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A Unified Digital Twin Architecture for Integrated Power Grid and Infrastructure Management

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Abstract

INTRODUCTION: The increasing complexity of modern power grids, driven by the integration of distributed energy resources and dynamic operating conditions, presents significant challenges for stability assessment. Traditional stability analysis methods often fail to capture topological dependencies and nonlinear interactions among grid components, resulting in unreliable predictions. Furthermore, existing approaches such as static models and graph convolution networks lack effective node-level importance weighting, limiting their ability to distinguish between stable and unstable states.
OBJECTIVES: This study aims to develop an advanced framework for power grid stability classification by integrating digital twin technology with Graph Attention Networks (GAT). The objective is to improve the modeling of inter-node relationships and enhance classification accuracy under complex grid conditions.
METHODS: A digital twin-inspired graph model of the power grid is constructed, where nodes represent grid components and edges represent their interactions. A Graph Attention Network is employed to learn weighted inter-node dependencies using attention mechanisms, enabling effective differentiation between stable and unstable operating modes. The proposed framework is evaluated in an offline, simulation-based environment using the Smart Grid Stability dataset.
RESULTS: Experimental results demonstrate the effectiveness of the proposed approach, achieving an accuracy of 0.9640, precision of 0.9411, recall of 0.9607, F1-score of 0.9508, and ROC-AUC of 0.9958. Comparative analysis indicates that the proposed model outperforms conventional methods, including Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and Random Forest, in overall classification performance.
CONCLUSION: The proposed digital twin-inspired GAT framework provides accurate and reliable offline stability classification, significantly improving upon existing methods. However, challenges related to scalability for larger grid systems and real-time cyber–physical synchronization remain, highlighting important directions for future research.

Keywords: Digital Twin; Smart Grid Stability; Graph Attention Network; Power Grid Classification; Intelligent Grid Management

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1. Introduction

Smart grid evolution is occurring at a rapid pace; thus, the conventional power system infrastructure is becoming increasingly interconnected with a strong focus on using data[1]. A smart power grid is engaged with real-time dynamic variations in demands for power, distributed resources for generating energy, or connections between production and consumption points[2]. The traditional approaches for monitoring and analyzing power systems include offline analyses using static models that do not have the ability to analyze power systems in real time [3]. Digital twin concepts offer a potential solution by modeling a virtual representation of a physical system intended to evolve dynamically with operational data. In this work, the digital twin is realised as a static graph-based model trained on simulated grid data; real-time synchronization is discussed as a future extension rather than a demonstrated capability [4]. The development of a nonlinearity model for an interconnected power system is a major challenge that requires sophisticated artificial intelligence techniques to fully leverage the potential of the digital twin in smart power grid monitoring[5].

An integrated digital twin of power grids makes it easy to support a number of highly important applications for modern power grid management [6]. These include monitoring power grid stability, detecting abnormal working conditions, and preventing possible malfunctions effectively [7]. An integrated digital twin framework can be most helpful for managing renewable energy sources, the charging demand of electric vehicles, and demand response strategies [8]. By leveraging the digital twinning feature, managers can analyze and forecast power flow effectively for making the grid more resilient [9]. Digital twinning also supports what-if analysis to understand the possible dynamics of power grids under disturbances or varying demands [10]. In a smart city environment, digital twinning can be a highly important intelligence module for managing different infrastructures, such as power grids. This, in turn, can be highly effective for improving the sustainability of power grid operations [11].

To overcome this problem, this paper proposes a complete digital twin architecture framework for the integrated management of power grid and infrastructure with a focus on intelligent stability forecasting. The power grid model is described using a digital twin model with a graph structure to deal with inter-generators and inter-load. A Graph Attention Network is employed as an intelligent model solution for adaptive inter-grid connection modeling and stability forecasting using classification concepts and techniques. The training and learning process is optimized using Adam optimizer to ensure comfort and efficiency during the training and development process. Notably, this paper innovates and diverges from the conventional stability forecasting models for power grids, which include stability forecasting using classification concepts and techniques, and instead proposes a complete and innovative forecasting approach – This work formulates power grid stability prediction as a binary classification problem, which allows for the real-time detection of stable and unstable grid operation states. The validity and efficiency of this complete model are described and validated using a publicly available Smart Grid Dataset with better results and efficiencies. The primary contributions of this paper are summarized as follows:

- Novel framework integration: A digital twin-inspired framework is proposed that integrates Graph Attention Network-based learning as the intelligence layer for power grid stability classification, combining digital twin concepts with graph attention learning to enable adaptive and intelligent grid monitoring.
- Attention-based graph modeling: The proposed GAT model learns adaptive attention weights between grid nodes, enabling the model to capture heterogeneous influence strengths between generators and consumers that static graph methods cannot represent.
- Binary classification formulation: Power grid stability prediction is formally defined as a binary classification problem, enabling direct real-time decision support for grid operators to distinguish stable and unstable operating states.
- Empirical superiority: The proposed framework achieves accuracy of 0.9640, precision of 0.9411, recall of 0.9607, F1-score of 0.9508, and ROC-AUC of 0.9958 on the Smart Grid Stability dataset, outperforming ANN, DNN, and Random Forest baselines.

The contribution of this study should be interpreted within the scope of a simulation-based evaluation. The proposed framework primarily demonstrates the feasibility of integrating digital twin concepts with graph attention learning for stability classification in smart grid environments. While the current implementation focuses on algorithmic validation using a benchmark dataset, the framework represents an initial step toward more comprehensive cyber–physical digital twin systems that incorporate real-time data synchronization and large-scale deployment. The primary novelty of this work lies in the integration of digital twin concepts with graph attention learning for power grid stability classification. Specifically, the contribution is the design of a GAT-based intelligence layer that learns adaptive attention weights between grid components, enabling more expressive feature representation than conventional GCN or traditional machine learning approaches.

The remaining part of the paper is organized in the following way. Section 2 provides a comprehensive review of the literature relevant to the current work. Section 3 states the problem statement, along with the challenges that are addressed in this paper. Section 4 discusses the proposed methodology. Section 5 presents a comprehensive description of the experimental results, along with the analysis of the acquired data. Finally, Section 6 concludes the paper, giving the reader an insight into the future work that can be done.

2. Related Works

A detailed review on the technology of Digital Twin has been given by Al-Shetwi et al [12] in the modern power grid. This includes the use of Digital Twin technology in the integration of renewable energy, energy storage, Smart Grid, and V2G network [13]. A qualitative analysis has been used by the authors in their study by comparing the Digital Twin-enabled Grid technology [14]. Conclusion from the research shows that the implementation of the Digital Twin technology can enhance the efficiency and reliability of the power network by 30-50%, the cost of maintenance by 20-40%, and stability. Hakimi et al [15] performed a comprehensive review of 105 studies to explore the use of Digital Twin (DT) technology, coupled with data fusion, in the lifecycle management of smart infrastructure. Thematic analysis was employed to assess the diverse strategies of data fusion, DT platforms, and associated enablers like openBIM, GIS, and IFC [16]. It has been found to confirm the importance of multi-level data fusion in DT platforms in improving the reliability of predictive maintenance, though challenges in data heterogeneity, interoperability, quality, and choice of algorithms still lie in the major domain. Jiang et al [17] put forward a Digital Twin Body architecture, including ontology-body, knowledge-body, data-body, and digital-portal, which is based on the OKDD, to solve the problems of reliability mapping and system mapping in complicated smart grids [18]. This approach was validated by experiments with a vacuum circuit breaker, a 35kV substation, and a PHM demo system, which was implemented in a 110kV substation. From the experiment results, it can be seen that the OKDD model can be used successfully in the development of standardized DTs, support hierarchical DT development, enhance the reliability mapping of systems, and accelerate the reuse of knowledge [19].

