Data-Driven Short-Term Voltage Stability Assessment Using Convolutional Neural Networks Considering Data Anomalies and Localization

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ABSTRACT Short-term voltage stability of power systems is governed by load dynamics, especially the proportion of small induction motors prevalent in residential air-conditioners. It is essential to efficiently monitor short-term voltage stability in real-time by detailed data analytics on voltage measurements acquired from phasor measurement units (PMUs). It is likewise critical to identify the location of faults resulting in short-term voltage stability issues for effective remedial actions. This paper proposes a time-series deep learning framework using 1D-convolutional neural networks (1D-CNN) for real-time short-term voltage stability assessment (STVSA), which relies on a limited number of phasor measurement units (PMU) voltage samples. A two-stage STVSA application is proposed. The first stage comprises a 1D-CNN-based fast voltage collapse detector. The second stage comprises of 1D-CNN-based regressor to quantify the severity of the short-term voltage stability event. Two novel indices are presented, and their predicted future values are used to quantify the severity of short-term voltage stability events. This work also considers DB-SCAN clustering-based fault detection and physics-based fault localization for effective short-term voltage stability assessment and remedial actions by identifying the most critical PMUs. A bad data pre-processing technique is also included to mitigate the impact of missing data and outliers on short-term voltage stability assessment accuracy. The proposed framework is validated using the standard IEEE test systems and compared against other machine learning models to demonstrate the superiority of 1D-CNN-based time-series deep learning for short-term voltage stability assessment.

INDEX TERMS Time-series, deep learning, short-term voltage stability, data-anomalies, 1D-convolution NN.

NOMENCLATURE
PMU Phasor measurement unit.
1D-CNN 1D-Convolutional neural networks.
STVSA Short-term Voltage stability Assessment.
LM Large Motor.
SM Small Motor.
FVC Fast Voltage Collapse.
SAR Severity Aware Regressor.
EBAD Ensemble-based Bad data Detector.
CLOD Composite load.
SVDI System Voltage Deviation Index.
SFSI System Fault Severity Index.
RF Random Forest.
SVM Support Vector Machine.
LSTM Long Short-term Memory.

I. INTRODUCTION
The voltage stability of the power system is critical to ensure secure and reliable operation. The present-day power grid operates in a stressed manner because of increasing load demand, push for economics and intermittent distributed...
resources but limited investment in grid infrastructure. International energy agency (IEA) predicts three times the growth of cooling load demand from 2016 to 2050 [1]. The increase in air conditioning demand is driven by climate change leading to a rise in average temperatures and a longer summer season. Specifically, residential air conditioning units rely on thermal tripping, which leads to prolonged stalling following a fault. This leads to a sudden increase in reactive power demand, leading to fault-induced delayed voltage recovery issues.

In the worst-case scenario, a short-term voltage stability event like a three-phase transmission line fault on a heavily loaded tie-line could lead to fast voltage collapse in a few seconds. A high induction motor demand could lead to prolonged voltage recovery even if the system does not face voltage collapse. It is essential to devise effective emergency control actions to ensure a stable post fault clearance response. Emergency control strategies can be divided into planning stage remedies and operational stage real-time post fault clearance remedial actions [2]. Planning stage remedies rely on deploying dynamic VAR devices like STATCOM and SVC to strengthen reactive power support in response to delayed voltage recovery [3]. During post-fault real-time remedies, the operational stage relies on taking real-time actions like Under-voltage load shedding (UVLS) based on voltage recovery response [4], [5]. To ensure reliable and fast post-fault real-time remedial actions, early detection of impending voltage collapse is necessary.

Traditionally, analytical approaches have been used for short-term and long-term voltage stability assessments based on dynamic time-domain simulations and repeated power flow simulations. These analytical approaches are useful for developing efficient planning strategies and event-based control actions but not suitable for the real-time post-fault response to deal with fault-induced delayed voltage recovery (FIDVR). Moreover, these approaches can be time-consuming and might require frequent evaluations with changes in operating conditions. The availability of wide-area PMU data provides an opportunity to devise real-time assessment and control approaches to deal with voltage stability issues.

Recent wide-scale deployment of PMUs enables data-driven voltage stability assessment and power system situational awareness. Decision trees (DTs) are used in [6]–[8] for long term voltage security assessment, in [9] for voltage stability margin computation and in [10]–[12] for dynamic voltage security assessment. In [13] authors present an intelligent hybrid system based on artificial neural networks for transient rotor angle stability assessment. Data-driven short-term voltage stability assessment (STVSA) approaches can be divided into two classes: i) Analytical data-driven approaches and ii) intelligent machine learning-based approaches. Analytical data-driven approaches rely on the calculation of specific indices like Lyapunov exponent [14], studying voltage response characteristics like the slope of deviation [15] and studying dynamic load model characteristics like kinetic energy deviation of induction motor [16] for stability assessment. Most of the machine learning-based research has been focused on long-term voltage stability, dynamic security assessment, and rotor angle stability, but recently researchers have also directed their attention towards real-time STVSA. In [17] DTs have been used for STVSA, and in [18] shapelet transform-based time-series classification has been used for STVSA. In [19] authors present a randomized neural network-based learning algorithm for probabilistic STVSA. The assessment approach in [17]–[19] considers binary classification, which is useful but cannot quantify the severity of short-term voltage stability events. In [20] authors present a hierarchical approach using an ensemble of neural networks with random weights for classification and severity assessment of short-term voltage stability events. In [20] authors use transient voltage severity index (TVSI) to quantify the severity of short-term voltage stability events. While TVSI provides useful information about FIDVR severity, it is difficult to interpret for devising emergency control actions because of the large range of variation. In [21] authors extend their work in [20] and use an extreme machine learning approach for hierarchical severity-driven voltage stability assessment. Both [20] and [21] use RELIEF [22] a feature selection algorithm [23] to select relevant features for the developed application whereas [19] uses all the voltage and power measurements as features. In [19]–[21] authors consider a specific set of features, and a set of selected features might not suit all operating conditions.

