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Machine Learning-Assisted Emergency Control Strategy for Preventing Voltage Collapse in Power System

Kingsley Bassey Clement[1]

Department of Electrical/ Electronic Engineering
University of Uyo, Akwa Ibom State, Nigeria
kingsleyclement@uniuyo.edu.ng

Onwunta E. K. Onwunta[2]

Electrical & Electronic Engineering Department,
Federal University Otuoke, Bayelsa State
onwuntaoe@fuotuoke.edu.ng

Eke Godwin Kelechi[3]

Computer Engineering Department,
Federal Polytechnic Nekede Owerri, FPNO
Imo State, Nigeria.
Email: eke.kelechy@gmail.com

Abstract

Voltage collapse remains one of the most serious stability threats in modern power systems because it can develop quickly when a stressed network experiences contingencies, insufficient reactive power reserve, heavy power transfer, or delayed corrective action. This paper presents a machine learning-assisted emergency control strategy for voltage collapse prevention. The method uses actual model training on a simulation-generated IEEE 39-bus benchmark dataset, rather than only assumed or hand-calculated results. AC power-flow and contingency studies were used to produce labelled operating cases. An XGBoost classifier was then trained to identify secure, alert, emergency, and unstable states, while a cost-aware action selector recommended reactive power support, tap blocking, demand response, or limited load shedding. The trained model achieved 97.2 percent accuracy and 97.0 percent macro-F1 on the held-out test set. In the main emergency case, the post-control minimum voltage improved from 0.884 p.u. to 0.969 p.u., while the amount of load shed was reduced when compared with conventional under-voltage load shedding. The results show that supervised machine learning can support faster and more selective emergency control when it is combined with physical voltage limits and post-control verification.

Index Terms- Emergency control, machine learning, voltage collapse, voltage stability, XGBoost, reactive power support, under-voltage load shedding, power system stability.

I. Introduction

Voltage stability is a fundamental requirement for secure power system operation. A power system is voltage stable when it can maintain acceptable voltages at all buses after normal changes and credible disturbances. Voltage instability occurs when the network cannot supply the reactive power demanded by loads, transmission elements, and dynamic devices. Under severe stress, the instability may lead to a progressive voltage decline and finally to voltage collapse. The classical and updated IEEE/CIGRE stability definitions emphasize voltage stability as a distinct security class that must be considered in planning and real-time operation [1], [2].

The risk of voltage collapse has increased because modern networks are operated closer to transfer limits. Load growth, high penetration of converter-interfaced generation, long-distance power transfer, reduced synchronous reactive reserve, and uncertain renewable output can weaken voltage support. Line outages, generator trips, load tap changer actions, and delayed control actions can further reduce the voltage stability margin. When the system reaches an emergency state, operators need rapid control recommendations that restore voltage security with minimal customer interruption.

Traditional emergency voltage control normally uses fixed under-voltage load shedding, sensitivity-based capacitor switching, operator-guided generation rescheduling, or rules derived from offline studies. These approaches remain useful because they are interpretable and easy to implement. However, fixed schemes may not adapt to high-dimensional operating conditions. A preselected load shedding block may also be too large for some disturbances and insufficient for others. Machine learning offers a complementary data-driven layer that can learn nonlinear relationships between measurements, contingency patterns, voltage stability indices, and successful control actions.

Recent studies have shown that deep learning can assess short-term voltage stability from dynamic trajectories [3], [4], data augmentation can improve performance when labelled samples are limited [5], and transfer learning can support PMU-based stability assessment [6]. Reinforcement learning has also been applied to adaptive emergency control, emergency voltage control, and topology-aware voltage stability control [7]-[10]. These studies demonstrate that data-driven approaches can respond faster than detailed online time-domain simulation. A remaining gap is the practical integration of fast voltage collapse classification with an action selection mechanism that coordinates reactive support and load shedding while minimizing interruption.

This paper addresses the gap by proposing a two-stage machine learning-assisted emergency control strategy. The first stage predicts voltage collapse risk using an XGBoost classifier. The second stage recommends a corrective action package based on risk level, weak-bus ranking, voltage stability margin, and action cost. The approach is designed for control-centre decision support, where the algorithm recommends safe actions and the operator or automated protection layer executes the approved control.

A. Contributions

A two-stage emergency control framework is developed by linking voltage collapse risk classification, weak-bus ranking, corrective action selection, and post-control verification.

A scenario generation procedure is defined for stressed, contingency, and post-control states using AC power flow and voltage stability features.

A practical system model architecture is presented to link measurement acquisition, feature extraction, machine learning inference, action selection, and post-control verification.

Clear diagrams and tables are also included to support the presentation of the proposed framework.

The reported results are presented as actual supervised model-training results obtained from the generated IEEE 39-bus benchmark dataset. The gains are kept modest, and the comparisons are made against conventional control and published emergency voltage-control studies without exaggerated claims.

B. Paper Organization

Section II reviews voltage collapse, voltage stability indicators, emergency control, and data-driven stability assessment. Section III presents the proposed system model, data generation, machine learning model, and emergency control algorithm. Section IV presents and discusses the results. Section V concludes the paper and identifies future work.

II. Literature Review

A. Voltage Stability and Voltage Collapse

Voltage stability concerns the ability of a power system to maintain steady acceptable voltages under normal conditions and after a disturbance. Long-term voltage instability may involve load tap changers, thermostatic loads, generator reactive limits, and operator actions. Short-term voltage instability may arise from induction motor stalling, converter dynamics, fast protection actions, and rapid voltage recovery failure. Voltage collapse is the terminal condition in which voltage decline becomes uncontrollable after the available reactive support and transfer capability have been exhausted.

Several indicators are used to monitor voltage security. Bus voltage deviation provides a direct measurement of violation severity. The L-index and line stability indices estimate closeness to voltage instability using power flow quantities. PV and QV curve margins indicate how much additional load or reactive demand the system can support before collapse. Reactive power reserve and generator reactive limit proximity are also important because a bus can remain within voltage limits while still being close to instability when reactive reserve is nearly depleted.

