trust

For operational acceptance, AI predictions must be interpretable. Explainable AI (XAI) methods such as SHAP values for tree models and gradient attribution for GNNs[11][15], are vital to building operator trust.

7.5 Coordinated Multi-Agent Control

Future grids will require cooperative control among multiple voltage support devices (STATCOM, DG inverters, OLTCs) using multi-agent reinforcement learning (MARL)[25],[1]. Coordination with grid-forming inverter controls and adherence to emerging standards [1]is an open research area.

Conclusion.

This paper reviewed recent (2022–2025) developments in voltage stability assessment and enhancement using artificial intelligence (AI) and metaheuristic optimization. AI models particularly graph-based and hybrid physics-informed architectures have achieved high accuracy and adaptability in predicting stability margins and identifying weak buses.
Metaheuristic algorithms remain crucial for non-convex, multi-objective optimization problems such as ORPD, FACTS device placement, and DG siting.
Comparative analysis revealed that:

1. AI-based VSA offers millisecond inference for real-time monitoring.
2. Metaheuristics provide robust optimization under complex operational constraints.
3. Hybrid AI metaheuristic frameworks combine speed with optimization accuracy.

Future research should focus on:

1. Enhancing model generalization to topology shifts.
2. Addressing PMU measurement sparsity with virtual sensing.
3. Incorporating uncertainty management into optimization and RL.

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4. Developing explainable AI frameworks to improve operator trust.
5. Implementing coordinated multi-agent voltage control under evolving grid standards.

These advances will enable sustainable and resilient voltage stability management in renewable-rich, dynamically evolving power systems.

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