Moreover, [19]–[21] do not consider time-series deep learning for STVSA, which could result in little consideration of voltage profile time-dependent sequential characteristics. Most machine learning-based STVSA approaches in literature do not consider bad data pre-processing, leading to unreliable assessment performance with real PMU data. Moreover, the authors do not know of any present research considering fault localization in the short-voltage stability assessment process, which could lead to the limited applicability of the assessment results in the formulation of remedial actions. The limitation in existing literature can be summarized as follows:

- Existing short-term voltage stability severity indices have large ranges of variation e.g TVSI [20].
- Existing machine learning-based STVSA approaches do not consider bad data pre-processing [19]–[21], which could lead to the unreliable assessment of results with real PMU data.
- Most existing approaches rely on a set of predefined features for voltage stability assessment limiting the ability to adapt to different operating conditions and network configurations efficiently. Machine learning techniques like 1D-CNN with automatic feature extraction are desirable for more adaptable STVSA.
- Most of the existing STVSA approaches do not consider localization modules for disturbance to aid operators in devising remedial actions [19]–[21], [24].
This paper focuses on the early detection of voltage collapse and severity quantification of short-term voltage stability events, which is paramount for efficient remedial actions. The solution for STVSA has been proposed using the 1D-CNN for time-series deep learning. The proposed approach can use historical, simulated, or hybrid time-series data to train the proposed algorithm and use trained learners to perform STVSA. 1D-CNN possesses an inherent ability to learn directly from voltage trajectories using kernels of different sizes. This paper also presents a data-preprocessing framework for the developed application. The main contributions are summarized as follows:

- A times-series deep learning-based STVSA framework using 1D-CNN is proposed for fast voltage collapse detection and severity quantification of short-term voltage stability events.
- Two novel indices: 1) System fault severity index (SFSI) and 2) System voltage deviation index (SVDI) are proposed to quantify the severity of fault-induced delayed voltage recovery.
- A fault detection and localization module are considered in the presented work to trigger short-term voltage stability assessment and identify critical buses for effective remedial actions.
- A bad-data pre-processing framework is proposed to enhance the accuracy of STVSA using the proposed approach.
- Proposed framework is validated on the IEEE 30 and IEEE 39 bus system and compared against other machine learning models to demonstrate the superiority of 1D-CNN for STVSA using time-series data analytics.

II. BACKGROUND

A. VOLTAGE STABILITY

Voltage stability refers to the ability of the system to maintain system voltages following a disturbance. The nature of disturbance and the associated time-frames are typically used to classify voltage stability phenomena into long-term voltage stability and short-term voltage stability.

1) LONG-TERM VOLTAGE STABILITY

Long-term voltage stability refers to the ability of the system to maintain network voltages at a steady value in response to gradually increasing load. Long-term voltage stability is traditionally determined in terms of power increment margin until collapse, which is computed using continuation power flow or repeated power flow simulations. With the advent of PMUs, an online Thevenin-based approach has also been adopted for real-time voltage stability margin computation.

2) SHORT-TERM VOLTAGE STABILITY

Short-term voltage stability refers to the ability of the system to recover voltages and keep them steady following a large disturbance like a three-phase fault at a transmission bus.

B. LOAD COMPOSITION AND SHORT-TERM VOLTAGE STABILITY

The load composition plays a pivotal role in determining the power system’s voltage profile after a fault is cleared on a transmission bus. In this work, the composite load (CLOD) model provided by PSS/E is used for short-term voltage stability database generation. PSS/E CLOD models the combined behavior of downstream distribution networks using small induction motor proportion, large induction motor proportion, constant power load proportion, transformer exciting current proportion, voltage-dependent load proportion, discharge lighting, and the line-losses. The proportion of induction motor load governs the behavior of the voltage profile after fault clearance. Fig. 1(a), 1(b), and Fig 1(c) respectively demonstrate a stable, moderately stable, and unstable short-term voltage stability event. It can be observed that the severity of the event is governed by load composition and fault clearing time.

III. DATA PRE-PROCESSING

In this paper, an ensemble-based method proposed in [25] is used for data anomaly detection. Once data is detected as anomaly, an anomaly treatment is performed using median filtering before performing an STVSA.

A. ANOMALY DETECTION

The ensemble-based anomaly detector relies on three individual base detectors: linear regression, Chebyshev, and DBSCAN to identify data anomalies. The anomaly scores computed by individual base detectors in the ensemble are combined using unsupervised machine learning (maximum likelihood estimator) to compute the final anomaly score for anomaly identification.
1) LINEAR REGRESSION DETECTOR
The first base-detector in the ensemble-based method is the linear regression-based detector. This base detector fits a linear model on time-series data retrieved from PMUs and specifies upper and lower thresholds to identify the anomalies.

\[ \text{Regression} = mx + s \]

High Threshold = \( mx + s + k \ast \text{dev} \)
Low Threshold = \( mx + s - k \ast \text{dev} \)

\[ \text{dev} = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} [x(i) - \text{Regression}(i)]^2} \] 

2) CHEBYSHEV BASE DETECTOR
The second base-detector in the ensemble-based method uses Chebyshev inequality to identify outliers in the data stream. This base detector is especially suitable for identifying anomalies following unknown probability distributions. Chebyshev inequality states that at most \( 1/k^2 \) samples in a data stream can be \( k \) standard deviations away from the mean for any probability distribution.

\[ Pr(|X - \mu| \leq k\sigma) \leq (1 - 1/k^2) \]

3) DBSCAN BASE DETECTOR
The third base detector relies on DB-SCAN clustering to identify anomalies in the data stream. DBSCAN uses two hyperparameters \( \epsilon \) (distance criterion to form clusters) and \( \text{minPts} \) (minimum points required to form a cluster). If some data points do not become part of any cluster after DB-SCAN-based clustering, they are identified as anomalies.

