Bus-Centric Temporal Graph Neural Network Framework for Fault Localization and- Risk Profiling Using PMU Time Series Data

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***Abstract*—In modern power systems, rapid and accurate detection of dynamic events at the bus level is critical for ensuring grid reliability and operational resilience. The paper proposes a novel bus-centric event detection framework that integrates a Temporal Graph Neural Network (TGNN) with unsupervised clustering and supervised classification for event localization and risk assessment using Phasor Measurement Unit (PMU) data. A rich set of twelve statistical and dynamic features per bus including voltage/frequency derivatives, phase angle trends, and rolling statistics is extracted to represent temporal-spatial behaviour withing power grid nodes. a bus-wise risk index is formulated by combining voltage, frequency, and angle deviations with regression-based R^2 stability trends, enabling the ranking of critical buses. Furthermore, the performance of the proposed framework will be rigorously evaluated using a comprehensive classification metrics, including Accuracy, F1-score and Matthews Correlation Coefficient (MCC). The proposed framework offers a scalable and interpretable solution for real-time contingency analysis, with strong implications for preventive control in smart grids.**

Keywords— Temporal Graph Neural Network (TGNN), Phasor Measurement Units (PMU), Power System Stability, Synchrophasor Analytics, Multivariate Time Series Analysis

I. INTRODUCTION

Modern power grids are becoming increasingly complex due to the rapid evolution of generation, load dynamics, and control mechanisms. In the transmission sector, the increasing vulnerability to dynamic load changes and fluctuating generation patterns are primarily driven by large-scale integration of renewables such as wind farms and solar parks. The incorporation of multiple HVDC links further introduces operational challenges, particularly in coordinating AC and DC subsystems. These advancements necessitate the deployment of extensive transmission line infrastructure and inverter-based resources. To ensure real-time observability and stability under such dynamic conditions, utilities are increasingly adopting Wide-Area Monitoring Systems (WAMS) using Phasor Measurement Units (PMUs). This shift enables fine-grained, time-synchronized data collection at the bus level, laying the foundation for bus-centric event detection and classification. Advanced learning frameworks such as Temporal Graph Neural Networks (TGNNs) are being employed to exploit both spatial and temporal dependencies in synchrophasor data, offering framework of detecting local anomalies, disturbances, and grid instabilities across buses.

In the distribution sector, the complexity is driven by the widespread electrification of transport and heating, which increases the variability and unpredictability of loads. This necessitates a deeper understanding of load diversity and the behaviour of end-use devices. The proliferation of rooftop solar panels, behind-the-meter battery storage, and smart electric meters has transformed traditionally passive distribution systems into active, bidirectional networks. The integration of these distributed energy resources (DERs), along with the emergence of microgrids and demand-side energy management, requires advanced monitoring and control strategies at the edge of the grid. The evolution of power grid significantly impacts the reliability of fault detection using rule-based schemes. These traditional methods are often reliant on static thresholds and impedance assumptions, which fail to adapt to topological changes, evolving load conditions, or measurement inaccuracies inherent in large-scale grids. As a result, there is an evident shift toward more adaptive, data-driven frameworks capable of learning from high-resolution synchrophasor data. Most classical approaches to fault analysis focus either on identifying the fault type or detecting its occurrence on specific transmission lines. However, such techniques typically do not account for the dynamic behaviour of modern grid configurations or scale efficiently with the inclusion of new monitoring features. This limitation necessitates a move toward advanced modelling paradigms that incorporate both temporal and spatial relationships in the grid.

Consequently, there is a discernible trend away from reliance on centralized, rule-based systems towards the adoption of more adaptive, data-driven approaches. Traditional fault analysis methods often rely on impedance-based calculations or pre-defined threshold-based techniques. Also, most of the traditional methods rely on static assumptions and vulnerable to inaccuracies in system parameters measurements, which further increases with complexity of modern power grids. Traditional approaches to fault analysis often focus on classifying the type of fault that has occurred or on detecting the occurrence of an event on a specific transmission line.3 However, this does not account for the topological changes in power systems or gets better with addition of more features, because the rules of classifying faults are generally established for a dynamic and evolving power system. This evolution is beneficial for sustainability and efficiency in Power system operation. However, it necessitates the development of more advanced fault detection and localization techniques to safeguard grid stability, operational reliability, and overall resilience.