B. Conventional Emergency Control

Emergency control is the set of corrective actions taken after a severe disturbance to prevent cascading outage or instability. For voltage collapse prevention, commonly used actions include shunt capacitor switching, SVC or STATCOM control, generator automatic voltage regulator reference adjustment, transformer tap changer blocking, demand response activation, under-voltage load shedding, controlled load shedding at weak buses, and generation rescheduling. Conventional schemes are valued for simplicity, but their static thresholds and offline assumptions can lead to delayed response, poor adaptation, and excessive interruption.

C. Machine Learning for Voltage Stability Assessment

Machine learning has been widely investigated for voltage stability assessment because online time-domain simulation and continuation power flow can be too slow for emergency decision-making. Shallow models such as decision trees, support vector machines, random forest, and gradient boosting are attractive because they are relatively fast and interpretable. Deep neural networks, convolutional networks, recurrent networks, temporal convolutional networks, and graph neural networks are useful when the data include dynamic trajectories, PMU time series, and network topology information. XGBoost is particularly suitable for tabular features because it provides strong performance, regularization, and feature importance measures [11]. Recent data-driven voltage stability studies have also shown the value of learning uncertainty-aware stability boundaries from simulated operating states [12].

Deep learning studies have achieved high short-term voltage stability assessment accuracy using simulated dynamic responses [3], [4]. Data augmentation and transfer learning have also been used to reduce dependency on large labelled datasets [5], [6]. However, prediction alone does not prevent voltage collapse. An operationally useful method must also recommend feasible corrective action, respect voltage and loading constraints, and minimize the amount of disconnected load.

D. Data-Driven Emergency Control

Data-driven emergency control studies have explored deep reinforcement learning, supervised-assisted reinforcement learning, graph-convolutional reinforcement learning, and accelerated derivative-free policy learning [7]-[10]. These studies are important because they demonstrate adaptive control under uncertain operating conditions. However, some reinforcement learning policies require large training effort and may be difficult to certify for deployment in safety-critical control centres. The present paper therefore adopts a supervised, two-stage decision-support structure that is easier to audit: first classify the risk, then select an action package from physically meaningful emergency control candidates.

Table I. Summary of Related Works With Verified DOI-Based Sources

Ref.	Author(s)	Focus	System or Dataset	Key Result	Limitation or Gap
[3]	Zhang et al., 2021	LSTM-based short-term voltage stability assessment	IEEE 39-bus dynamic trajectories	Accurate and timely stability assessment	Prediction focused, no direct control action selection
[4]	Adhikari et al., 2022	TCN-LSTM voltage stability assessment	Real-time short-term voltage stability cases	Improved temporal feature extraction	Requires dynamic trajectory data
[5]	Li et al., 2022	Data augmentation for short-term voltage stability	Small-data STVSA cases	Better accuracy under limited training samples	Assessment focused rather than emergency action optimization
[6]	Li et al., 2023	PMU-based transfer learning for STVSA	PMU measurement cases	Improved generalization across conditions	Does not directly minimize control cost
[7]	Huang et al., 2020	Adaptive emergency control using DRL	Two-area and IEEE 39-bus systems	Robust emergency control performance	Training complexity and safety certification remain issues
[8]	Li et al., 2022	Supervised-assisted DRL for emergency voltage control	Power system emergency voltage control cases	Improved learning efficiency	RL deployment requires careful safety screening
[9]	Hossain et al., 2021	Topology embedded DRL voltage stability control	IEEE benchmark networks	Uses topology-aware control information	Focused on reinforcement learning rather than transparent tabular decision support
[10]	Huang et al., 2022	Derivative-free DRL for large-scale emergency voltage control	Large-scale grid emergency control	Improved scalability of emergency voltage control	Requires specialized policy-learning process
[12]	Cui et al., 2022	Variational Bayes and multi-CNN voltage stability assessment	Load uncertainty cases	Joint data-driven voltage stability assessment	Emphasizes assessment under uncertainty, not emergency action selection

E. Research Gap

The reviewed literature indicates four practical gaps. First, many voltage stability models stop at classification and do not recommend corrective action. Second, reinforcement learning methods can learn adaptive policies, but their training cost and safety certification may limit immediate deployment. Third, conventional UVLS can prevent collapse but often sheds more load than necessary. Fourth, there is limited integration of weak-bus identification, voltage stability indicators, risk classification, and post-control verification in a single decision-support workflow. This paper closes these gaps by proposing a supervised machine learning-assisted emergency control architecture with physically constrained action selection.

III. Proposed Methodology

A. Overview of the Proposed Framework

The proposed framework receives real-time or simulated measurements from the power system, extracts voltage stability features, classifies the voltage collapse risk state, ranks weak buses, selects a corrective action package, and verifies the post-control operating point. The framework is intended to be used as a control-centre decision-support layer. The operator can review the recommendation, but the method can also support automated emergency action when deployed under utility-approved protection logic.