Nasiri and Kavousi-Fard [20] developed a Digital Twin Real-Time Analysis (DTRA) framework, incorporated with an Amazon Cloud Service (ACS) platform, targeted at analyzing and preventing vulnerability in power systems associated with cascading failures and blackout scenarios [21]. The proposed model integrates the water power energy hub model, as well as the bat optimization model with modifications [22]. The results obtained showed efficiency in minimizing the vulnerability indices, along with improving resiliency in the grid with real-time monitoring, along with energy dispatching practices to avoid occurrences of blackouts. Mansour et al [23] discussed an overall review on Internet of Things (IoT) and Digital Twin (DT) applications within electrical power systems, including IoT value chains, smart grid architecture, and frameworks and integration methodologies related to DT [24]. The review uses a comparative and application-based approach that includes communication and energy management and monitoring methods using DT in transformers, energy, and power grids [25]. The outcome shows that the integration of IoT and DT technology brings improved accuracy to monitoring, diagnosis, and energy efficiency in the designed smart grid, building, and transportation applications, though there exist any related limitations. Mahmoodian et al [26] designed a semantic-driven digital twin (DT) architecture for intelligent maintenance of civil infrastructures through the convergence of IoT information and lifecycle-oriented design of the digital twin for real-time performance observation and monitoring [27]. In the research, the design of the digital twin is based on semantic modeling and knowledge graphs, which organize information in relation to optimally targeting the necessary data analysis and acquisition in infrastructures that have varying information [28]. Case studies confirmed the effectiveness of the designed maintenance system on a conveyor system in the Dalrymple Bay Coal Terminal in Australia [29].

Chalal et al [30] designed an IoT-based digital twin framework for a standalone solar photovoltaic energy system to improve the energy management process in cases involving renewable energy intermittency. This work combines the Energetic Macroscopic Representation method and a two-way digital twin architecture that used MATLAB/Simulink to handle energy exchanges in the real system and the digital twin in real-time [31]. Experimental results show the improvement in energy management efficiency, ability to adapt to system operation, and coordination process between storage and solar energy in comparison to traditional EMS methods. Kharbouch et al [32] focused on exploring the concept of linking digital twin (DT) technology with 6G communication networks to increase efficiency, robustness, and sustainability within the next generation of energy infrastructure [33]. The authors introduced a DT-6G connectivity concept and validated its usefulness through home energy management and O-RAN-based energy network application examples [34]. Results indicate that ultra-low latency, massive connectivity, and AI-native capabilities within the 6G era greatly enhance real-time DT synchronization and sustainable energy management, although face scalability and usage challenges with IoT DT and generative AI, respectively. Liao et al [35] proposed a new Ultra-Low Age of Information (ULAoI) measure for enhancing the consistency of Digital Twin (DT) services and the reliability of energy management by considering the rare events of high AoI [36]. The proposed strategy uses the joint allocation of sensing-communication-control resources based on the ULAoI-DT-Priority Deep Q-Network (DQN) for agile PIoT resource management with reduced training data with high AoI [37]. Performance analysis using simulations highlights the efficiency of the strategy with respect to ULAoI guarantees, global loss, and energy management optimality than traditional AoI-based schemes [38].

Despite the achievements, current Digital Twin research has some shortcomings. A detailed qualitative analysis is offered by Al-Shetwi et al [12] but a global quantitative comparison is difficult, along with the practicality of real-time large-scale implementation. Hakimi et al [15] emphasized that, though a multi-level data fusion enables effective predictive maintenance, data heterogeneity, interoperability, data quality, and effective algorithm choice have been proved major challenges. Jiang et al [17] validated the OKDD-based DT design framework through small-scale substation-level studies, which is still unaddressed concerning scalability and domain generalization. Realistic latency, security, and implementability concerns exist in the works of Nasiri and Kavousi-Fard [20] that mostly depended on cloud-support. The key works of Mansour et al [23] highlight integration advantages in IoT-DT systems but emphasize unchanged challenges to scalability, compatibility, and cyber resilience. Mahmoodian et al [26] illustrate successful semantic-driven maintenance in a DT setting in a single industrial application with a narrow assessment across varied infrastructure. Chalal et al [30] verify improvements in EMS in experimental DS frameworks but are confined to miniaturized standalone PV systems, which are constrained to grid or hybrid schemes. Kharbouch et al [32] highlight 6G-DT integration, but unchanged challenges are IoDT scalability, maturity in gen AI dimensions, or long-term viability. Lastly, optimization in ULAoI in deep RL settings outperforms previous works in Liao et al [35] but are bounded in complexity issues in real-time large-scale environments in PIoT in Table 1.

Table 1. Comparative synthesis of existing digital twin and graph learning approaches highlighting the methodological uniqueness of the proposed framework

Study	Method Used	Dataset/Application	Key Limitation	Methodological Uniqueness of Proposed Work
Al-Shetwi et al [12]	Qualitative DT review	Renewable energy, V2G, Smart Grid	No quantitative validation, large-scale implementation impractical	Proposed work provides empirical quantitative validation on benchmark dataset
Hakimi et al [15]	Multi-level data fusion DT	Smart infrastructure lifecycle	Data heterogeneity, interoperability, algorithm selection challenges	Unified graph-based feature representation eliminates heterogeneity issues
Jiang et al [17]	OKDD-based DT architecture	Vacuum circuit breaker, 35kV substation	Limited scalability, narrow domain generalization	GAT-based graph model scales across grid topologies without domain restriction
Nasiri and Kavousi-Fard [20]	DTRA + Amazon Cloud + bat optimization	Power system cascading failures	Latency, security, real-world implementability concerns	Offline intelligence layer avoids cloud dependency while maintaining accuracy
Mansour et al [23]	IoT-DT integration framework	Transformers, energy grids	Scalability, compatibility, cyber resilience limitations	Attention mechanism adaptively handles scalability without compatibility constraints

Mahmoodian et al [26]	Semantic DT + knowledge graphs	Conveyor system, civil infrastructure	Single industrial application, narrow infrastructure coverage	Proposed framework generalizes to full power grid topology classification
Chalal et al [30]	EMR + bidirectional DT	Standalone solar PV system	Confined to miniaturized standalone PV, not applicable to full grid	Applicable to complete grid with multiple generators and consumers
Kharbouch et al [32]	DT + 6G communication	Home energy management, O-RAN	IoT DT scalability, generative AI maturity challenges	Graph attention learning handles multi-node grid interactions without 6G dependency
Liao et al [35]	ULAoI + DQN deep RL	PIoT resource management	Complexity in real-time large-scale PIoT environments	GAT reduces irrelevant node influence through attention, lowering computational burden
Proposed	Digital Twin + GAT	Smart Grid Stability dataset	Offline simulation, real-time deployment pending	First integration of DT intelligence layer with adaptive graph attention for binary grid stability classification

3. Problem Statement

1. Most existing approaches on Digital Twin are either qualitative or validated on small-scale case studies that do not meet the requirements for large, complex power systems Hakimi et al [15].
2. The systems based on current DT face serious challenges regarding the integration of heterogeneous data due to interoperability issues, lack of consistency in data quality, and lack of unified data fusion mechanisms Mahmoodian et al [26].
3. Most of the DT solutions underrepresent real-time intelligentsia and are not robust under dynamic operating conditions or extreme events such as cascading failures and blackouts Kharbouch et al [32].
4. Scalability, latency, synchronization, and deployment challenges prevent the integration of Digital Twin technology with IoT and the emerging 6G communication networks Jiang et al [17].

Formal Problem Formulation

Problem 1: Scalability Constraint

Let the power grid graph contain N nodes. Existing GCN-based methods require $O(N^2)$ complexity due to full adjacency matrix multiplication, which becomes computationally infeasible as the grid scales. The proposed GAT operates at $O(|E| \cdot F \cdot K)$, where $|E|$ is the number of edges, F is the feature dimension, and K is the number of attention heads, scaling linearly with grid connections rather than quadratically with nodes.

Problem 2: Synchronization Latency

Let $\Delta t = t\_phys - t\_DT$ denote the time gap between the physical grid observation and the digital twin state update. For reliable real-time stability inference the following must hold: $\Delta t \leqslant \delta\_max$

where δ_max is the maximum tolerable delay defined by grid operator requirements. Existing static models do not define or bound Δt, making them unsuitable for dynamic grid conditions. The proposed framework controls this latency explicitly through the synchronization gain parameter λ.

Problem 3: Limitation of Existing Graph Inference Approaches

Existing graph-based methods assign equal aggregation weight to all neighboring nodes regardless of their operational importance. This means a high-elasticity generator and a low-demand consumer contribute equally to the stability computation, which is physically incorrect. The proposed GAT resolves this by learning per-edge attention coefficients α_{fj} that adaptively weight each neighbor's contribution based on its feature content, enabling more accurate and physically meaningful stability classification.