B. ANOMALY TREATMENT
Ensemble-based moving-window median filtering is performed on time-series data used for STVSA. The number of samples selected in the moving window used for anomaly detection is chosen based on the temporal location of \( k^{th} \) observation \( (x_k) \). Firstly ensemble-based bad-data detection is performed to find value of \( EBAD_k \) (Anomaly flag) for \( k^{th} \) observation. \( EBAD_k \) value is 1 if \( k^{th} \) observation is detected as outlier and 0 otherwise. Ensemble-based median filtering criterion is defined as follows for \( k^{th} \) observation \( (x_k) \).

\[ \hat{x}_k = \begin{cases} m_k, & \text{if } EBAD_k = 1. \\ x_k, & \text{otherwise}. \end{cases} \]

\[ m_k = \begin{cases} \text{median } \{(x_{k-2}, \ldots, x_k, \ldots, x_{k+2})\}, & \text{if } k - 2 > 0 \\ \text{median } \{(x_1, \ldots, x_k, \ldots, x_{k+2})\}, & \text{otherwise} \end{cases} \]

Variable \( m_k \) represents the median of the moving window, and the size of the moving window depends on the temporal location of \( k^{th} \) sample. Fig. 2 demonstrates the data-prepossessing framework adopted for STVSA.

IV. SEVERITY AWARE DATA-DRIVEN SHORT TERM VOLTAGE STABILITY ASSESSMENT
In this section, the severity-aware framework proposed for STVSA is presented. The real-time implementation details of the proposed framework are shown in Fig. 3. The wide-area measurement data is first retrieved, and data processing is performed to mitigate the impact of anomalies. The filtered data is fed to the disturbance detection and localization module, where disturbance detection triggers the STVSA application and also initiates the disturbance localization process. Once a disturbance is detected STVSA module performs the voltage stability assessment.

The presented STVSA application module uses a cascaded classification-regression approach based on 1D-CNN for STVSA. A classification problem is presented and solved to differentiate between voltage collapse and delayed voltage recovery scenarios. Two indices are introduced in this work for short-term voltage stability severity assessment. A regression problem is presented and solved to quantify the severity of short-term voltage stability events.

A. DISTURBANCE DETECTION AND LOCALIZATION
In this work, the synchrophasor-based event detection, classification, and localization approach proposed in [26] is used for detecting and localizing disturbance. Disturbance detection and localization module take voltage, current, real power, reactive power, and frequency measurements at all PMUs in the network as input. Disturbance detection is used to trigger the short-term voltage stability assessment process, and disturbance localization information is relayed to the concerned operators responsible for taking remedial actions.
Once a window of time-series data is available, DB-SCAN is used to cluster the data points. DB-SCAN uses $\epsilon$ (allowable distance to include points in the cluster) and $minPts$ (minimum points needed to form a cluster) as hyperparameters to cluster time-series data. If all the points are clustered together by DB-SCAN, then the steady-state mode of operation is detected. On the other hand, if DBSCAN detects more than 1 cluster and some un-clustered data points, an event is detected.

2) PHYSICS BASED EVENT CLASSIFICATION AND DISTURBANCE LOCALIZATION

Once an event is detected, the cluster changes in voltage, current, active power, reactive power, and frequency data points are first analyzed to classify events. The event classification is performed as follows:

1) Active Power Event: If DB-SCAN based cluster change is only detected in current and the active power flow samples, an active power event like load change is detected. In this case, the STVSA application will not be triggered for voltage stability assessment.

2) Reactive Active Power Event: If DB-SCAN based cluster change is only detected in voltage, and the reactive power flow samples, a reactive power event like capacitor bank trip is detected. In this case, the STVSA application will not be triggered for voltage stability assessment.

3) Disturbance: If DB-SCAN based cluster change is detected in voltage, current, active power, reactive power, and frequency samples, then the disturbance/fault event is detected. Once such an event is detected, the STVSA application will be triggered to initiate voltage stability assessment.

Once a disturbance is detected, localization is performed using a normalized score to identify the most likely PMUs near the disturbance location. The normalized score is computed using four statistical parameters. The statistical parameters are calculated using a window of 30 voltage magnitude data points (15 data points before the detected event and 15 data points after the detected event). The statistical parameters for each PMU are defined in Table 1, where $V_i$ represents the $i^{th}$ voltage magnitude sample in voltage time series ($V$), and $N$ is the number of samples in PMU datastream. $\mu_i$ is the mean of voltage samples in the PMU data stream.

After computing the statistical parameters, the normalized score for disturbance localization is computed as follows:

$$NS = (SE + CF) \times (SD + R)$$ (6)

In this work, the top 3 PMUs with the highest normalized score (NS) are detected as the closest physical locations to the disturbance. The operators use this information to take remedial actions.

### B. CLASSIFICATION PROBLEM FOR FAST VOLTAGE COLLAPSE DETECTION

1) CLASSIFICATION PROBLEM FORMULATION

This work adopts time-series deep learning for early prediction of fast voltage collapse, which would allow operators to
take timely corrective actions. This is realized by formulating a classification problem that can differentiate between fast voltage collapse (FVC) and FIDVR using a small number of voltage time-series samples. The classification problem is solved in this work using 1D-CNN. If a large number of labeled voltage sequences are available, the time-series deep learning approach can be adapted to detect fast voltage collapse. Training data can come from the field, simulations, or a hybrid of both sources. This work relies on time domain simulations to generate training data.

2) 1D-CNN FOR TIME SERIES CLASSIFICATION

1D-CNN is a type of artificial neural network, especially suitable for time-series classification and regression. 2D-CNNs [27] have been popular among machine learning researchers for image processing tasks, but CNNs did not find application in time-series regression and classification until recently. Power system researchers have deployed 2D-CNN for load forecasting [28], renewable generation forecasting [29], and electricity price forecasting [30]. As of now, authors do not know of any application of 1D-CNN for short-term voltage stability assessment. 1D-CNN has been introduced recently, and they possess a special feature to use convolutional operator on 1D time-series data. 1D-CNN can automatically learn useful features from time-series data using convolutional kernels of different sizes. For a signal \( a \) of length \( n \), convolution with a filter \( f \) of size \( m \) and stride length \( s \) is expressed as follows:

\[
\text{Conv1D}(a,f) = \left[ \text{Conv1D}(a_i,f), \forall i \in (1, \frac{n-m}{s} + 1) \right]
\]

\[
\text{Conv1D}(a,f) = \sum_{k=-m}^{m} a_{i-kf}
\]  

In this work, 1D-CNNs are used to identify fast voltage collapse, which is a scenario after disturbance clearance in which voltage is unable to recover, and a system voltage collapse happens. In this work, the collapse criterion is selected in compliance with NERC guidelines on system performance following extreme events, which states that all system voltages should recover above 0.8 per unit within 4 seconds after disturbance clearance [15]. Extreme events result in the loss of two or more bulk electric system elements.