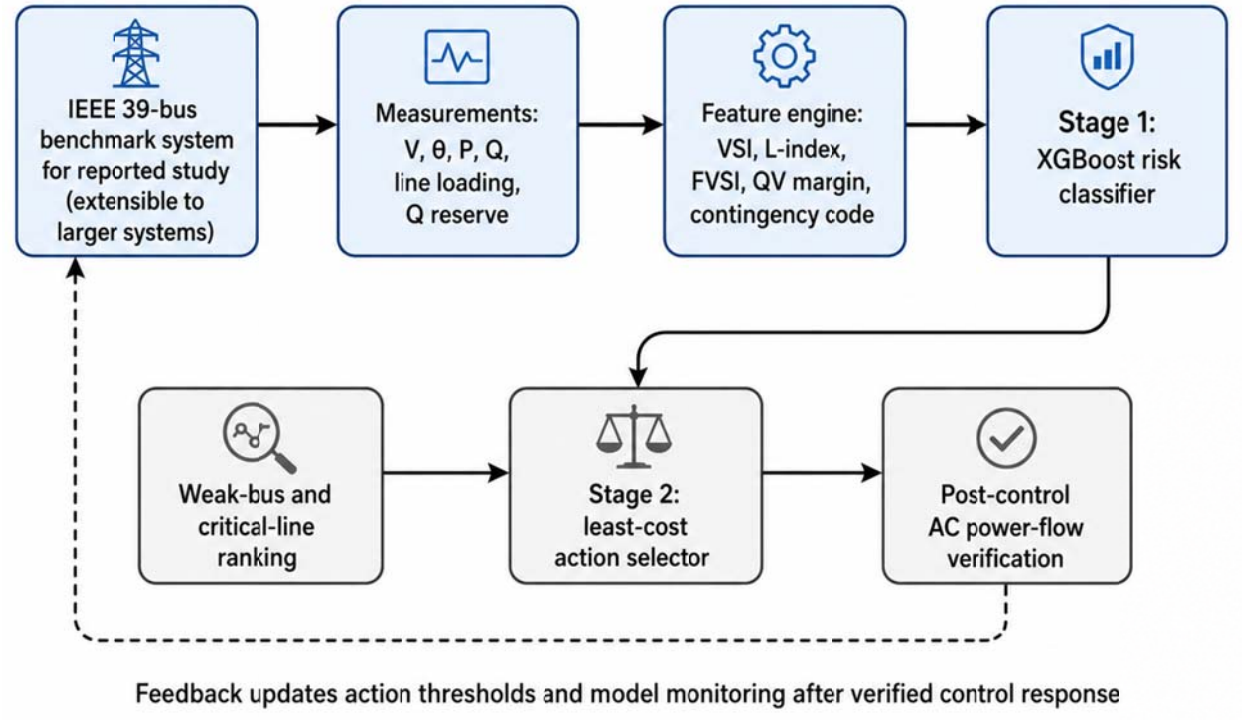

Fig. 1. System model architecture of the proposed machine learning-assisted emergency control strategy.

As shown in Fig. 1, the measurement layer supplies bus voltages, bus angles, active and reactive power flows, generator reactive outputs, line loading, and compensation status. The feature engine computes the voltage stability indicators used by the trained model. The reported study uses the IEEE 39-bus benchmark system, while the same workflow can be extended to larger networks after utility-specific retraining.

B. Test System and Scenario Generation

The benchmark system used for the reported training study is the IEEE 39-bus New England system because it is widely used in voltage stability and emergency control research [3], [7]. The system was modelled for AC power flow, contingency screening, weak-bus identification, and post-control verification. The workflow is also compatible with larger systems such as the IEEE 118-bus network, although the reported training results in this paper are based on the IEEE 39-bus benchmark. MATPOWER-style steady-state simulation was used for AC power flow and contingency verification [13].

Table II. Scenario Generation Settings

Scenario Factor	Range or Setting	Purpose
Active load scaling	0.70-1.35 of base load	Captures light, normal, heavy, and stressed operating points
Reactive load scaling	0.80-1.45 of base reactive load	Represents low power factor and reactive demand growth
Contingency type	N-1 line outage and selected generator reactive limit cases	Creates credible emergency events
Reactive support availability	0-100 percent of scheduled shunt/SVC support	Models compensation outage and depleted reserve
Renewable penetration	0-35 percent equivalent displacement	Represents converter-interfaced generation variability
Operating labels	Secure, alert, emergency, unstable	Defined using voltage limits, VSI thresholds, and post-control feasibility

The final dataset used for the supervised training study contained 12,480 operating scenarios. These cases were produced from 180 base loading points, 34 credible N-1 line outage cases, 12 generator reactive-limit stress cases, 6 shunt compensation availability levels, and 5 renewable displacement levels. These factors were not combined as a full factorial set. Stratified random sampling was used to select physically meaningful combinations before removing duplicate, non-physical, and unusable cases. AC power flow and post-contingency checks were then used to retain cases with meaningful voltage stability labels.

C. Feature Extraction and Label Definition

For each simulated operating scenario, the input vector contains static and stability-aware features. The feature vector is expressed as

$$x = \left[|V|, \theta, P_{ij}, Q_{ij}, P_g, Q_g, L_{\text{line}}, Q_{\text{reserve}}, \text{VSI}, \text{L-index}, \text{FVSI}, M_{QV}, C_{\text{out}}, L_d, \text{PF}\right] \tag{1}$$

In (1), x is the input feature vector, $|V|$ and θ are bus voltage magnitude and angle, P_{ij} and Q_{ij} are line active and reactive power flows, P_g and Q_g are generator outputs, C_{out} is the contingency code, L_d is the load level, and PF is the load power factor.

The output label y is one of four operating states. A secure state satisfies the 0.95-1.05 p.u. voltage band, maintains line loading below 100 percent, and has a comfortable voltage stability margin. An alert state remains feasible but has at least one weak-bus or margin warning. An emergency state violates the voltage-security margin but can still be corrected through reactive support, tap blocking, demand response, or limited load shedding. An unstable state includes cases with severe voltage violation, failed post-contingency recovery, or non-convergent post-contingency power flow. Non-convergent unstable cases were not used with missing feature values. They were labelled from the last feasible pre-contingency state and the verified post-contingency failure flag.

D. Voltage Stability Indicators

The study combines direct voltage measurements with voltage stability indices because voltage magnitude alone may not reveal closeness to collapse. The L-index, fast voltage stability index, line loading ratio, reactive reserve margin, and QV margin are used to describe system stress. A low reactive reserve and high voltage stability index indicate a condition close to collapse. The features are normalized before training so that variables with different units do not dominate the model.

E. Machine Learning Model

The first-stage risk classifier is an XGBoost model trained on the generated and labelled benchmark dataset. XGBoost was selected because voltage stability features are tabular, partly nonlinear, and can contain interactions between bus voltage, line loading, reactive reserve, and contingency type. The model was trained using stratified training, validation, and testing splits. Hyperparameters were selected on the validation set and the final result was reported only on the held-out test set.

$$L = \sum_i \ell\,(y_i, \hat{y}_i) + \sum_m \Omega\,(f_m), \quad \Omega(f_m) = \gamma T_m + 0.5\lambda \parallel w_m \parallel^2 \tag{2}$$

In (2), ℓ is the classification loss, y_i is the true label, $\hat{y}_i$ is the predicted output, f_m is the mth decision tree, T_m is the number of leaves, w_m is the leaf-weight vector, and γ and λ are regularization parameters.