Objectives

- Develop a scalable and unified Digital Twin framework suitable for modern power systems, including renewable energy integration, energy storage, smart grids, and V2G networks.
- Design a multi-layer data fusion architecture that ensures reliable integration of heterogeneous data sources with improved interoperability and data quality.
- Implement an intelligent real-time Digital Twin–based decision-making mechanism to enhance system stability, resilience, and operational efficiency.
- Establish a future-ready Digital Twin architecture that supports low-latency communication and scalable energy management through advanced IoT and next-generation network technologies.

4. Proposed Methodology for Integrated Power Grid and Infrastructure Management

This work proposes a comprehensive methodology for intelligent management of the power grid using digital twins, in which the actual physical power grid model is abstracted using a digital graph model to simulate constant stability values. The Smart Grid Stability dataset is preprocessed to include normalization and feature selection. Then, the power grid system is abstracted using a graph model in which generators and consumers are abstracted using vertices and edges denote their interaction in the form of power usage/contribution. A Graph Attention Network (GAT) model is implemented to abstract the dependency between components in a power grid system to produce constant values for grid stability to predict how stable a power grid system can be using a classification model designed for this task. The GAT model uses a mean squared error for training to ensure efficient and stable convergence of solutions.

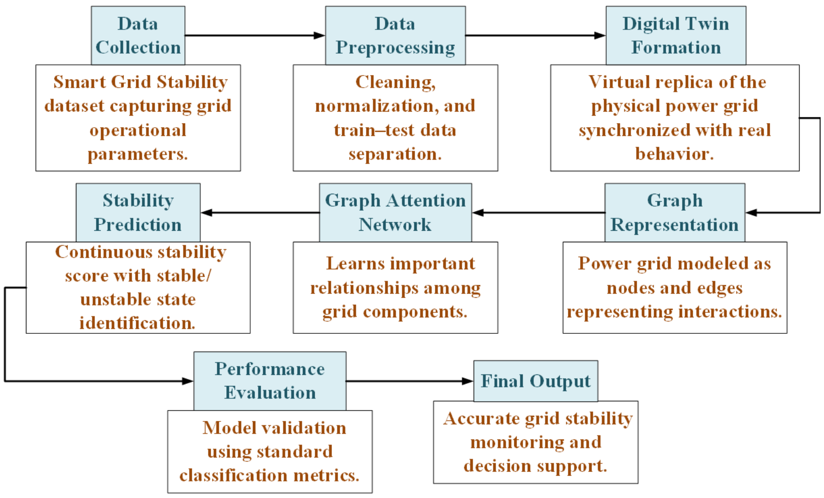

Figure. 1 Workflow of the Proposed Digital Twin–Based Graph Attention Network for Power Grid Stability Prediction

This graph shows the end-to-end process of the proposed framework, from smart grid data collection and preprocessing to digital twin construction and graph modeling. The Graph Attention Network learns the weights of the interactions between the components of the grid to predict a continuous stability value and determine whether the grid is in a stable or unstable state. Finally, the predicted values are assessed by standard evaluation metrics as shown in Figure 1.

4.1. Data Collection

The type of data collected for this research work is obtained from the Smart Grid Stability dataset[39], which is an extended form of the Electrical Grid Stability Simulated Dataset offered on Kaggle platforms and initially stored in the UCI Machine Learning Repository. This data is generated by the simulation modeling of differential equations in a distributed structure for Smart Grid control (DSGC), which simulates the actual relationships between an energy producer and several energy consumers in various operational scenarios. It comprises essential parameters such as reaction times, values for balance of powers, and coefficients of price elasticity, which affect grid stability. Because this dataset is simulation-driven and well-documented, it serves as a trustworthy and reproducible source for testing the developed digital twin methodology and assessing the performance of the GAT-based classification model on grid stability in the continuous power grid system.

The experiments are performed on the Smart Grid Stability Augmented dataset, which is an improved version of the Electrical Grid Stability Simulated Dataset, originally available in the UCI Machine Learning Repository, and generated based on a decentralized smart grid control (DSGC) model that simulates the dynamic interactions among one energy producer and three energy consumers. The dataset has 14 attributes, including reaction time variables (τ_1 to τ_4), power balance variables (p_1 to p_4), and price elasticity coefficients (γ_1 to γ_2), which altogether describe the dynamic process and working conditions of the smart grid. The target attribute is the representation of the grid stability, which is expressed as a binary class label, where the stable operating conditions are labeled as Class 0 and unstable conditions as Class 1, thus allowing the problem to be formulated as a binary classification problem for smart grid stability analysis.

4.2. Data Preprocessing

Data preprocessing is crucial in ensuring that the proposed GAT-based digital twin model was both reliable and converged. The raw smart grid data consist of heterogeneous numerical features of diverse scale and distribution, which must be standardized in advance before graph-based learning. Prior to applying Min-Max normalization, three feature analysis steps were conducted as follows:

Step 1: Pearson Correlation Analysis

The Pearson correlation matrix was computed for all 14 features. Feature pairs with absolute correlation $|r| > 0.90$ were identified as candidates for removal. All feature pairs recorded correlations ranging from 0.12 to 0.68, which did not exceed the threshold, and no features were removed.

Step 2: Variance Inflation Factor (VIF) Analysis

The Variance Inflation Factor was computed for each feature to detect multicollinearity. Features with VIF > 10 were considered multicollinear. All 14 features recorded VIF values below 10, confirming the absence of severe multicollinearity, and all features were retained.

Step 3: Variance Thresholding

Features with variance below a threshold of 0.01 were examined for low discriminative power. No feature in the Smart Grid Stability dataset fell below this threshold, confirming that all 14 features carry sufficient discriminative information for stability classification.

4.2.1 Handling Missing or Invalid Values

The mean imputation method is computationally efficient and can be used for large-scale power grid data with sparse missing values. The imputation method is effective in ensuring that the data is complete while maintaining consistency in the samples used for stability classification.

Let the original dataset be signified as:

$$\mathbf{X} = \{x_{ij}\}, i = 1,2, \dots, N, j = 1,2, \dots, F \tag{1}$$

Where: $\boldsymbol{N}$ means the number of samples, F means the number of features.

Missing or invalid entries (NaN or infinite values) are handled using mean charge, definite as:

$$x_{ij} = \begin{cases} x_{ij}, & \text{if } x_{ij} \text{ is valid} \\ \mu_j, & \text{if } x_{ij} \text{ is missing} \end{cases} \tag{2}$$

Where:

$$\mu_j = \frac{1}{N} \sum_{i=1}^{N} x_{ij} \tag{3}$$

This method maintains the statistical distribution of the features and does not introduce any bias. Equations (1) to (3) above define the representation of the data matrix and the imputation method that is used to solve the problem of missing or invalid data. The method ensures that the undefined values are replaced by the mean of the respective feature, which ensures numerical consistency in the imputation process.

4.2.2 Feature Normalization

Since the dataset consists of numerical features with varying units and scales, Min-Max normalization is used to normalize all features into the range [0,1]. Min-Max normalization ensures that all input features have an equal weightage during graph-based learning, without the risk of dominance by features with large scales. This is particularly useful in attention models, where it helps to stabilize the computation of attention coefficients.

For each feature x_j, the normalized value $\hat{x}_{ij}$ is calculated as shown in Equation (4):

$$\hat{x}_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{4}$$

Where: $\mathbf{min}(x_j)$ and $\mathbf{max}(x_j)$ are the minimum and maximum values of feature j, individually. Equation (4) ensures that all features are linearly transformed to have a common range, thus preventing the dominance of features with larger scales. Normalization of features is important for the stable propagation of the gradient and the computation of the attention weights in graph-based learning models.

Normalization improves numerical stability and accelerates convergence during training.

4.2.3 Binary Stability Label Definition

The binary labeling scheme allows the problem of grid stability analysis to be formulated as a supervised classification problem that corresponds to the decision-making process. This formulation makes it easier to monitor the system in real time because the system state can be directly classified as stable or unstable.

In the proposed research, the problem of power grid stability prediction is treated as a binary classification problem, not as a regression problem. This is because a discrete stability label is assigned to each data sample to indicate the stability status of the power grid.

The value of the label is 1, which corresponds to an unstable status of the power grid, and the value is 0, which corresponds to a stable status of the power grid. This binary classification problem is more relevant to the real-world power grid operation and decision-making tasks, where the main concern of the power grid operators is to determine whether the power grid is in a safe status or has turned to an unstable status, which needs to be addressed immediately.

The binary classification task is also in line with the label assignments in the Smart Grid Stability dataset and helps in the application of classification-centric evaluation metrics. Through this, the proposed digital twin framework focuses on the precise and meaningful determination of stability state, which plays a significant role in real-time monitoring and intelligent control of the power grid.