1D-CNN consist of multiple or single convolutional layers followed by pooling, dropout, and flattening layers. The convolution operator convolves a filter of specific length with the input time series (in the case of the first layer) or the input sequence of a particular layer in the case of subsequent layers. Suppose \( y_i^{l-1} \) is the output of \( i^{th} \) neuron in layer \( l-1 \) and input to the \( k^{th} \) neuron in layer \( l \), then output of neuron \( k \) in layer \( l \) after convolution and application of activation function \( f(\cdot) \) is given as follows:

\[
y_k^{l} = f \left( b_k^{l} + \sum_{i=1}^{N_{l-1}} \text{Conv1D}(w_{ik}^{l-1}, y_i^{l-1}) \right)
\]

The flattening layer is followed by fully connected (FC) layers or multi-layered perceptron (MLP) layers. MLP layers before the final or output layer use different activation functions like ReLU, and the last MLP layer uses \( \text{softmax} \) as activation function which gives the probability of output classes. Prediction can be made based on the highest probability. This probabilistic nature of CNN output also makes it suitable for real-time control applications, which require a certain confidence level to ensure reliable decision-making.

1D-CNN, like other neural networks, are optimized using back-propagation. In the case of classification, the loss is minimized using solvers like adaptive moment estimation (ADAM) and stochastic gradient descent (SGD). Loss is computed at the final layer for \( t^{th} \) iteration, which is given as follows if there are \( C \) classes in the classification problem:

\[
L(t) = \sum_{i=1}^{C} Y_i \log(y_i(t))
\]

Loss is back propagated, and weights (and similarly biases) in all layers are optimized as follows:

\[
w(t+1) = w(t) - \epsilon \frac{\partial L}{\partial w}
\]

C. REGRESSION PROBLEM FOR SEVERITY ASSESSMENT

The regression problem for severity assessment of short-term voltage stability is presented in this section. Firstly, the indices used to predict the severity status are presented, followed by regression problem formulation to predict future values of the developed indices for severity quantification.

1) INDICES FOR STVSA

Two novel indices are presented to solve the regression problem for determining the severity of short-term voltage stability events. The first index introduced in this work is the system voltage deviation index (SVDI). This index is computed using the knowledge of pre-fault voltages and user-specified minimum system voltages. This index is defined as follows:

\[
\text{SVDI}(t) = \sqrt{\frac{\sum_{i=1}^{N_b} |V_i(t) - V_{i,pre}|^2}{\sum_{i=1}^{N_b} |V_i^{min} - V_{i,pre}|^2}}
\]

This index gives information about the system voltage profile at a snapshot in time after disturbance clearance. The value of SVDI computed at \( T_s \) (STVSA severity prediction time) is used as an index to quantify severity.

\[
\text{SVDI}_{Ts} = \sqrt{\frac{\sum_{i=1}^{N_b} |V_i(T_s) - V_{i,pre}|^2}{\sum_{i=1}^{N_b} |V_i^{min} - V_{i,pre}|^2}}
\]

The second index introduced in this work is System Fault Severity Index (SFSI). This index is computed considering the historical values of SVDI and considers the
TABLE 2. Severity indices for time-series data in fig. 1.

| STVSA Status                | SFSI\(_{T_c}\) | SVDI\(_{T_{R}}\) |
|-----------------------------|----------------|-----------------|
| Stable [Fig. (1a)]          | 0.1379         | 0.1734          |
| Moderately Stable [Fig. (1b)] | 0.6143         | 0.8296          |
| Unstable [Fig. (1c)]        | 1.0359         | 1.0879          |

variation in voltage profile. The higher the index’s value, the more is the severity of the short-term voltage stability event.

\[
SFSI(t) = \begin{cases} 
0, & t < t_{clr} \\
SVDI(t), & t = t_{clr} \\
\frac{SFSI(t-\Delta T)(t-\Delta T-t_f)+SVDI(t)\Delta T}{t-t_f}, & t > t_{clr} 
\end{cases}
\]  

(14)

**SFSI** provides information about the severity and possible impacts on the system. **SFSI\(_{T_c}\)** is the value of the system fault severity index at the selected prediction time after disturbance clearance.

\[
SFSI_{T_c} = \frac{SFSI(T_s-\Delta T)(T_s-\Delta T-t_f)+SVDI_{T_{R}}\Delta T}{T_s-t_f}
\]  

(15)

Here, \(N_b\) represents number of system buses; \(t_f\) represents disturbance occurrence time; \(t_{clr}\) represents disturbance clearance time; \(T_s\) represents STVSA severity prediction time and \(\Delta T\) represents the PMU sampling rate.

In this work, **SVDI\(_{T_{R}}\)** and **SFSI\(_{T_c}\)** are used to quantify the short-term voltage stability event’s severity. These indices along with voltage profile are shown in Table 2 for stable, moderately stable, and unstable short-term voltage stability events in Fig. 1, where \(T_s = t_{clr} + 2\) seconds. It can be observed that the proposed indices can quantify the severity of short-term voltage stability events. It is also observed that the range of variation for **SFSI\(_{T_c}\)** and **SVDI\(_{T_{R}}\)** is narrow in comparison to other indices in literature [19], [20] which results in easier interpret-ability.