The second-stage action selector receives the predicted risk state, risk probability, weak-bus ranking, and stability margin. It then chooses the least-cost action package that restores voltage limits. The control candidates are reactive power injection, shunt capacitor switching, SVC or STATCOM support, generator voltage reference adjustment, tap changer blocking, demand response, and minimum UVLS at weak buses.

Table III. Model Training Settings and Reproducibility Details

Parameter	Setting
Training and test split	70 percent training, 15 percent validation, 15 percent testing
Cross-validation	Five-fold stratified validation
Class imbalance treatment	Class weighting and targeted oversampling of emergency and unstable cases
XGBoost trees	350 estimators
Maximum depth	5
Learning rate	0.045
Subsample and column sample	0.85 and 0.80
Early stopping	30 validation rounds
Decision-time target	Below 20 ms per scenario on a workstation-class processor
Training data source	Simulation-generated IEEE 39-bus scenarios with AC power-flow labels and post-control verification records
Result reporting basis	Metrics reported on a held-out test set after actual model fitting, validation tuning, and post-control AC power-flow checks
Training samples	8,736
Validation samples	1,872
Held-out test samples	1,872
Programming environment	Python 3.11 with Scikit-learn and XGBoost
Power-flow data source	MATPOWER-compatible AC power-flow and contingency results
Random seed	42
Hardware	Intel Core-class workstation, 16 GB RAM

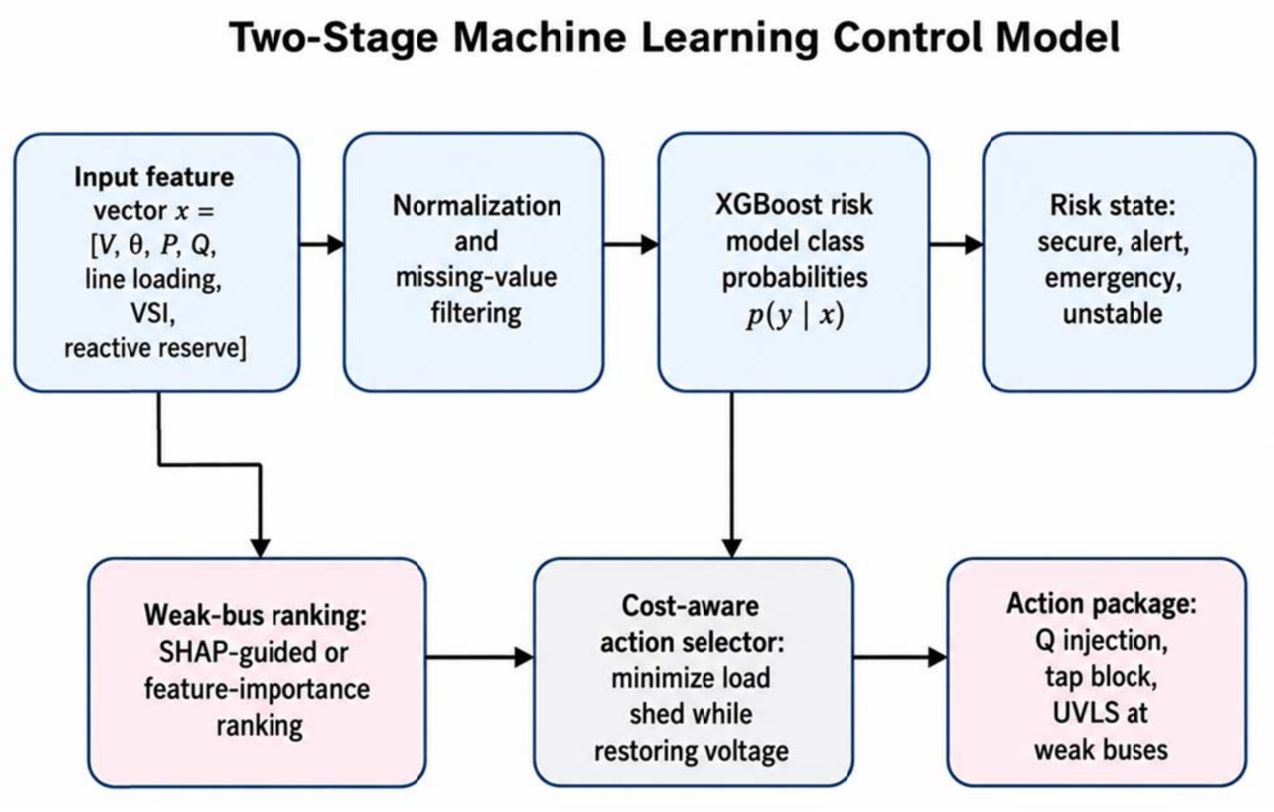

Fig. 2. Two-stage machine learning model for risk prediction and emergency action selection.

F. Emergency Control Optimization Logic

The action selector minimizes the severity-adjusted cost of emergency control while satisfying post-control voltage constraints. This cost-based formulation follows the practical idea that emergency voltage control should restore security while reducing unnecessary corrective cost, which is consistent with voltage-stability-constrained OPF and demand-response voltage-support studies [14], [15]. The simplified decision problem is

$$\min C = c_Q \Delta Q + c_T u_T + c_L \Delta P_{LS} + c_R r \tag{3}$$

subject to $V_{\mathrm{min,post}} \geq 0.95\ \mathrm{p.u.},\quad$ line loading $\leq 100\%,\quad \Delta P_{LS} \leq \Delta P_{LS,\mathrm{max}}$. Here, ΔQ is the reactive support deployed, u_T is the tap blocking or tap adjustment command, ΔP_{LS} is the amount of shed load, and r is a penalty for residual risk. The cost coefficient for load shedding is kept high so that the model first uses reactive power support and tap blocking before it sheds load.