II. LITERATURE REVIEW

Event detection using Phasor Measurement Unit (PMU) time series data has become a crucial resource for understanding and identifying a wide range of events within power systems. The high-frequency, time-synchronized measurements provided by PMUs enable accurate detection of various events, such as transient faults, system oscillations, and anomalies, enhancing situational awareness and grid reliability. Recent studies have demonstrated the effectiveness of machine learning and deep learning techniques in analysing PMU data for event detection and classification. Well established modelling such as Convolutional Neural Networks (CNNs) excel at capturing local patterns in time series data, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly effective at modelling sequential and long-range temporal dependencies.

For example, one study applied machine learning algorithms to several months of PMU data from the Western US power system, validating event detection results against utility event logs to ensure accuracy. Another research effort utilized CNNs and LSTMs to detect and classify both common and rare events, including cyberattack-induced anomalies, by leveraging the rich temporal and spatial information in PMU streams. Overall, the body of research confirms that event detection using PMU time series data is a well-established and actively evolving field, with a diverse array of machine learning and deep learning approaches successfully applied to identify and classify a broad spectrum of power system events. In paper [1], a hybrid deep-learning model that combines convolutional neural networks (CNN) and recurrent neural networks (RNN) was developed to forecast energy consumption in industries. Trained on real-world manufacturing data, the model achieved a mean absolute energy variance (MAEV) of less than 1%, outperforming traditional machine learning methods.

Recent years have witnessed significant advancements in the application of graph-based deep learning techniques, particularly Graph Neural Networks (GNNs) [2], across various tasks within power systems. Comprehensive reviews of GNN applications in power systems highlight the broad applicability of these techniques, covering a wide range of architectures and their successful implementation in transmission and distribution sector [3]. A diverse range of GNN architectures includes fundamental architectures like Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs), as well as more specialized temporal variants such as Temporal Graph Neural Networks (TGNNs). For example, a joint GAT-based framework has been proposed for the analysis of dynamic power flow and fault characteristics, with a strong emphasis on achieving computational efficiency [4]. Moreover, the concept of Topology-Aware Graph Neural Networks, which incorporate both the spatial structure of the grid and physical constraints into the learning process, and Typed Graph Neural Networks, which differentiate between various types of buses based on their operational roles, GNNs have emerged as promising solutions for a multitude of power system challenges, encompassing power flow prediction [6],[6],[7], state estimation [8],[9], fault analysis [10],[11], Anomaly detection [12], [13], [14], and security assessment [15], have been introduced to further enhance the performance of GNNs in power system analysis. The development of Temporal Recurrent Graph Neural Networks (TR-GNNs) for fault diagnostics has also shown significant potential. These models are capable of extracting complex spatio-temporal features from voltage measurements obtained at critical buses, enabling accurate fault event detection, fault type and phase classification, as well as precise fault location identification.

The ongoing exploration and adaptation of various GNN architectures within the power systems domain indicate a focused effort to identify the most effective models for specific analytical tasks, such as accurate fault detection and efficient power flow analysis. The choice of a particular architecture often depends on the specific requirements of the problem at hand. For example, Hybrid of Convolution and Graph neural network was achieved in [16], a 1-D Convolutional Graph Convolutional Network (1D-CGCN) has been introduced for fault detection specifically in microgrids. This hybrid architecture combines the strengths of 1-D Convolutional Neural Networks (CNNs) for extracting temporal features from voltage measurements with the ability of GCNs to model spatial correlations within the network [18 The data anomalies are different from events since most of the data anomaly sources are independent of each other and are mostly due to communication issues [16]. Therefore, the study accounts for time series data containing events features only.