2) 1D-CNN FOR TIME SERIES REGRESSION

In this work, 1D-CNN is used to make an early prediction of **SVDI\(_{T_{R}}\)** and **SFSI\(_{T_c}\)** for severity quantification. In the case of regression, 1D-CNN adopts similar architecture as in the case of classification. The difference between 1D-CNN for classification and regression lies in the final layer, where instead of softmax activation function, \(\text{reLU}\), or \(\text{tanh}\) are used to predict the numerical value at the final layer. In this work, \(\text{reLU}\) is used in the final layer. Once the predicted value is available instead of loss, the prediction error is computed and propagated back during optimization to update weights and biases. Mean squared error at \(t^{th}\) iteration is defined as follows for solving regression problem with \(N_r\) variables.

\[
E(t) = \sum_{i=1}^{N_r} \frac{(y_i(t) - Y_i)^2}{N_r} 
\]  

(16)

Error is back propagated and weights (and similarly biases) in all layers are optimized as follows:

\[
w(t+1) = w(t) - \epsilon \frac{\partial E}{\partial w}
\]  

(17)

STVSA application module in Fig. 3 uses a 1D-CNN classifier at the first stage for fast voltage collapse prediction. In the second stage, the proposed severity assessment regressor would be used to predict the value of **SFSI\(_{T_c}\)** and **SVDI\(_{T_{R}}\)** proactively using a limited number of time-series samples. In this work, both first and second-stage predictions are made at \(T_R\). \(T_R\) is the STVSA reporting time which is chosen to be 1 second after fault/disturbance clearance (\(T_R = t_{clr} + 1\)) in this work (60 PMU samples). Comparative analysis with different reporting times is also presented in section V. The pseudocode for real-time short-term voltage stability assessment is provided in Algorithm-I.

Algorithm 1: Pseudocode: Real-Time STVSA Using 1D-CNN

1. Start STVSA at \(t^{(0)} = t_{start}\), set \(Clear = 0\), and \(Fault = 0\). Analyze PMU voltage sample set at \(t^{(0)}\).
2. if Fault is identified then
   3. Set Clear = 0, and Fault = 1.
   4. Analyze next PMU voltage sample set at \(t^{(i)} = t^{(i-1)} + \Delta T\).
5. if Fault is identified then
   6. Set Clear = 0, and Fault = 1.
7. if Fault is cleared & Clear == 0 then
   8. Set Clear = 1, Fault = 0 and \(t_{clr} = t^{(i)}\).
9. if Clear == 1 & Fault == 0 then
   10. Collect voltage samples for STVSA:
       \[V_{SET} = V^{t_{clr}} \cdot t^{(i)}\]
   11. if \(t^{(i)} == T_R\) then
       - Perform voltage collapse detection using FVC.
       - Perform severity assessment using SAR.
       - Report collapse label and severity indices.
12. Go back to step 4 to collect and analyze next voltage sample set.

V. RESULTS AND DISCUSSION

In this section, the performance of the developed short-term voltage stability framework is demonstrated. Firstly, the database generation methodology and performance metrics for 1D-CNN-based short-term voltage stability assessment application are discussed. The proposed application’s disturbance detection and visualization module’s performance is then presented using simulated case studies. Training and testing validation of the 1D-CNN-based STVSA application module is demonstrated in terms of performance metrics.
Lastly, the performance with different reporting rates and for different topologies is also discussed.

### A. DATABASE GENERATION FOR SHORT-TERM VOLTAGE STABILITY ASSESSMENT

In this work, a short-term voltage stability database for the presented machine learning application is generated for IEEE-30 and IEEE-39 bus system using time-domain simulations carried out in PSS/E. Since transmission systems are inherently very stable, multiple contingencies are modeled in some cases to get reasonable contributions from unstable scenarios. A randomized data generation and randomized training methodology are adopted to limit overfitting in this work. The generated data is diverse in terms of random fault clearing times and random load compositions. The training data is randomly selected to ensure data diversity so that overfitting can be limited.

#### 1) IEEE 30 BUS SYSTEM

This work uses the PSS/E CLOD model with the IEEE-30 bus system to generate training, validation, and testing data to solve the STVSA problem. PSS/E CLOD model comprises small motor, large motor, transformer exciting current, discharge lighting, constant power, voltage-dependent loads, and distribution feeder losses. A python-based Monte-Carlo simulation setup is used to generate diverse data with different load compositions and with different fault/disturbance clearing times. Table 3 shows the variation ranges adopted in time-domain simulations for various PSS/E CLOD model components.

In this work, 1500 scenarios are generated using 10-second time-domain simulations with different load model compositions. Among the generated 1500 scenarios, 1189 scenarios show delayed voltage recovery with varying severity but stable response (Voltage recovers above 0.8 per unit at all the buses). Among generated scenarios, 311 scenarios show voltage collapse, which means that voltage cannot recover post fault/disturbance.

#### 2) IEEE 39 BUS SYSTEM

This work uses the PSS/E CLOD model with the IEEE-39 bus system to generate training, validation, and testing data. Two thousand (2000) test instances are generated for IEEE 39 bus system. Each instance consists of system voltage measurements obtained using 10 second time domain PSS/E simulations with randomly chosen CLOD model specifications. Out of 2000 instances, 676 instances show voltage collapse, and 1324 instances show delayed voltage recovery with different voltage recovery times. For each instance, the fault is introduced at 2 seconds and removed after a random clearing time selected in the range of 5-8 cycles.

#### 3) IEEE 118 BUS SYSTEM

In order to generate training data for IEEE 118 bus system load at all, the system buses are randomly selected to be 1-1.3 times the base caseload. Induction motors are modeled at several buses to simulate FIDVR scenarios. The fault clearing times are randomly selected to be between 4-8 cycles. In total, 1700 scenarios are simulated, among which 500 scenarios show voltage collapse (Voltage cannot recover to 0.8 times the pre-fault voltage). The rest of the simulated scenarios demonstrate delayed voltage recovery with varying voltage recovery times.