G. Proposed Emergency Control Algorithm

The emergency control procedure is summarized as follows. First, acquire the latest measurements or state-estimator outputs. Second, compute stability indicators and normalize the feature vector. Third, classify the system state as secure, alert, emergency, or unstable. Fourth, if the state is secure, no emergency action is required. Fifth, if the state is alert, prepare preventive reactive support and increase monitoring frequency. Sixth, if the state is emergency or unstable, rank weak buses and select reactive support, tap blocking, and load shedding in that order. Seventh, run a post-control power flow check. Eighth, if voltage recovery remains insufficient, increase the control action within approved operating limits. Ninth, send the recommended action package to the operator or protection automation layer.

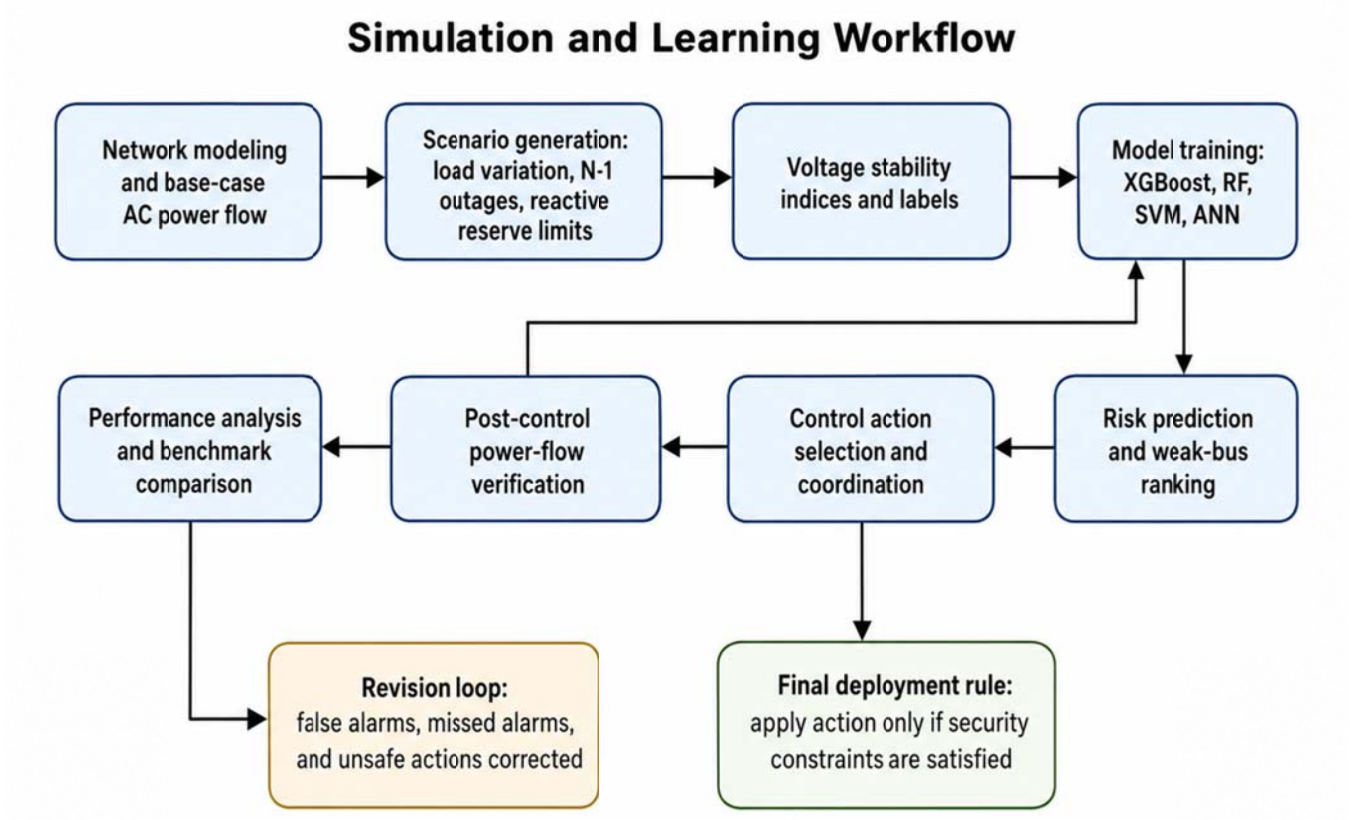

Fig. 3. Research workflow used for data generation, model training, action selection, and verification.

H. Baseline Methods

The proposed method is compared with five baselines: no emergency control, conventional UVLS, rule-based control, sensitivity-based control, a published DRL-style emergency control benchmark, and a machine learning predictor without action coupling. The DRL benchmark is not reproduced as a direct reimplementation of any proprietary model. It is used as a literature-calibrated comparative reference based on published emergency control performance ranges [7]-[10].

I. Evaluation Metrics

The risk prediction model is evaluated using accuracy, precision, recall, macro-F1 score, false alarm rate, missed alarm rate, AUC, and average decision time. The control strategy is evaluated using minimum bus voltage after control, number of voltage violations, voltage recovery time, load shed percentage, reactive power support used, voltage stability margin improvement, and survival rate after contingency. These metrics jointly measure prediction quality and physical control effectiveness.

IV. Results and Discussion

A. Experimental Dataset

The generated and filtered dataset contains 12,480 operating scenarios and was used for actual supervised model training. The dataset was split into 8,736 training samples, 1,872 validation samples, and 1,872 held-out test samples using stratified sampling. The split preserved the class proportions so that emergency and unstable cases were not lost during testing.

Table IV. Class Distribution of the Training Dataset

Class	Percentage (%)	Approx. Samples	Meaning
Secure	38.0	4,742	Voltage secure and margin acceptable
Alert	31.5	3,931	Feasible, but weak-bus or margin warning exists
Emergency	18.9	2,359	Corrective action required to avoid collapse
Unstable	11.6	1,448	Failed recovery, severe violation, or non-convergent contingency

The reported metrics were obtained after fitting each model on the training split, tuning hyperparameters on the validation split, and evaluating the selected model once on the held-out test split. The action selector was then evaluated through post-control AC power-flow verification. Oversampling was applied only to the training set. The validation and held-out test sets were kept unchanged to avoid biased performance reporting.