The voltage signal-based event detection is also sufficient for fault detection techniques but for localization of faults, frequency values are necessary [17]. This research proposes a novel TGNN framework that utilizes PMU data, specifically voltage magnitude, frequency, phase angle, and their temporal gradients, as node features within the power grid graph. The TGNN is designed to learn embeddings of the buses over defined time windows, thereby capturing complex spatio-temporal patterns. TGNN classification layer is used to classify the fault specifically at the bus level, leveraging the clusters identified in the preceding unsupervised stage. For instance, experiments conducted on IEEE test systems have demonstrated that GNNs can accurately predict power flow solutions and exhibit scalability to larger systems, often outperforming traditional computational solvers in terms of processing time.

III. FEATURE ENGINEERING

In this study, feature engineering was performed by extracting twelve key features from the raw PMU signals at each bus. To capture dynamic behaviour, the first and second derivatives of voltage and phase angle, as well as the first derivative of frequency, were computed, providing insights into the rates and accelerations of change during transient events [19]. Additionally, localized grid stability was characterized using five-point moving averages and standard deviations of voltage magnitude and highlighting local variability. Finally, deviation features voltage deviation (Vdev) and phase angle deviation (θdev) were derived by comparing each bus's signal to the system-wide average, enabling the identification of localized anomalies and synchronization issues. In paper [20], the objective is to identify weak buses in power systems using combined voltage and line stability indices. By applying these metrics to effectively determine the most vulnerable buses, aiding system stability enhancement and contingency planning.

Similarly in table 1, the obtained results provide a comprehensive risk assessment for six power system buses by evaluating their vulnerability across three key parameters: voltage, frequency, and phase angle. Each bus is assigned individual risk scores for these parameters, which are then combined into a single Combined Risk Score to reflect the overall threat level. Additionally, the table includes R^2 values for voltage, frequency, and angle, indicating the accuracy of the predictive models used to assess risk. An Average R^2 Score is calculated to summarize the model performance across all three dimensions. Finally, a Risk Index is derived, integrating both the combined risk and model reliability, helping to prioritize attention toward critical buses.

The importance of leveraging the grid's topology for achieving accurate and efficient power system analysis has been highlighted, particularly in contrast to models like Multi-Layer Perceptron (MLPs) that do not possess the inherent capability to model this crucial structural information. The increasing number of successful applications of GNNs across various critical power system tasks suggests their growing maturity and significant potential for practical, real-world deployment. And, the innovative application of unsupervised learning techniques to identify characteristic fault patterns even in the absence of extensive labelled data.

A. Risk Assessment

Events were segmented from the label transitions and evaluated for their voltage risk, frequency deviation, and trend stability using regression R2 score. Each event was assigned a type (e.g., Voltage Sag, Line Fault) and a combined risk index. This supported interpretability and potential use in real-time grid response. Collectively, these features enabled a comprehensive multi-dimensional representation of the static and dynamic behaviour of the power system, forming the basis for subsequent risk assessment and dynamic stability analysis.

$$\text{Instantaneous } Risk_i(t) = \frac{|\Delta V_i(t)|+|\Delta f_i(t)|+|\Delta\theta_i(t)|}{3} \tag{1}$$

At each time step t, the instantaneous risk for bus i-th is calculated as the average of the absolute deviations in voltage magnitude, frequency, and phase angle.

TABLE 1: THE RISK PROFILING OF POWER SYSTEM BUS USING PMU TIME SERIES DATA

Bus	*Voltage Risk*	*Frequency Risk*	*Angle Risk*	*Combined Risk Score*	*Voltage R2*	*Frequency R2*	*Angle R2*	*Average R2 Score*	*Risk Index*
5	0.0975	0.04140	0.7355	0.2919	0.0002	0.00054	0.5914	0.1974	1.0940
4	0.0870	0.03832	0.7379	0.2877	9.79E-	0.00038	0.5972	0.1992	1.0885
3	0.0777	0.03952	0.7328	0.2833	6.58E-	0.00053	0.5972	0.1992	1.0840
2	0.0865	0.03949	0.7249	0.2836	0.0014	0.00429	0.5946	0.2001	1.0835
6	0.0877	0.03949	0.7252	0.2841	0.0007	0.00140	0.6001	0.2007	1.0833
1	0.0913	0.04197	0.7181	0.2838	5.85E-	0.00149	0.6033	0.2016	1.0821

GNNs utilizes adjacency matrix, which defines the connections between buses, to facilitate the process of message passing between neighbouring nodes within the network. During the feature extraction process, the features associated with each bus, known as node features, are aggregated from their directly connected neighbours based on the defined graph structure. This aggregation mechanism allows the model to learn rich representations that inherently incorporate the topological information of the power grid.