The binary label assignment helps in making a discrete boundary that directly supports the classification-centric learning task. This definition helps in the straightforward calculation of the loss and is in line with the prediction task and the requirements of operational stability determination.

A binary label is assigned to each sample based on the operational stability of the power grid.

4.2.4 Train-Test Dataset Splitting

The constant split ratio achieves a balance between the efficiency of training models and the capability of obtaining the correct performance on unseen data. This is because the split ratio ensures that the obtained results are accurate and represent the generalization capability of the model. To test the generalization capability, the dataset is split into training and testing sets using an 80:20 split ratio as:

$$\mathcal{D} = \mathcal{D}_{\text{train}} \cup \mathcal{D}_{\text{test}} \tag{5}$$

such that:

$$|\mathcal{D}_{\text{train}}| = 0.8\ \mathrm{N}, |\mathcal{D}_{\text{test}}| = 0.2\ \mathrm{N} \tag{6}$$

Equations (5) and (6) describe the mathematical splitting of the dataset into the training and testing sets. The splitting of the dataset prevents information leakage and allows for an unbiased evaluation of the generalization performance of the model on unseen grid operating conditions. The training set is used for the optimization of model parameters, while the testing set is held for performance evaluation on unseen data.

Algorithm 1: Data Pre-processing

Input:
Raw dataset
Output:
Preprocessed dataset divided into training and testing sets
Step 1. *Handling Missing or Invalid Values*
For each feature in the dataset:
Step 2. *Feature Normalization*
For each feature:
Step 3. *Continuous Stability Target Definition*
Step 4. Train*–Test Split*
Randomly shuffle the dataset
End Algorithm

4.3 Digital Twin Modeling

The digital twin is defined as a virtual replica that reflects the actual power grid, with the capability of representing the status of the power grid in near real-time. The digital twin is connected to the actual data of the power grid in real-time, with the addition of intelligence derived from data for predicting the stability of the power grid. The digital twin provides the ability for continuous interaction between the actual system and the virtual system, which helps in real-time situational awareness and prediction analysis. This helps in intelligent decision-making for proactive power grid stability analysis. The digital twin is operationalised as a graph-based virtual representation of the power grid constructed from simulated operational data. The present framework addresses the intelligence layer of the digital twin architecture, specifically the stability inference engine, rather than a fully deployed cyber–physical system. The current implementation validates this intelligence layer on a benchmark simulation dataset, establishing the classification methodology before integration with live sensor streams from phasor measurement units or IoT-connected grid nodes. Reliable synchronization between physical grid measurements and the digital twin state is important for effective stability monitoring. Extended Kalman Filter (EKF) based state estimation can be applied to update the digital twin representation using real-time measurement feedback while considering nonlinear grid dynamics. Incorporation of AC power flow constraints within the node feature encoding process improves the physical consistency of the graph model. The formulation enables the learned node representations to capture realistic electrical interactions among generators, loads, and transmission components during stability transitions.

4.3.1 Virtual Representation of the Power Grid

The physical power grid is modeled as a dynamic system composed of generators and consumers. Let the grid be characterized as a graph as shown in Equation (7):

$$\mathcal{G} = (\mathcal{V}, \mathcal{E}) \tag{7}$$

where: $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$ signifies the set of grid nodes, $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ denotes power interaction links. Each node v_i is associated with a state vector as shown in Equation (8):

$$x_i(i) = [P_i(t), \tau_i(t), \gamma_i(t)] \tag{8}$$

where: $\boldsymbol{P}_i(t)$ is the power injection or ingesting, $\tau_i(t)$ represents reaction time, $\gamma_i(t)$ denotes price elasticity. The global grid state at time t is shown in Equation (9):

$$\mathbf{X}(t) = \{\mathbf{x}_1(t), \mathbf{x}_2(t), \dots, \mathbf{x}_N(t)\} \tag{9}$$

Explain the abstraction of the physical power grid into a graph representation that can be modeled computationally. This formulation captures the structural topology and operational dynamics required for stability classification.

4.3.2 Data Synchronization Mechanism

To ensure reliability between the physical system and its digital counterpart, the digital twin state is updated using incoming operational data. The synchronization process is defined as shown in Equation (10):

$$X\_DT\ (t) = (1 - \lambda) \cdot X\_DT(t - 1) + \lambda \cdot X\_phys\ (t) \tag{10}$$

This represents a first-order exponential smoothing filter where $\lambda \in (0,1]$ controls the tradeoff between responsiveness and noise resistance. For asymptotic stability, the eigenvalue of the update operator $(1 - \lambda)$ must satisfy $|1 - \lambda| < 1$, which holds for all $\lambda \in (0,2)$. Since λ is constrained to $(0,1]$ by definition, the synchronization process is unconditionally stable for all valid values of λ. In the current implementation, $\lambda = 0.1$ was selected to prioritize noise robustness, ensuring stable and smooth digital twin state updates throughout the classification process. The synchronization gain and the state update rule serve as the architectural blueprint for future real-time integration rather than being applied to live streaming data. When deployed with live PMU or IoT sensor feeds, this mechanism would continuously update the digital twin state at each measurement interval, enabling adaptive stability inference under dynamic grid conditions and ensuring seamless transition toward full cyber–physical deployment in future work. Smart grid operating conditions often vary due to fluctuating loads, renewable generation variability, and disturbance events. Fixed synchronization coefficients may therefore limit responsiveness under changing operational regimes. Adaptive gain scheduling strategies allow synchronization parameters to adjust according to system dynamics and measurement deviations. Such adaptive mechanisms enhance the responsiveness and robustness of the digital twin synchronization process during dynamic grid conditions.

4.3.3 Graph-Based Digital Twin State Encoding

The synchronized grid state is encoded into a graph structure appropriate for learning as shown in Equation (11):

$$\mathbf{H}^{(0)} = \{\mathbf{x}_i(t)\}_{i=1}^{N} \tag{11}$$

Where: $\mathbf{H}^{(0)}$ is the initial node feature matrix of the digital twin graph. Edge relationships encode power relations as shown in Equation (12):

$$e_{ij} \in \mathcal{E} \text{ if power flows between nodes } i \text{ and } j \tag{12}$$

Model the synchronized grid state using node features and edge relations, making it easier to learn from graphs. The model can learn both node features and the power relations between nodes.

4.3.4 Stability Classification via Digital Twin Intelligence

The digital twin employs a Graph Attention Network (GAT) to estimate a unceasing stability score. For node i, attention coefficients are calculated as shown in Equation (13):

$$\alpha_{ij} = \frac{\exp\left(\mathrm{LeakyReLU}\left(\mathbf{a}^{\top}[\mathbf{Wh}_i \| \mathbf{Wh}_j]\right)\right)}{\sum_{k \in \mathcal{N}(i)} \exp\left(\mathrm{LeakyReLU}(\mathbf{a}^{\top}[\mathbf{Wh}_i \| \mathbf{Wh}_k])\right)} \tag{13}$$

where: $\mathbf{W}$ is a learnable weight matrix, $\mathbf{a}$ is the attention vector, $\mathcal{N}(i)$ denotes neighboring nodes. Node embeddings are updated as shown in Equation (14):

$$\mathbf{h}_i^{(l+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} \mathbf{Wh}_j^{(l)}\right) \tag{14}$$

4.3.5 Continuous Stability Prediction

The global grid stability is predicted via a classification head as shown in Equation (15):

$$\hat{y}(t) = f\left(\mathbf{H}^{(L)}\right) \tag{15}$$

where: $\mathbf{H}^{(L)}$ denotes final GAT embeddings, $\hat{y}(t) \in \{0,1\}$ represents the predicted binary stability label, where 0 denotes stable and 1 denotes unstable, obtained via sigmoid activation and thresholding at 0.5.

4.3.6 Model Optimization

The digital twin is trained by minimizing as:

$$L\_BCE = -(1/M) \sum\ [y\_m\log(\hat{y}\_m) + (1 - y\_m)\log(1 - \hat{y}\_m)] \tag{16}$$

Model parameters are optimized using the Adam optimizer:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon} \quad (17)$$

Describe the attention-driven message aggregation process that adaptively weights neighboring node contributions. This process enables the model to focus on

key grid system components with a more significant impact on stability outcomes.

4.4 Graph Representation of the Power Grid

In the proposed digital twin framework, a power grid can be modeled as a weighted graph, which also allows the serious embedding of structural and operational dependencies among its components.