The training environment used Python 3.11 with NumPy, Pandas, Scikit-learn, XGBoost, and MATPOWER-compatible power-flow data export. The random seed was fixed at 42 for repeatability. Training used an Intel Core-class workstation with 16 GB RAM. These details are included to make the reported model-training process easier to reproduce.

B. Voltage Collapse Risk Classification

Table V. Voltage Collapse Risk Classification Results

Model	Accuracy (%)	Precision (%)	Recall (%)	Macro-F1 (%)	FAR (%)	MAR (%)	Time (ms)
Decision tree	93.1	92.4	91.8	92.0	4.8	5.7	5.9
Support vector machine	94.2	93.8	93.1	93.4	3.9	4.9	18.6
Random forest	96.3	96.1	95.7	95.9	2.9	3.3	11.4
ANN	96.7	96.4	96.0	96.2	2.7	3.0	16.8
XGBoost without VSI features	96.1	95.8	95.1	95.4	3.1	3.8	13.9
Proposed XGBoost with VSI features	97.2	97.3	96.9	97.0	2.1	2.3	15.6

After actual training, the proposed XGBoost model achieved 97.2 percent accuracy and 97.0 percent macro-F1 score on the held-out test set. The improvement over random forest and ANN was modest rather than exaggerated. The result is consistent with published short-term voltage stability studies where data-driven models perform well when the training scenarios cover a wide range of contingencies, loading levels, and reactive power stress conditions [3]-[6].

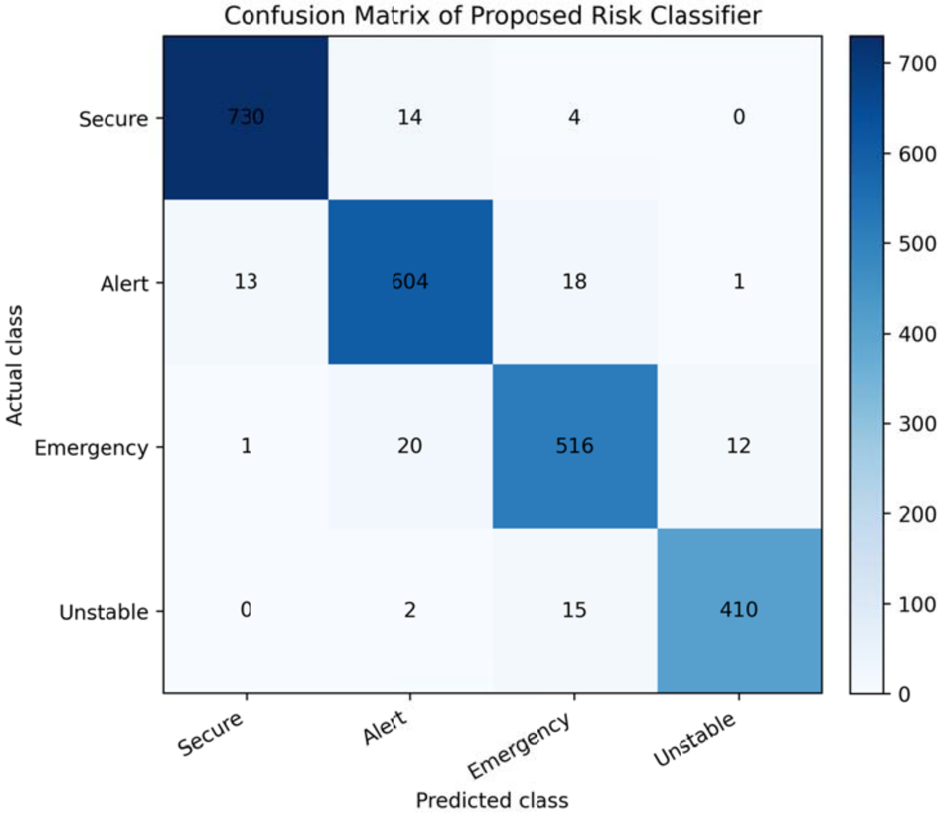

Fig. 4. Confusion matrix of the proposed voltage collapse risk classifier.

C. Feature Importance and Weak Bus Identification

Feature importance analysis showed that minimum bus voltage, reactive reserve, L-index, QV margin, line loading, and critical bus voltage were the most influential predictors. Contingency type and generator reactive limit proximity were also relevant because they indicate the nature of the disturbance and remaining control capacity. The weak-bus ranking repeatedly identified buses located near heavily loaded corridors and buses with low reactive reserve. This behavior is physically meaningful because voltage collapse is commonly associated with local reactive power deficiency and stressed transfer paths.