This captures the momentary vulnerability of each bus relative to nominal operational conditions.

$$\text{Average } Risk = \frac{1}{T}\sum_{t=1}^{T} \text{Instantaneous } Risk_i(t) \tag{2}$$

The average risk for each bus is computed by taking the mean of the instantaneous risks across all time steps. It reflects the overall static vulnerability of the bus throughout the monitoring period.

$$Risk\ Index_i = Average\ Risk_i + (1 - R^2) \quad (3)$$

The final risk index for bus i-th integrates both the static risk (average deviation) and the dynamic instability (captured via the average R^2 score from regression analysis). A higher risk index indicates a bus that is simultaneously deviating more from nominal conditions and exhibiting poor predictability, thus requiring prioritized attention.

B. Bus-Level Risk Assessment

Bus-wise voltage, frequency, and angle variations were computed, and a combined risk score was derived by aggregating average deviation and trend stability (R2). This identified the most vulnerable buses in the grid and provided spatial context for contingency planning. In Table 1, achieving granular fault localization at the individual bus level is a primary objective in contemporary power system research, as it offers the most specific information for implementing targeted and effective interventions. Several recent studies have specifically focused on this goal.

IV. FINAL EVALUATION

To evaluate the efficacy of our proposed TGNN-based framework for event classification and risk assessment in power systems, we conducted a comprehensive comparative analysis with various baseline and hybrid deep learning models, including LSTM, CNN, Bi-LSTM, GRU, and CNN-LSTM. The experiments were performed on multivariate PMU datasets using both event-wise and bus-wise feature engineering.

A. Baseline Performance Comparison

The classification results are summarized in Table 2, the TGNN model achieved the best performance across all four metrics, demonstrating its superiority in capturing both spatial dependencies among buses and temporal trends in the PMU signals.

TABLE II. THE PERFORMANCE OF EACH MODEL IS SUMMARIZED

Model	*Accuracy*	*F1 Score*	*MCC*	*AUC*
LSTM	0.9702	0.9654	0.9594	0.9778
CNN	0.9452	0.9354	0.9259	0.9517
Bi-LSTM	0.9744	0.9697	0.9651	0.9788
GRU	0.9563	0.9482	0.9405	0.9653
CNN-LSTM	0.9728	0.9681	0.9631	0.9766
TGNN	**0.9766**	**0.9731**	**0.9682**	**0.9843**

B. Proposed TGNN Architecture

The proposed model adopts a TGNN architecture designed to capture both spatial dependencies among buses and temporal evolution of PMU measurements. The model consists of two main components: a graph convolutional layer for spatial feature extraction and a gated recurrent unit (GRU) for temporal modelling. At each time step, the multivariate PMU data from all buses (e.g., voltage, frequency, and phase angle) are first represented as node features in a power grid graph, where edges denote electrical or topological connectivity between buses. The spatial component utilizes a Graph Convolutional Network (GCN) or Graph Attention Network (GAT) to aggregate features from neighbouring buses, effectively embedding the grid's spatial structure into the feature representation. The TGNN processes multivariate PMU time-series data structured over a graph, where denotes the set of buses (nodes) and the electrical or topological connections (edges) between them. Each node at time is associated with a feature vector.

1) Graph Convolution for Spatial Feature Extraction

$$H^{(l+1)} = \sigma(\widetilde{D}^{-1/2}\tilde{A}\widetilde{D}^{-1/2}H^{(l)}W^{(l)} \quad (4)$$

$\tilde{A} = A + I$ is the adjacency matrix with added self-loops,
$\widetilde{D}$ is the degree matrix of $\tilde{A}$
$H^{(l)}$ is the input to layer , and
$W^{(l)}$ is the trainable weight matrix,
σ is a nonlinear activation (ReLU).