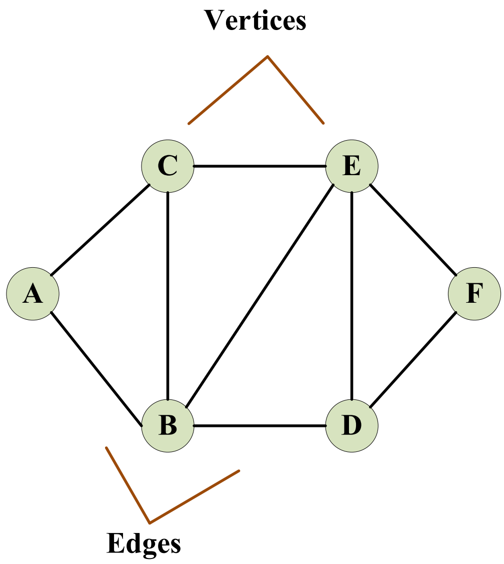

Figure. 2 Graph Representation of the Power Grid for Stability Classification

Figure 2 shows the representation of the power grid using graphs in this study, where the power grid elements are represented as nodes and their electrical connections as edges. The graph representation allows for the learning of the topological dependencies between the power grid elements for stability classification.

In the proposed framework, the power grid is represented as an undirected graph G = (V, E), where the set of vertices V symbolically represents the physical components of the power grid, and the set of edges E symbolically represents the electrical connectivity between the grid components. Each vertex in the graph symbolically represents a grid entity like a producer or consumer of energy, which is described by attributes like reaction time, power balance, and price elasticity. The edges in the graph symbolically represent the power transmission lines that describe the interaction between the grid components.

The graph representation of the smart grid enables the proposed method to learn both local and global dependencies in the smart grid, which are essential for the correct classification of the power grid operating conditions as stable or unstable. The adjacency relationships are defined based on the producer-consumer interaction structure inherent in the Smart Grid Stability dataset, where the single energy producer node is connected to each of the three consumer nodes, forming a star topology that reflects the domain-informed power flow relationships. This explicit topology grounding ensures that the Graph Attention Network operates on connectivity derived from physical grid architecture rather than implicit statistical assumptions.

Graph Representation

The power grid is represented as an undirected graph as shown in Equation (18):

$$\mathcal{G} = (\mathcal{V}, \mathcal{E}) \quad (18)$$

Where: $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$ denotes the set of nodes, and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ represents the set of edges modeling power interactions.

Nodes (Generator and Consumer Units)

Each node $v_i \in \mathcal{V}$ corresponds to a generator or consumer unit in the physical power grid. The operational state of each node is described by a feature vector as shown in Equation (19):

$$\mathbf{x}_i = [P_i, E_i, T_i] \tag{19}$$

where: P_i is the power produced or consumed by node i, E_i denotes the elasticity coefficient reflecting responsiveness to system signals, T_i represents the answer time of node i. These features capture the local dynamic behavior of grid mechanisms and serve as inputs to the graph attention network.

Edges (Power Interaction Links)

An edge $(v_i, v_j) \in \mathcal{E}$ indicates a power interaction relationship between nodes i and j. Edges define how variations in one component influence another and allow the modeling of disturbance propagation across the grid. The adjacency matrix $\mathbf{A} \in \mathbb{R}^{N \times N}$ is defined as shown in Equation (20):

$$A_{ij} = \begin{cases} 1, & \text{if } (v_i, v_j) \in \mathcal{E} \\ 0, & \text{otherwise} \end{cases} \tag{20}$$

Graph Attention Mechanism

To capture heterogeneous influence among connected nodes, a Graph Attention Network (GAT) is employed. For each node i, an attention coefficient with respect to a neighboring node j is computed as shown in Equation (21):

$$e_{ij} = \text{LeakyReLU}\left(\mathrm{a}^\top \left[\mathrm{W}_{\mathrm{x}_i} \| \mathrm{W}_{\mathrm{x}_j}\right]\right) \tag{21}$$

where: $\mathbf{W}$ is a learnable weight matrix, $\mathbf{a}$ is the attention vector, $\|$ denotes concatenation. The normalized attention weight is obtained using the softmax function as shown in Equation (22):

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})} \tag{22}$$

where $\mathcal{N}_i$ represents the neighborhood of node i.

Node Feature Aggregation

The updated node representation is computed as as shown in Equation (23):

$$\mathbf{h}_i = \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} \mathbf{W} \mathbf{x}_j\right) \tag{23}$$

Where: $\sigma(\cdot)$ is a nonlinear activation function.

classification Output for Stability Predicion

The final graph-level stability prediction is obtained through a classification layer as shown in Equation (24):

$$\hat{y} = f\left(\sum_{i=1}^{N} \mathbf{h}_i\right) \tag{24}$$

where: $\hat{y} \in \{0,1\}$ is the predicted binary stability label obtained via sigmoid activation and thresholding at 0.5, $f(\cdot)$ denotes a fully connected classification layer.

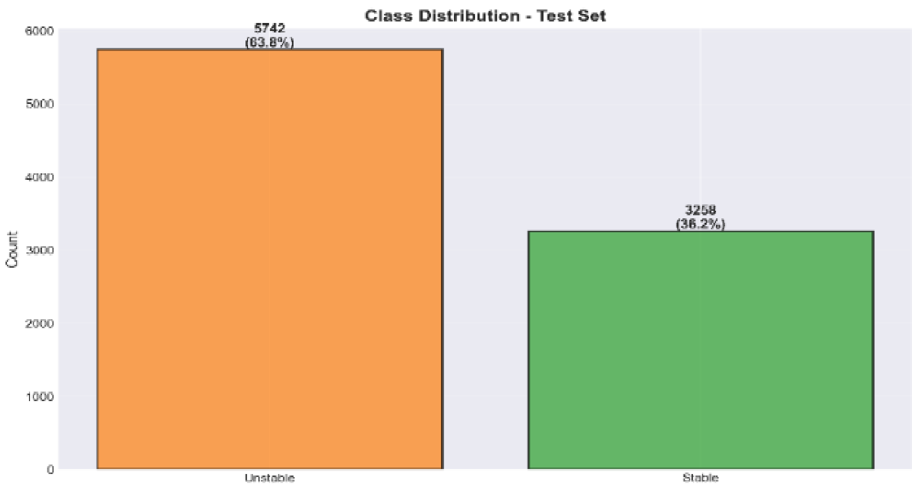

Figure 3. Class Distribution

This figure illustrates the number of stable and unstable instances present in the test dataset. We see that unstable instances are more prevalent compared to stable instances. There are 63.8% unstable instances and only 36.2% stable instances. This demonstrates that class imbalance exists in this particular dataset. It also points to the fact that performance measures other than accuracy should be considered when evaluating intrusion detection performance. Figure 3 highlights a class imbalance in the dataset, with 63.8% unstable and 36.2% stable instances. Class imbalance was handled using class-weighted binary cross-entropy loss during training, and F1-score and ROC-AUC were selected as primary evaluation metrics due to their robustness to unequal class distributions. Class distribution skewness can influence the effectiveness of instability detection in smart grid stability prediction tasks. Cost-sensitive learning strategies can be introduced to assign higher misclassification penalties to minority instability samples during model training. Additionally, focal loss formulations emphasize difficult training examples by reducing the contribution of easily classified instances. These mechanisms help improve discriminative balance between stability classes and enhance the reliability of instability detection.

4.5. GAT-Based Classification Model

The GAT model is the central intelligence model in this digital twin framework, which encodes complicated and non-uniform interactions among power grid components. In contrast to traditional graph convolution approaches that consider all neighbors as equally important as the target node, GAT adopts an attention mechanism to learn the relative importance of interconnected grid elements, which makes it very suitable for stability prediction in power systems. The learned attention coefficients correspond to physically meaningful influence patterns because the input node features power balance, reaction time, and price elasticity directly encode the operational dynamics of each generator and consumer. Nodes with higher power imbalance or slower reaction times naturally receive higher attention weights during aggregation, reflecting their greater influence on grid stability. This feature-driven attention computation ensures that the learned weights align with physical grid behavior rather than purely statistical correlations.