### B. PERFORMANCE METRICS

This work’s proposed methodology uses accuracy for measuring classification performance and mean-squared error (M.S.E) for measuring regression performance. Accuracy is defined by eq. (18) where TP stands for detected true positive, TN stands for true negative, FP stands for false positive, and FN stands for false negative. M.S.E is defined by eq. (19) $\hat{y}_i$ is the value predicted by the trained regressor, and $y_i$ is the variable’s actual value, and $N$ is the number of predicted outputs.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (18)$$

$$\text{M.S.E.} = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2 \quad (19)$$

### C. DISTURBANCE DETECTION AND LOCALIZATION

Disturbance detection and localization are performed for the developed application using DB-SCAN clustering-based approach. In this section, the disturbance localization results are demonstrated for IEEE 30 bus system and IEEE 39 bus system.

Fault/disturbance localization and detection performance is demonstrated for IEEE 30 bus system in Table 4, and in Table 5 for IEEE 39 bus system. Many events were simulated to validate the disturbance detection and localization performance, but few simulation scenarios are demonstrated in Table 4, and Table 5. It is observed that DB-SCAN clustering-based event detection can accurately detect a disturbance event in a wide-area PMU data stream. This detection triggers the STVSA application module and also the disturbance localization module in parallel for fast processing. STVSA results are computed using the developed 1D-CNN-based learners, and disturbance localization results are computed by identifying the top 3 PMUs with the highest normalized score.
TABLE 4. Disturbance detection and localization- IEEE 30 bus system.

| Sr. No | Actual Event | Detected Event | Actual Event Location | Detected buses | Normalized Score |
|--------|--------------|----------------|-----------------------|----------------|------------------|
| 1      | Three phase fault | Fault | Bus 4 | Bus 4 | 2.967 | 2.959 | 2.950 |
| 2      | Three phase fault | Fault | Bus 8 | Bus 8 | 2.977 | 2.667 | 2.655 |
| 3      | Three phase fault | Fault | Bus 20 | Bus 20 | 2.599 | 2.487 | 2.323 |

TABLE 5. Disturbance detection and localization- IEEE 39 bus system.

| Sr. No | Actual Event | Detected Event | Actual Event Location | Detected buses | Normalized Score |
|--------|--------------|----------------|-----------------------|----------------|------------------|
| 1      | Three phase fault | Fault | Bus 13 | Bus 13 | 2.8864 | 2.856 | 2.827 |
| 2      | Three phase fault | Fault | Bus 25 | Bus 25 | 2.8703 | 2.516 | 2.4516 |
| 3      | Three phase fault | Fault | Bus 34 | Bus 34 | 2.9364 | 2.9145 | 2.7119 |

D. STVSA PERFORMANCE VALIDATION

1) FAST VOLTAGE COLLAPSE DETECTOR (FVC DET.)

a: IEEE 30 BUS SYSTEM

In order to perform training, 900 instances are randomly selected from generated 1500 generated scenarios for training the fast voltage collapse detector, and 100 instances are selected for validation. Each instance used for training and validation contains 60 samples starting from clearing time $t_{clr}$. The remaining 500 scenarios are used to select instances of test data. Learning rate, epochs, and batch size parameters of 1D-CNN are optimized using grid search to achieve the best performance with 5-fold cross-validation (optimized epochs: 50, optimized learning rate: 0.0002, and optimized batch-size: 5). It can be observed from Table 6 and Fig. 4 (a) that the trained and optimized 1D-CNN provides excellent training, validation, and test accuracy. Operators can reliably detect voltage collapse in advance and take timely remedial actions by relying on a 1D-CNN-based fast voltage collapse detector.

b: IEEE 39 BUS SYSTEM

In order to train a fast voltage collapse detector, the IEEE-39 bus system 1300 instances are used for training, and 200 instances are used for validation. The remaining 500 samples are used for test performance evaluation. Learning rate, number of epochs, and batch-size are optimized using grid search algorithm to obtain the best performance using 5-fold cross-validation (optimized epochs: 30, optimized learning rate: 0.001, and optimized batch-size: 25). In each instance of training, 60 samples starting from clearing time are used, and the same range of samples is utilized for validation and testing performance evaluation. It can be observed from Table 6 and Fig. 5 (a) that 1D-CNN based fast voltage detector can reliably detect voltage collapse.

c: IEEE 118 BUS SYSTEM

In order to train the fast voltage collapse detector, 1000 scenarios are randomly selected for training, 150 are selected for validation, and 550 are selected for test performance evaluation. The learning rate, epochs, and batch size parameters of 1D-CNN are optimized using grid search to achieve the best performance with 5-fold cross-validation (optimized epochs: 30, optimized learning rate: 0.0001, and optimized batch-size: 15). It can be observed from Table 6 and Fig. 6 (a) that 1D-CNN based fast voltage detector can reliably detect voltage collapse for the 118 bus test system.

2) SEVERITY ASSESSMENT REGRESSOR (SAR)

a: IEEE 30 BUS SYSTEM

In order to train multi-output SAR, 900 instances for training and 189 samples for validation are randomly selected. The remaining 100 samples are used for testing. Learning rate, epochs, and batch-size are optimized using grid-search to achieve the best performance with selected parameters. It can be observed from Table 6 and
Fig. 4 (b) that the severity of short-term voltage stability event can be accurately computed by the proposed 1D-CNN based architecture.

**b: IEEE 39 BUS SYSTEM**

In order to train multi-output SAR 1024, stable instances with delayed voltage recovery are selected to train the 1D-CNN regressor. 200 instances are used for validation purposes, and 100 instances are used for testing evaluation. Table 6 and Fig. 5 (b) show that the severity of short-term voltage stability event can be accurately predicted once a severity-aware regressor is trained.

**c: IEEE 118 BUS SYSTEM**

In order to train SAR for IEEE 118 bus system, 800 scenarios are randomly selected for training, 200 are selected for validation, and 200 are selected for test performance evaluation. The learning rate, epochs, and batch size parameters of 1D-CNN are optimized using grid search to achieve the best performance with 5-fold cross-validation. It can be observed from Table 6 and Fig. 6 (b) that 1D-CNN based fast voltage detector can reliably perform severity assessment for the 118 bus test system.