These spatially enriched node embeddings are then passed sequentially through a GRU-based recurrent module that captures the temporal dependencies in the time-series data. The GRU learns the evolution patterns of disturbances across time, allowing the model to differentiate between transient and persistent events.

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \quad (5)$$
$$r_t = \sigma(W_z x_t + U_z h_{t-1}) \quad (6)$$
$$\tilde{h}_t = tanh(W_z x_t + U_h(r_t \odot h_{t-1})) \quad (7)$$
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widetilde{h_t} \quad (8)$$

Finally, the learned temporal graph representations are passed through a fully connected classification layer, followed by a softmax activation to predict the event class for each input sequence. The entire network is trained in a supervised manner using cross-entropy loss, with backpropagation through time (BPTT) applied to optimize both spatial and temporal parameters.

$$\hat{y} = \text{Softmax}(W_o h_T + b_o) \quad (9)$$

2) Loss Function and Optimization

The TGNN model is trained using the **categorical cross-entropy loss function**, which is well-suited for multi-class classification tasks. For a given input sequence x with true class label, and the predicted class probabilities.

$$\mathcal{L}_{CE} = -\sum_{C=1}^{C} y_c \log(\widehat{y_c}) \quad (10)$$

Backpropagation through time (BPTT) is applied to update both the spatial (GCN/GAT) and temporal (GRU) components jointly. To prevent overfitting and encourage generalization, L2 regularization (weight decay) is applied during training. The model is optimized using the Adam optimizer, selected for its adaptive learning rate capability and computational efficiency. A grid search over hyperparameters including learning rate, hidden dimensions, dropout rate, and weight decay was conducted to identify the best-performing configuration. Training was conducted with a batch size of 32, a learning rate of 0.001, and an early stopping criterion based on validation loss convergence.

C. *TGNN Fold-Wise Performance*

In table 3, the highest fold accuracy of 0.9920 was achieved in Fold 3, confirming the model's strong generalization capability. TGNN significantly outperformed all baseline models in terms of both average and fold-wise metrics. The consistent performance across multiple folds and low misclassification rates validates its effectiveness for reliable event classification using PMU data. This table shows the TGNN model's performance across 5 folds. It achieves consistently high accuracy, F1 score, MCC, and AUC, all above 0.96 indicating strong and stable classification performance with excellent precision, balance, and reliability across different data splits.

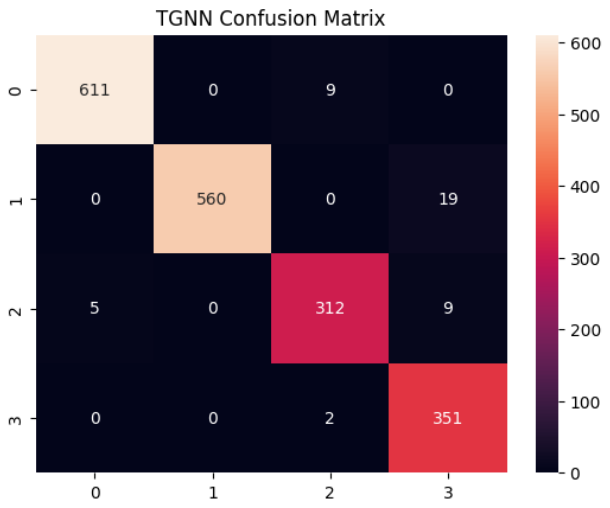
TABLE III: THE PERFORMANCE OF TGNN ACROSS MULTIPLE FOLD

Fold	*Accuracy*	*F1 Score*	*MCC*	*AUC*
TGNN Fold 1	**0.9887**	**0.9867**	**0.9845**	**0.9915**
TGNN Fold 2	0.9734	0.9685	0.9637	0.9776
TGNN Fold 3	0.9920	0.9901	0.9891	0.9932
TGNN Fold 4	0.9820	0.9788	0.9756	0.9882
TGNN Fold 5	0.9760	0.9717	0.9677	0.9823