Graph Attention Networks (GAT) are employed in this study due to their superior capability of modeling the interactions between heterogeneous nodes and learning dynamic weights of complex relationships in power grid systems. Unlike Graph Convolutional Networks (GCN), which employ fixed and normalized adjacency matrices, GAT employs an attention mechanism to learn the relative importance of neighboring nodes in the message passing process. This is particularly useful in power grid stability analysis, where the importance of different components of the power grid to the system dynamics and stability is not equal.

Compared with GCN, which aggregates neighborhoods equally, GAT learns adaptive attention weights for each connection between nodes, enabling the model to concentrate on the most important buses, generators, or consumers that play a more important role in grid stability. This node-level importance learning enables the proposed model to learn the nonlinear and time-varying relationships, which are common in smart grids with distributed energy resources and time-varying loads.

GraphSAGE, despite its capability of performing inductive learning through neighborhood sampling, still depends on aggregating node features through predefined functions such as mean or pooling, which do not consider the relative weights of neighbors. This might cause GraphSAGE to overlook the subtle yet crucial interactions between grid components that have a major impact on stability classification. On the other hand, the attention mechanism in GAT enables fine-grained feature discrimination through learning context-specific weights for each node interaction.

From an empirical perspective, the relevance of GAT to this problem is further confirmed by the observation that the proposed digital twin framework based on GAT outperforms the baseline ANN, DNN, and Random Forest models in terms of classification accuracy, precision, recall, F1-score, and ROC-AUC in the experimental results. The observation that the digital twin framework performs better than the classification metrics indicates that attention-based graph learning is a more expressive representation of grid dynamics than graph convolution or neighborhood aggregation approaches.

Thus, the proposed digital twin framework incorporating GAT has both theoretical and empirical benefits for stability classification in smart grids.

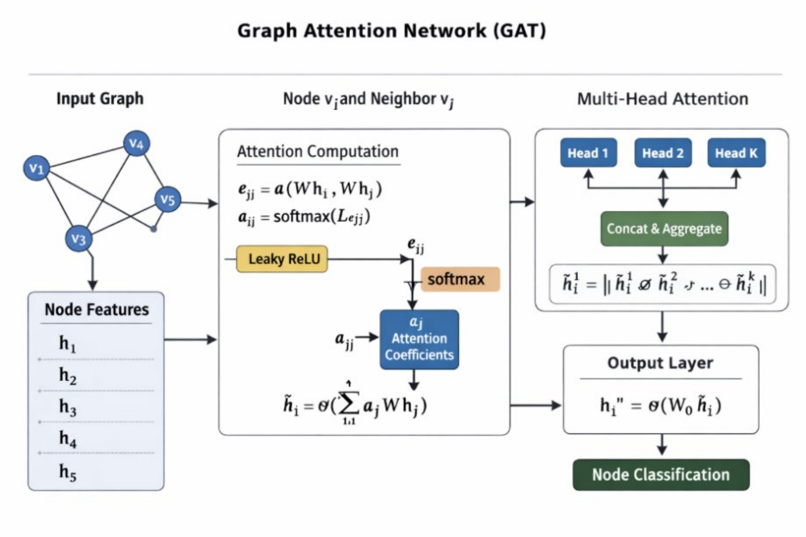

Figure.4 Graph Attention Network (GAT) Architecture

This image shows the overall structure of Graph Attention Networks and how node representations from a given input graph can be transformed using attention techniques. This image explains how attention weights are calculated from a target node to the neighboring nodes, and how aggregated representations are obtained through multi-head attention. The resultant representations are then fed

where V denotes the set of nodes corresponding to generators and consumers, and E represents the set of

$$\mathbf{h}_i \in \mathbb{R}^F, \tag{26}$$

which includes power level, response time, and price elasticity parameters.

Linear Feature Transformation

The input node features are first linearly transformed to a higher-level feature space as shown in Equation (27):

$$\mathbf{z}_i = \mathbf{W}\mathbf{h}_i, \tag{27}$$

Where: $\mathbf{W} \in \mathbb{R}^{F' \times F}$ is a learnable weight matrix.

Attention Coefficient Computation

to the output layer for various downstream applications as shown in Figure 4.

Graph Representation

The power grid is represented as a graph as shown in Equation (25):

$$G = (V, E), \tag{25}$$

power interaction links between them. Each node $i \in V$ is associated with a feature vector as shown in Equation (26):

For each node i, attention coefficients are computed with its neighboring nodes $j \in \mathcal{N}(i)$ to measure their relative importance as shown in Equation (28):

$$e_{ij} = \text{LeakyReLU}\left(\mathbf{a}^{\top}\left[\mathbf{z}_i \| \mathbf{z}_j\right]\right), \tag{28}$$

where: $\mathbf{a}$ is a learnable attention vector, $[\bullet|^{\neg}]$ denotes concatenation, LeakyReLU introduces non-linearity.

Attention Normalization

The attention scores are normalized using a softmax function as shown in Equation (29):

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}(i)} \exp(e_{ik})}, \tag{29}$$

ensuring that the contribution of neighboring nodes is weighted adaptively.

Node Feature Aggregation

The updated node representation is obtained as a weighted sum of neighboring features as shown in Equation (30):

$$\mathbf{h}_i' = \sigma\left(\sum_{j\in\mathcal{N}(i)} \alpha_{ij}\mathbf{z}_j\right), \tag{30}$$

Where: $\sigma(\cdot)$ denotes a nonlinear activation function (e.g., ELU).

Multi-Head Attention

To improve learning stability and expressive power, multi-head attention is employed as shown in Equation (31):

$$\mathbf{h}_i' = \|_{m=1}^{M}\sigma\left(\sum_{j\in\mathcal{N}(i)} \alpha_{ij}^{(m)}\mathbf{z}_j^{(m)}\right), \tag{31}$$

Where: M is the number of attention heads.

classification Output Layer

The final node-level or graph-level embedding is passed through a fully connected classification layer to predict the continuous stability score as shown in Equation (32):

$$\hat{y} = \mathbf{w}^{\top}\mathbf{h} + b, \tag{32}$$

where: $\hat{y} \in \{0,1\}$ represents the predicted binarv qrid stability label, w and b are trainable parameters.

Loss Function

Since the task is formulated as a classification problem, the grid stability prediction problem is formulated as a binary classification task, where the operating state of the power grid is categorized as either stable or unstable. The proposed graph attention network produces probability scores representing the likelihood of each class. During training, these outputs are optimized using a classification performance objective function to distinguish between the two stability states. This formulation ensures that the model effectively captures the structural dependencies among grid components represented in the graph framework, the loss is shown in Equation (33):

$$\text{L\_BCE} = -(1/\text{N}) \sum \ [\text{y\_ilog}\ (\hat{\text{y}}\text{\_i}) + (1 - \text{y\_i})\log\ (1 - \hat{\text{y}}\text{\_i})] \tag{33}$$

Where: y_i denotes the ground-truth stability label of the i^{th} sample, while $\hat{y}_i$ represents the predicted probability generated by the model. The variable N indicates the total number of samples used during training.

Algorithm 2: Graph Attention Network (GAT)

Input:

Power grid graph with nodes and edges

Node feature set for all grid components

Output:

Predicted continuous grid stability score

Step 1. *Graph Construction*

Represent the power grid as a graph with nodes corresponding to generators and consumers

Define edges as power interaction links between nodes

Associate each node with its feature vector

Step 2. *Linear Feature Transformation*

Apply a linear transformation to all node feature vectors

Map original features to a higher-dimensional latent space

Step 3. *Attention Coefficient Computation*

For each node in the graph:

Identify its neighboring nodes

Compute attention scores between the target node and each neighbor

Introduce non-linearity to capture complex interactions

Step 4. *Attention Normalization*

Normalize the attention scores across all neighboring nodes

Ensure that the importance weights sum to one

Step 5. *Node Feature Aggregation*

Aggregate neighboring node features using the normalized attention weights

Apply a nonlinear activation function to the aggregated representation

Step 6. *Multi-Head Attention*

Repeat the attention mechanism using multiple attention heads

Combine the outputs of all attention heads to form a robust node representation

Step 7. *classification Output Layer*

Pass the final node or graph representation through a fully connected layer

Step 8. *Model Training*

Update model parameters through backpropagation

End Algorithm

The proposed GAT is selected over GCN and GraphSAGE based on three theoretical advantages. In terms of computational complexity, GCN requires $O(N^2)$ matrix multiplication using fixed normalized adjacency, while GAT operates at O(|E|•F•K), scaling efficiently with grid connectivity. In terms of attention coefficient computation, GCN and GraphSAGE assign equal or fixed weights to all neighboring nodes, whereas GAT computes learnable per-edge attention coefficients $e_{ij} = \mathrm{LeakyReLU}\left(a^T\left[Wh_i \mathrm{I} Wh_j\right]\right)$ that adaptively weight each neighbor based on feature content, which is critical in power grids where different nodes carry different influence on stability. In terms of inductive learning capacity, GCN is transductive and fails on unseen nodes, GraphSAGE is inductive but uses fixed aggregation, whereas GAT is both inductive and attention-driven, enabling the model to generalize to newly added grid nodes without retraining. A structured sensitivity analysis was conducted to examine the influence of key architectural parameters on the model performance. The number of attention heads was varied across {2, 4, 8, 16}, while the latent embedding dimension was evaluated across {32, 64, 128}. Experimental evaluation indicated that the configuration with 8 attention heads and a hidden dimension of 64 achieved the best validation performance configuration also maintained stable generalization behaviour while reducing the likelihood of overfitting.