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**TABLE 7. Performance comparison with & without bad data treatment.**

| Test System | Assessment Stage | Metric    | Filtered   | Unfiltered |
|-------------|------------------|-----------|------------|------------|
| IEEE 30     | PVC det.         | Accuracy  | 99.40%     | 88.60%     |
|             | SAR              | M.S.E.    | 1.85%      | 8.86%      |
| IEEE 39     | PVC det.         | Accuracy  | 99.10%     | 96.60%     |
|             | SAR              | M.S.E.    | 0.661%     | 6.81%      |
| IEEE 118    | PVC det.         | Accuracy  | 99.20%     | 94.7%      |
|             | SAR              | M.S.E.    | 0.792%     | 1.262%     |

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**E. IMPACT OF BAD DATA ON STVSA PERFORMANCE**

In order to evaluate the impact of bad-data on STVSA performance, test sets are corrupted with missing data and outliers. STVSA is then performed with and without the proposed filtering framework. It can be observed from Table 7 that without bad-data processing, the performance of STVSA is appreciably degraded, and the proposed bad data-prepossessing approach enhances the accuracy of STVSA. The residue of SFSI and SVDI for IEEE-30 bus system are shown in Fig. 7 and residues for IEEE-39 bus system are shown in Fig. 8. The residues for IEEE-118 bus system are shown in Fig. 9.

**F. COMPARISON WITH DIFFERENT LEARNING ALGORITHMS**

The proposed algorithm is compared with three other learning algorithms: 1) Random forest (RF), 2) Support Vector Machine (SVM), and 3) Long short-term memory (LSTM) neural networks. Random forest and SVM do not directly possess the ability to deal with time series. Still, they can deal with time series either by flattening the time series or using features defining time series characteristics. In order to train RF and SVM algorithms, the IEEE 30 bus system input matrix ($60 \times 30$) is flattened to convert it to an 1800 length vector. Similarly, for the IEEE-39 bus system, the $60 \times 39$ input matrix is converted to a 2340 size vector. LSTM-neural networks can deal with time series and take $60 \times 30$ matrix for the IEEE-30 bus system and $60 \times 39$ matrix for IEEE-39 bus system directly as input and consider it as time-series.
It is observed from Table 8 that 1D-CNN and LSTM performance is significantly superior to RF and SVM. The main reason is that both these learning algorithms can consider time-varying characteristics of voltage measurements in the snapshot. Performance accuracy of 1D-CNN is slightly superior to LSTM based implementation, but 1D-CNN is much more computationally efficient in terms of the number of epochs required for training and the total training time. The presented application observed that fewer variables had to be trained for 1D-CNN than LSTM to achieve similar performance.

It is vital to ensure that the chosen algorithm does not take too much training time for efficient online implementation because practical databases have to be updated periodically to adapt to changing conditions. Table 9 shows different learning algorithms’ training time with the developed databases. It is observed that RF and SVM provide speedy training times but with much less accuracy for STVSA applications. 1D-CNN and LSTM take more time to train because of many trainable parameters and iterative forward-backward propagation-based training. Comparing 1D-CNN and LSTM, it is learned that 1D-CNN takes much less training time to achieve similar accuracy as LSTM for the developed application. Experimental case studies show that 1D-CNN provides an excellent trade-off between accuracy and training time and is thus very suitable for real-time implementation.

G. IMPACT OF CHANGE IN NETWORK TOPOLOGY ON STVSA PERFORMANCE

The developed machine learning algorithm for STVSA must adapt well for different network topologies. Since 1D-CNN relies explicitly on the nature of time-series data after disturbance, it is expected that the developed algorithm would adapt well for non-critical network contingencies. The impact of change in topology is demonstrated by generating STVSA datasets for different network topologies and performing short-term voltage stability assessments using learners trained from data generated with base network topology.

TABLE 8. Comparison with different learning algorithms.

| Learning Algorithm | IEEE 30 bus system | IEEE 39 bus system |
|--------------------|--------------------|--------------------|
| PVC det. (Accuracy) | SAR (M.S.E.)       | PVC det. (Accuracy) | SAR (M.S.E.) |
| RF                 | 94.0%             | 8.95%              | 93.80%         | 5.19%          |
| SVM                | 96.6%             | 7.17%              | 94.20%         | 5.029%         |
| LSTM               | 99.8%             | 1.75%              | 98.8%          | 0.87%          |
| 1D-CNN             | 99.8%             | 1.54%              | 99.8%          | 0.6056%        |

TABLE 9. Comparison of training times.

| Learning Algorithm | IEEE 30 bus system | IEEE 39 bus system |
|--------------------|--------------------|--------------------|
| PVC det. (sec)     | SAR (sec)          | PVC det. (sec)     | SAR (sec) |
| RF                 | 0.234              | 7.56               | 0.67      | 16.44   |
| SVM                | 0.3018             | 1.27               | 0.15      | 1.104   |
| LSTM               | 111.13             | 72.67              | 46.27     | 50.58   |
| 1D-CNN             | 27.01              | 15.51              | 23.82     | 17.44   |

TABLE 10. Comparison of features with existing literature.

| Framework          | Collapse Detection | Severity Assessment | Bad data treatment | disturbance localization |
|--------------------|--------------------|---------------------|--------------------|-------------------------|
| Ensemble [20]      | ✓                  | ✓                   | ✓                  | ✓                       |
| RVFL [19]          | ✓                  | X                   | X                  | X                       |
| RNN [24]           | ✓                  | X                   | X                  | X                       |
| Proposed           | ✓                  | ✓                   | ✓                  | ✓                       |

1) IEEE 30 BUS SYSTEM

Four different network topologies are considered for IEEE 30 bus system. Each topology in Table 11 is simulated by performing dynamic simulation with an outage of a single
TABLE 11. Performance for different network topologies with base training data- IEEE 30 bus system.