D. *Confusion Matrix Analysis*

The TGNN confusion matrix in figure 3 revealed the following performance per class: Most misclassifications occurred between class 2 and its adjacent classes, indicating a need for further separation in feature space. Overall, TGNN demonstrated excellent class-wise precision and minimal inter-class confusion. This confusion matrix shows that the TGNN model performs well, especially on classes 0 and 1, with high true positives (611 and 560). However, class 2 has some misclassifications (notably into class 3), and class 3 also has minor confusion with class 2. Overall, the model's classification is strong but could be improved for class 2.

FIGURE 3: TGNN CONFUSION MATRIX



E. *Hyperparameter Setting*

In table 4, the hyperparameter tuning on all models using a parameter grid over learning rate, hidden dimension, dropout rate, and weight decay was performed. Based on F1-score, the three best-performing models were Nominated. TGNNs exhibited consistently high F1 and AUC. Bi-LSTM: Benefitted from bidirectional temporal learning, showing strong recall and precision. CNN-LSTM: Achieved a balanced representation by combining convolutional feature extraction and sequential modelling.

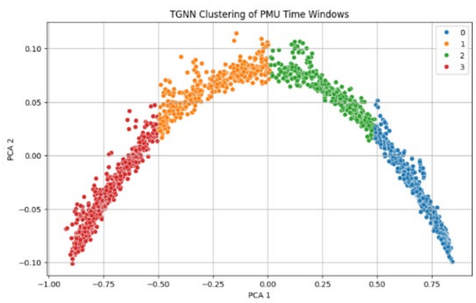
TABLE IV. HYPERPARAMETER SETTING OF TOP NOMINATED MODELS

Model	*Dropout*	*Hidden Dim*	*LR*	*Weight Decay*	*Accuracy*	*F1 Score*
TGNN	***0.3***	***32***	***0.010***	***0.0010***	***0.9887***	***0.98***
	0.2	64	0.010	0.0001	0.9854	0.98
	0.2	32	0.001	0.0001	0.9707	0.96
Bi-LSTM	0.2	64	0.01	0.0010	0.9827	0.98
	0.2	32	0.01	0.0010	0.9827	0.98
	0.2	32	0.01	0.0001	0.9820	0.97
CNN-LSTM	0.3	32	0.010	0.0001	0.9814	0.97
	0.2	32	0.010	0.0001	0.9707	0.96
	0.2	64	0.001	0.0010	0.9627	0.95

F. *Clustering Evaluation*

The framework involves unsupervised clustering of the time-series sequences to identify latent event patterns without relying on labelled data. The algorithm groups together latent embeddings that are similar to each other, based on the assumption that similar spatio-temporal patterns in the power grid data correspond to similar underlying events or operating conditions. Validation is performed using the Silhouette Score and Principal Component Analysis (PCA) visualization, which managed to achieve a silhouette score of 60.89.

FIGURE 4: SILHOUETTE SCORE OF 60.89



V. CONCLUSION

Research efforts have increasingly focused on achieving fault localization at the bus level, with GNN-based methodologies demonstrating significant promise in leveraging PMU data to obtain granular localization information. The use of PMU time series data for the detection of various power system events is a well-established area of research, with a diverse range of deep learning techniques proving their effectiveness in this context. Furthermore, hybrid architectures, including Temporal Graph Neural Networks (TGNNs) and combinations of Graph Attention Networks (GATConv) with Gated Recurrent Units (GRU), have shown considerable success in capturing both the spatial and temporal dependencies inherent in time-evolving graph data, making them highly suitable for the proposed bus-centric fault analysis framework. The proposed research introduces a novel approach by focusing on a bus-centric methodology for fault localization through the development of a TGNN framework. The TGNN model demonstrated state-of-the-art classification performance (Accuracy = 0.9766, F1 Score = 0.9731, MCC = 0.9682, AUC = 0.9843), consistency across multiple folds, and strong interpretability through both event-level and bus-level risk evaluations. This enhanced precision enables faster and more targeted responses to system events.

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