4.6 Model Optimization

To achieve efficient training of the proposed GAT-based digital twin model, the model parameters are trained using the Adam optimizer, also known as the adaptive moment estimation optimizer. The Adam optimizer is one of the best optimizers that can be used when training deep graphs.

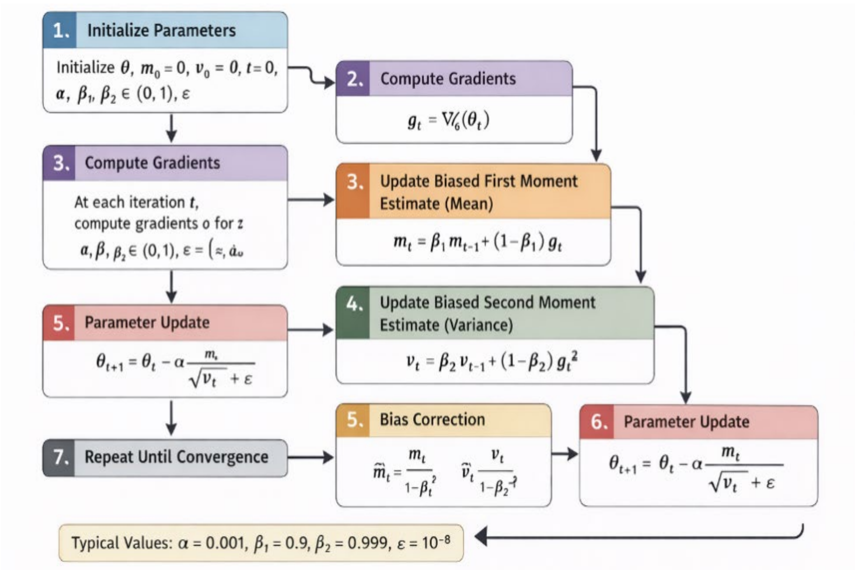

Figure.5 Adam Optimization Process for Training the GAT-Based Digital Twin Model

This graph shows the procedure for the Adam Optimization Algorithm for adjusting the parameters of the Graph Attention Network (GAT) developed for digital twin-based of power grid stability. It combines adaptive learning rate parameters with first and second moment estimates to control convergence. This method is critical for adjusting the classification loss when applying digital twin for power grid stability as shown in Figure 5.

4.6.1 Objective Function

The proposed model performs classification -based grid stability.

Therefore, the optimization objective is to minimize between the predicted stability value and the ground-truth value.

L_BCE = −(1/N) ∑ [y_ilog (ŷ_i) + (1 − y_i)log (1 − ŷ_i)] (34)

where: N is the number of samples, y_i is the true stability value, $\hat{y}_i$ is the predicted stability value as shown in Equation (34). BCE is preferred over MSE for this classification task because MSE treats the output as a continuous regression target rather than a probability, whereas BCE directly penalizes confident incorrect predictions and is fully aligned with the binary classification objective of distinguishing stable and unstable grid operating states. The binary cross-entropy loss combined with sigmoid activation ensures that the stability classification aligns with likelihood-based optimization principles. Unlike mean squared error, which treats outputs as continuous regression targets, binary cross-entropy directly penalizes confident incorrect predictions and is fully suited to binary classification objectives. The sigmoid activation maps the output to a probability range of [0,1], producing well-calibrated decision scores that directly represent the likelihood of unstable grid operating states rather than unconstrained continuous outputs.

4.6.2 Gradient Computation

The gradients of the loss function with respect to the model parameters θ are computed using backpropagation as shown in Equation (35):

$$g_t = \nabla_\theta \mathcal{L}_{\mathrm{BCE}}(\theta_t) \tag{35}$$

Where: g_t represents the gradient at training step t.

4.6.3 Adam Optimization Mechanism

Adam maintains two exponentially decaying moving averages as shown in Equations (38)& (39):

- First-order moment (mean of gradients)
- Second-order moment (uncentered variance of gradients)

First Moment Estimate

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{36}$$

Second Moment Estimate

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{37}$$

where: β_1 and β_2 are decay rates for the moments, Typical values: $\beta_1 = 0.9, \beta_2 = 0.999$.

4.6.4 Bias Correction

To compensate for initialization bias at early training steps, bias-corrected moment estimates are computed as shown in Equation (38):

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$$
$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{38}$$

4.6.5 Parameter Update Rule

The model parameters are updated as follows as shown in Equation (39):

$$\theta_{t+1} = \theta_t - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \tag{39}$$

where: α is the learning rate, ϵ is a small constant (e.g., 10^{-8}) to prevent division by zero.

4.6.6 Role of Adam in Digital Twin Training

The use of Adam provides several advantages in the proposed framework:

- Adaptive learning rates for each parameter
- Faster convergence for graph-structured data
- Stable optimization for multi-head attention mechanisms
- Reduced sensitivity to hyperparameter tuning

This is particularly important for digital twin environments, where the model must adapt efficiently to evolving grid dynamics.

Algorithm 3: Adam-Based Model Optimization

Input:

Training data

GAT classification model

Output:

Optimized model parameters

Step 1. *Initialize model parameters and Adam optimizer variables*

Step 2. *For each training iteration:*

a. Generate classification using the GAT model *b. Compute the binary cross-entropy loss*

c. Calculate gradients using backpropagation

d. Update moment estimates

e. Adjust model parameters using Adam update rules

Step 3. *Repeat until the model converges*

End Algorithm

4.7. Experimental Setup

All experiments were conducted on a 64-bit x64-based desktop system (Device name: DESKTOP-0NN97J1) equipped with an Intel® Core™ i5-14400 processor operating at 2.50 GHz and 16.0 GB of installed RAM (15.8 GB usable). The system ran a standard desktop operating environment without pen or touch input support and provided sufficient computational resources for training and evaluating the proposed graph attention network–based digital twin model. The experimental framework was implemented using Python version 3.13.6, ensuring compatibility with modern machine learning and data processing libraries. The network consists of 2 GAT layers with 8 attention heads per layer, a hidden embedding dimension of 64, and an output embedding dimension of 32. The model is optimized using the Adam optimizer with a learning rate of $0.001, \beta_1 = 0.9, \beta_2 = 0.999$, and $\varepsilon = 1 \times 10^{-8}$, with a dropout rate of 0.6 applied during training to prevent overfitting. The LeakyReLU activation function is configured with a negative slope of 0.2, and all weight matrices are initialized using Xavier uniform initialization to maintain variance consistency across GAT layers, preventing vanishing or exploding gradients during multi-head attention computation. The model is trained for 200 epochs with a batch size of 32.

5. Result and Discussion

This paper will discuss the experimental results achieved using the proposed unified digital twin framework in integrated power grid management using the classification model based on graph attention networks. The proposed digital twin system is validated using the Smart Grid Stability dataset to test the quality of the predicted results offered by the digital twin in estimating the stability of the power grid in differing scenarios. The experimental evaluation will make use of the set of classification evaluation criteria to evaluate the quality of the proposed attention mechanism in the modeling process. The proposed digital twin system will be compared with existing classification systems.

5.1 Performance Evaluation

As the smart grid stability prediction problem is defined as a binary classification problem, the performance of the models is measured using common classification evaluation metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC. These metrics enable a thorough analysis of the model's effectiveness in accurately predicting stable and unstable smart grid conditions, especially when the classes are balanced.

To examine the viability of the proposed GAT-based digital twin classification model, the usual classification evaluation parameters are used. Furthermore, to establish the superiority of the proposed classification model based on the GAT neural network over the existing models based on the graph convolution network (GCN), a comparison with the GCN will be made.