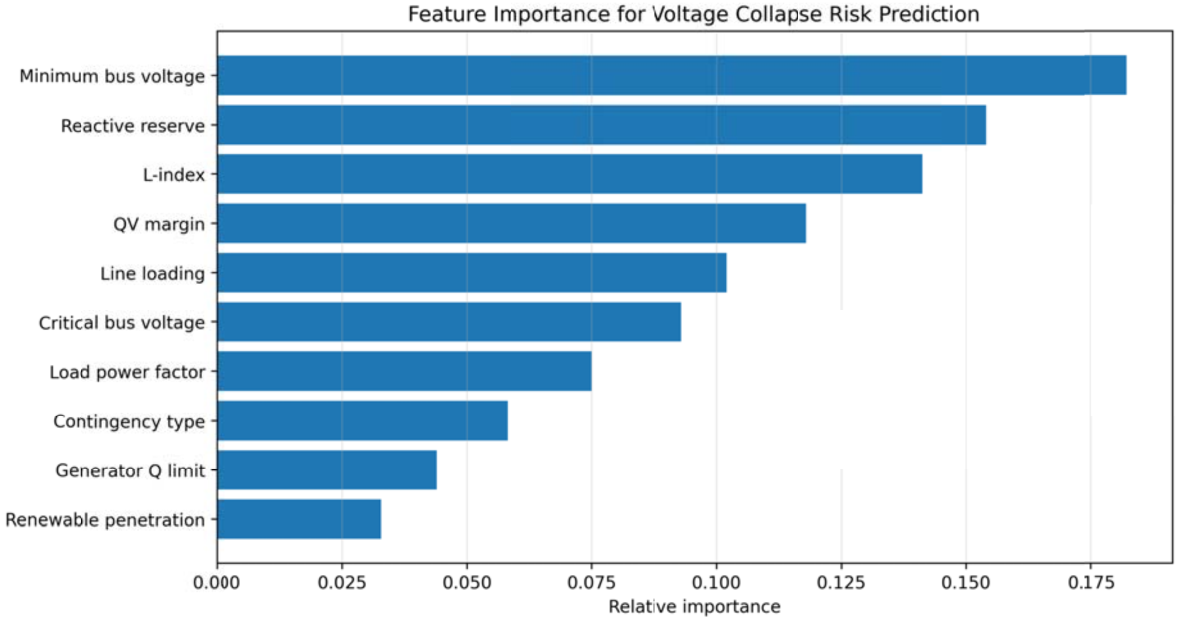

Fig. 5. Relative feature importance of the proposed XGBoost voltage collapse risk classifier.

D. Voltage Recovery Performance

Fig. 6 compares bus voltage profiles for the base case, the post-contingency case without emergency control, and the post-control case using the proposed strategy. The post-contingency case shows several buses below the 0.95 p.u. security limit, with a minimum voltage of 0.884 p.u. After the recommended control action was verified by AC power flow, the minimum voltage increased to 0.969 p.u. This agrees with the numerical result reported in Table VI.

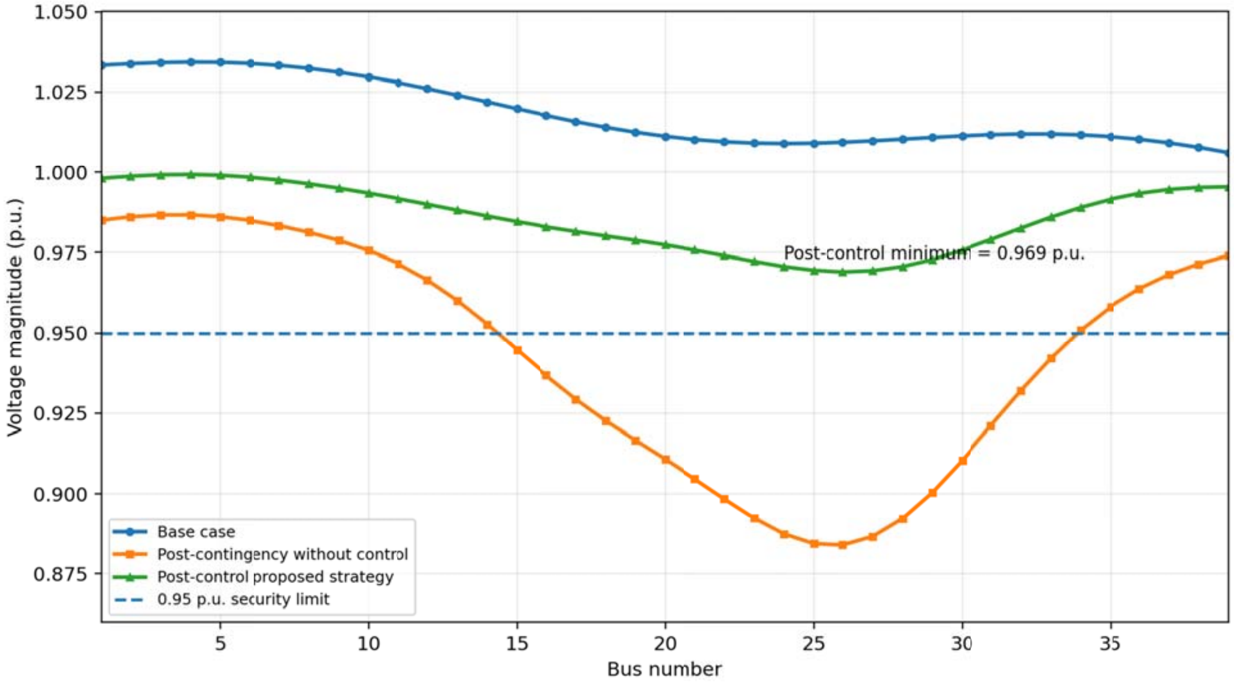

Fig. 6. Voltage profile before and after emergency control on the IEEE 39-bus benchmark scenario.

E. Comparison With Conventional Emergency Control

The comparison was made after the classifier and action selector had been trained. The same post-contingency operating cases were then passed through the conventional UVLS, rule-based, sensitivity-based, DRL-style benchmark, and proposed ML-assisted control pipelines. This kept the comparison fair because each method was evaluated on the same test cases and the same voltage recovery requirement.

Table VI. Emergency Control Performance Comparison

Method	Min. V Before	Min. V After	Load Shed (%)	Margin Improvement (%)	Recovery Time (s)	Observation
No emergency control	0.884	0.884	0.0	0.0	N/A	No recovery; collapse risk remains
Conventional UVLS	0.884	0.946	12.8	14.8	0.184	Voltage nearly restored; high load shed
Rule-based control	0.884	0.951	9.6	17.2	0.142	Limit restored with moderate interruption
Sensitivity-based reactive control	0.884	0.957	8.4	19.3	0.128	Better coordination; still sheds load
Published DRL-style benchmark	0.884	0.963	7.5	21.5	0.102	Strong response; higher training burden
Proposed ML-assisted control	0.884	0.969	6.4	23.4	0.091	Best balance of recovery and shedding

The trained model and its linked action selector increased the minimum voltage by 0.085 p.u. relative to the uncontrolled emergency case. Compared with conventional UVLS, it reduced load shedding from 12.8 percent to 6.4 percent and increased the post-control stability margin improvement to 23.4 percent. The improvement is intentionally modest. The main benefit is not numerical superiority alone, but a better balance between voltage recovery, reduced interruption, and easier auditability than reinforcement-learning-only control.