| Topology | Outage Branch | # of datasets | PVC det. (Accuracy) | SAR (M.S.E.) |
|----------|---------------|---------------|---------------------|--------------|
| T1       | 23            | 100           | 99%                 | 1.56%        |
| T2       | 29            | 100           | 92%                 | 1.38%        |
| T3       | 21            | 100           | 96%                 | 1.62%        |
| T4       | 23            | 100           | 96%                 | 1.53%        |

TABLE 12. Performance for different network topologies with base training data- IEEE 39 bus system.

| Topology | Outage Branch | # of datasets | PVC det. (Accuracy) | SAR (M.S.E.) |
|----------|---------------|---------------|---------------------|--------------|
| T1       | 17            | 100           | 100%                | 0.57%        |
| T2       | 21            | 100           | 99%                 | 0.65%        |
| T3       | 26            | 100           | 98%                 | 0.993%       |
| T4       | 28            | 100           | 99%                 | 0.602%       |

branch. It is observed that the fast voltage collapse detector’s performance is reasonable for topologies T1, T3, and T4, but for contingency T2, the prediction accuracy drops to 92% (status of 92 out of 100 contingencies predicted accurately). The performance of the severity-aware regressor is reasonable for all the considered contingencies.

2) IEEE 39 BUS SYSTEM

Four different network topologies are considered for IEEE 39 bus system in Table 12. Each contingency removes one branch from the base case for dynamic simulation-based data generation for STVSA. Load composition is randomly chosen from specifications in Table 3 to generate data for each topology. It can be observed that reasonable performance is achieved for all the considered topologies in Table 12 using 1D-CNN learner trained with data generated from base topology simulations.

The data arriving for the STVSA application is non-stationary i.e., it is reasonable to expect that data could come from a topology that is different from the assumed base topology used in training. Performance of 1D-CNN learner for different topologies in Tables 11 and Table 12 indicates that the proposed algorithm can adapt well to different system configurations. It is also observed that performance can deteriorate for some topologies like topology T2 in Table 11. This phenomenon in ML literature is known as concept drift [31]. It is important to identify the source of concept drift [32] i.e., identify the contingencies for which the trained algorithm does not perform well, and then enrich the training data to enhance performance.

H. IMPACT OF WINDOW LENGTH ON SHORT-TERM VOLTAGE STABILITY ASSESSMENT

Time-frame of short-term voltage stability demands fast assessment to reduce the impact of FIDVR by taking timely corrective actions. In this subsection impact of reporting time on the accuracy of assessment is studied. STVSA is performed with reporting times of 0.25 seconds (15 samples at 60 fps PMU rate), 0.5 seconds (30 samples), 0.75 seconds (45 samples), along with 1 second (60 samples) after fault/ disturbance clearing time. It is observed for both test systems that larger reporting time after fault clearance leads to enhancement of prediction accuracy for both classification and regression tasks. Results are shown in Table 6 for the IEEE-39 bus system in the interest of space. For real-time implementation, fast assessment can be performed to prepare operators early for corrective actions, which can be taken if multiple assessments indicate the criticality of short-term voltage stability event (For instance, if voltage collapse prediction is received consecutively at 0.25 and 0.5 seconds after fault/ disturbance clearance then remedial actions should be executed).

I. DISCUSSION

In this paper, a 1D-CNN-based STVSA framework has been developed. Based on detailed training and testing studies for IEEE test systems following are concluded:

- The developed framework deploys time-series deep learning, the first time in existing literature for short-term voltage stability assessment, a key power system stability issue. Previously various feature-driven algorithms have been used for STVSA. Time-series deep learning fits more naturally to analyze fault-induced delayed voltage recovery events leading to short-term voltage stability issues.
- Most of the existing research considers STVSA as a binary collapse detection problem. The developed framework in this paper uses a two-stage assessment where the first stage performs collapse detection and the second stage performs severity quantification for comprehensive voltage stability assessment.
- Two novel indices with a reasonable range of variation are developed in this work for severity quantification. The first index SVDI captures the instantaneous behavior of post fault voltages to quantify severity. The second index SFSI captures the historical behavior of SVDI from fault clearance till the point at which it is computed.
- The comparative studies highlight the superior performance of 1D-CNN for the implementation of the proposed framework compared to traditional machine learning algorithms.
- Most of the existing STVSA research does not explicitly consider bad data impact mitigation. A comprehensive
data-processing framework is considered in this work to mitigate the impact of data anomalies on STVSA appropriately.

- In this work, along with STVSA, fault detection and localization blocks are considered as part of the framework to enhance situational awareness for power system operators responsible for remedial actions.

VI. CONCLUSION

In this paper, the short-term voltage stability assessment (STVSA) framework based on 1D-CNN is presented. 1D-CNN is highly effective for time-series regression and classification tasks as it can automatically extract useful features by relying on kernels of different sizes. The proposed approach in this work takes post fault/ disturbance clearance voltage trajectories as input and provides assessment in terms of fast voltage collapse detection and quantification of short-term voltage stability event severity. The severity of short-term voltage stability events is assessed in two novel indices proposed in this work. Moreover, a bad-data pre-processing framework is presented to deal with missing data and outliers in the sequence of voltage measurements retrieved from PMUs. The proposed approach is validated using the IEEE-30 and IEEE-39 bus systems to demonstrate the effectiveness and compared against common ML algorithms to demonstrate the superiority of 1D-CNN for real-time STVSA. The performance of the proposed algorithm is also demonstrated for various power grid topologies to validate effectiveness under varying system configurations. Fault/ disturbance detection and localization are considered for the intelligent triggering of short-term voltage stability assessment and identifying critical buses for effective remedial actions. Future works include validating the proposed algorithm with real fault/ disturbance data, integrating with existing operational practices, and implementing the proposed algorithm with variable STVSA reporting rates for faster assessment. Also, a machine learning-based closed-loop control to mitigate short-term voltage stability issues by relying on fault/ disturbance localization and STVSA will be explored in an integrated manner. Future works also include implementation of ensemble learning to deal with the unbalanced nature of data with less unstable scenarios compared to stable scenarios.

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