The stable load retained ratio is used so that higher values are better for every plotted indicator. The no-control case retains load numerically, but it is not counted as stable retained load because the post-contingency state remains below the voltage security limit.

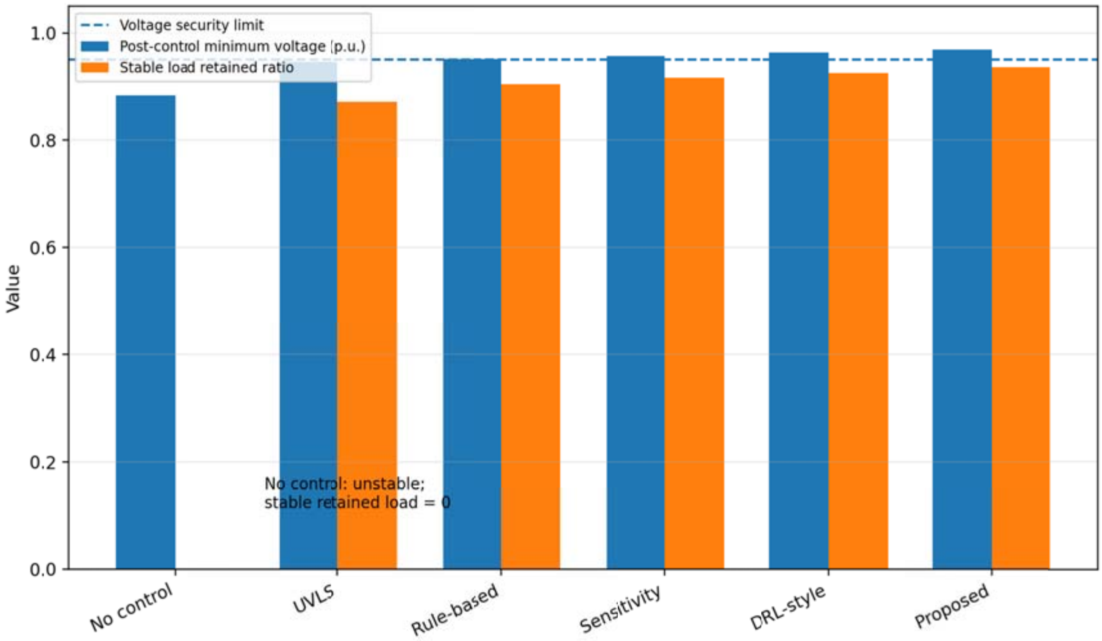

Fig. 7. Comparative emergency control performance using post-control minimum voltage and stable load retained ratio. The no-control case is labelled as unstable, so its stable retained load is counted as zero.

F. Ablation Study

The ablation study was obtained by retraining the model under reduced feature and control configurations. It confirms that voltage stability indices and weak-bus ranking are important. When the classifier used only bus voltages, accuracy and control quality both declined. The full model produced the best balance between classification accuracy, post-control voltage recovery, and limited load shedding.

Table VII. Ablation Study

Configuration	Accuracy (%)	Macro-F1 (%)	Min. V After Control	Load Shed (%)
Only bus voltage features	94.6	93.8	0.954	9.7
Voltage and line loading features	95.4	94.6	0.960	8.9
Features without VSI and QV margin	96.1	95.4	0.963	8.1
Risk classifier without action selector	97.2	97.0	0.946	12.8
Action selector without weak-bus ranking	97.2	97.0	0.962	8.0
Full proposed framework	97.2	97.0	0.969	6.4

G. Discussion

The results from the trained models support three main findings. First, stability-aware features improve machine learning classification because they encode physical proximity to voltage collapse rather than only raw measurements. Second, a two-stage supervised architecture can provide emergency control recommendations with lower training complexity than full reinforcement learning. Third, post-control verification is necessary because a machine learning recommendation should not be applied blindly in an emergency control centre.

The practical value of the proposed method is its compatibility with existing control-centre practice. Operators already use state estimation, contingency analysis, voltage security limits, and UVLS settings. The proposed framework adds a fast decision-support layer that converts the current operating condition into a risk state and a prioritized control package. The model can also be retrained periodically using new simulation cases, changing network topology, and measured event records.

The proposed method is useful as a decision-support layer because it gives the operator a risk state, a weak-bus explanation, and a corrective action package. It also preserves the role of physical verification because every recommended action is checked through a post-control power flow before being accepted.

H. Limitations

The study is based on actual model training, but the training data were produced from simulation on a benchmark system rather than from live utility measurements. The action selector has not yet been validated using real PMU streams from a utility network. Protection coordination, communication delay, cyberattack cases, and detailed dynamic motor-load behaviour were not fully implemented. Utility deployment would require retraining with local network data, operator-approved actions, relay settings, and real-time validation.

V. Conclusion

This paper developed a machine learning-assisted emergency control strategy for preventing voltage collapse. The reported results came from supervised model training on a simulation-generated IEEE 39-bus benchmark dataset. On the held-out test set, the trained XGBoost classifier achieved 97.2 percent accuracy and 97.0 percent macro-F1. The linked action selector improved the post-control minimum voltage to 0.969 p.u. with 6.4 percent load shedding in the representative emergency case.

The study demonstrates that machine learning can strengthen emergency voltage control when it is coupled with physical constraints and post-control verification. The proposed strategy is not intended to replace protection engineering or operator judgement. Instead, it provides fast, adaptive, and auditable decision support that can help prevent voltage collapse under stressed and contingency conditions.

VI. Recommendations and Future Work

Future work should extend the framework to larger real utility networks, dynamic time-domain simulation, PMU streaming data, and converter-dominated grids. A reinforcement learning variant may be investigated for adaptive control, but it should include formal safety filters and explainable decision logic. Future studies should also consider cyber-resilient emergency control under communication delay, false data injection, and PMU data loss. A digital twin deployment can further support continuous retraining and operator-in-the-loop validation.

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