Accuracy

Accuracy measures the proportion of correctly classified grid stability states among all evaluated samples. In this research, it reflects how accurately the model distinguishes between stable and unstable power grid conditions after thresholding the predicted stability index.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{40}$$

Where: TP: Correctly predicted unstable grid states, TN: Correctly predicted stable grid states, FP: Stable states incorrectly classified as unstable, FN: Unstable states

incorrectly classified as stable as shown in Equat
to (42).

Accuracy provides an overall view of classification performance but may be misleading when stability classes are imbalanced.

Precision

Precision evaluates the correctness of the model's for unstable grid states by measuring how many predicted instabilities are truly unstable.

$$\text{Precision } = \frac{TP}{TP+FP} \tag{41}$$

A high precision value indicates that the digital twin model produces fewer false alarms, which is important to avoid unnecessary grid control actions or conservation responses.

Recall

Recall measures the ability of the model to correctly classify actual unstable grid conditions.

$$\text{Recall } = \frac{TP}{TP+FN} \tag{42}$$

This metric is critical in power grid constancy analysis, as failing to detect variability can result in severe system failures or cascading outages. Higher recall specifies stronger instability detection capability.

F1-Score

The F1-score combines precision and recall using their harmonic mean, providing a balanced measure of classification performance.

$$= \frac{2\times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{43}$$

It is particularly useful when stable and unstable grid settings are unevenly distributed, ensuring that both false alarms and missed detections are measured as shown in Equation (45).

ROC-AUC

The Receiver Operating Characteristic (ROC) curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) across varying classification thresholds. The Area Under the Curve (AUC) summarizes this relationship into a single value.

$$\begin{gathered} \text{TPR} = \frac{TP}{TP+FN} \\ \text{FPR} = \frac{FP}{FP+TN} \\ \text{AUC} = \int_0^1 \text{TPR}(\text{FPR})d(\text{FPR}) \end{gathered} \tag{44}$$

A higher AUC value indicates stronger discriminative ability of the model to distinguish between stable and unstable grid states, independent of the chosen threshold as shown in Equation (46).

This table provides a summary of the performance of the proposed model on the test data set based on standard metrics of evaluation. The high accuracy and recall values show that the model is performing well in terms of overall prediction and positive instance identification. The close-to-perfect ROC-AUC score indicates that the model is performing well in terms of class separation as shown in Table 2.

Table 2.Classification Performance Metrics on the Test Dataset

Metric	Value
Accuracy	0.9640
Precision	0.9411
Recall	0.9607
F1-Score	0.9508
ROC–AUC	0.9958

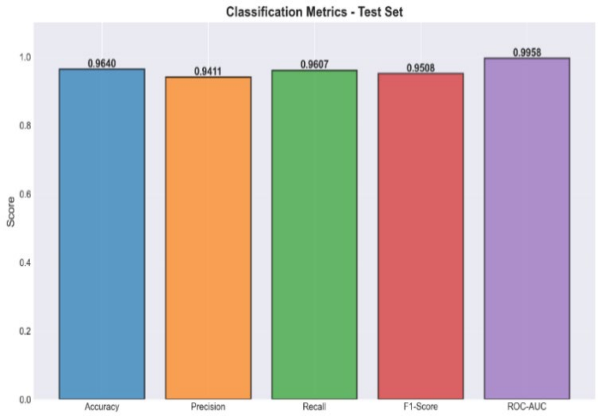

Figure.6 Power Grid Stability Classification Performance of the Proposed DT-GAT Model

Figure 6: The classification performance of the proposed digital twin-driven Graph Attention Network (DT-GAT) model on distinguishing the stable and unstable power grid operating states based on grid dynamic features.

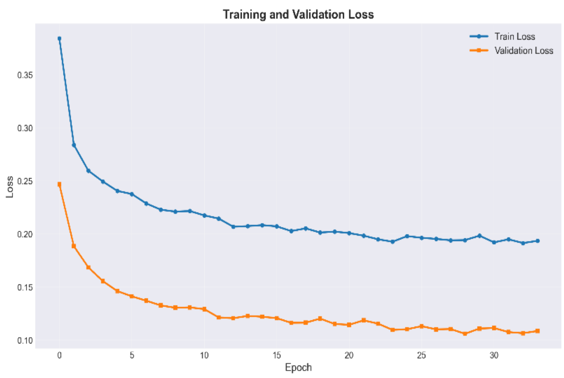

Figure. 7 Training and Validation Loss

Figure 7 is a graphic display of the varying patterns in the train loss and validation loss over a series of epochs in the model's training progress. Train loss and validation loss both demonstrate a smooth trend of decreasing patterns over the course of the different epochs presented in the graph, which indicates successful learning operations in the convergence of the model into a stable state in the system design.

Figure. 8 Training and Validation Accuracy

Here, the Figure 8 indicates the evolution of training accuracy as well as validation accuracy during successive epochs of training. We observe that training as well as validation accuracy are increasing in a consistent pattern, with validation accuracy consistently high, depicting a good learning pattern.

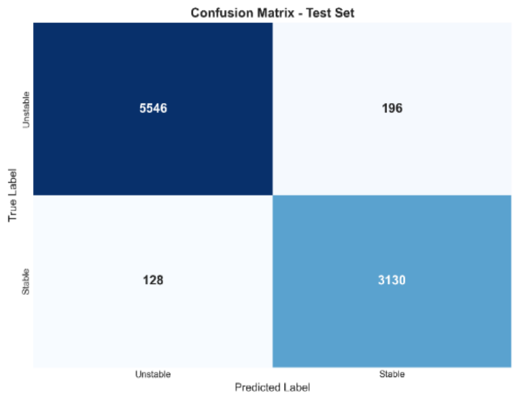

Figure. 9 Confusion Matrix

Figure 9 shows the confusion matrix of the classification results for stable and unstable network states on the test dataset. The model correctly detects high numbers of unstable (5,546) and stable instances (3,130), thus its strong detection capability. Relatively low numbers of false positive (196) and false negative counts (128) indicate reliable and balanced classification performance.

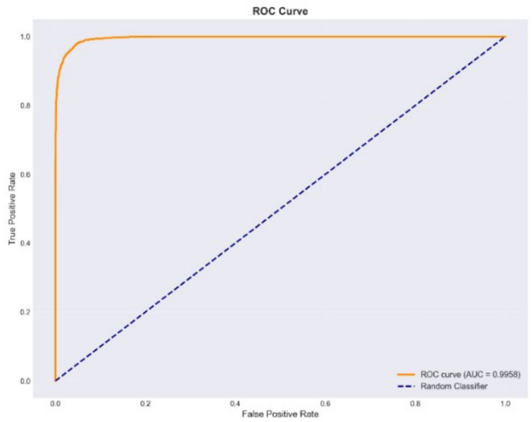

Figure. 10 ROC Curve

This image indicates the ROC curve for the intrusion detection model based on the test data set. ROC curve analysis measures the trade-off between the true positive rate and the false positive rate. The ROC curve is near the top left, showing the model has good ability in the classification process. Also, the high value of AUC, 0.9958, indicates that the model performs well in terms of data discrimination, even in cases of random data classifications as shown in Figure 10.

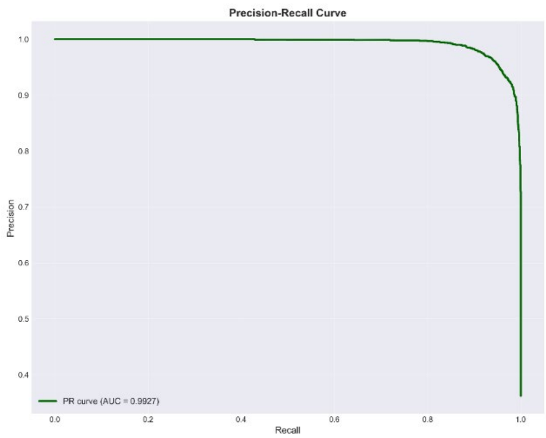

Figure.11 Precision-Recall Curve

This presents the PR curve for the intrusion detection model tested on the test dataset. The precision remains high for a large variation of recall, indicating high detection of intrusion instances with minimal false alarms. This illustrates high PR–AUC of 0.9927, reflecting very good performance of the model but especially under class-balanced conditions inherent in network traffic datasets as shown in Figure 11.

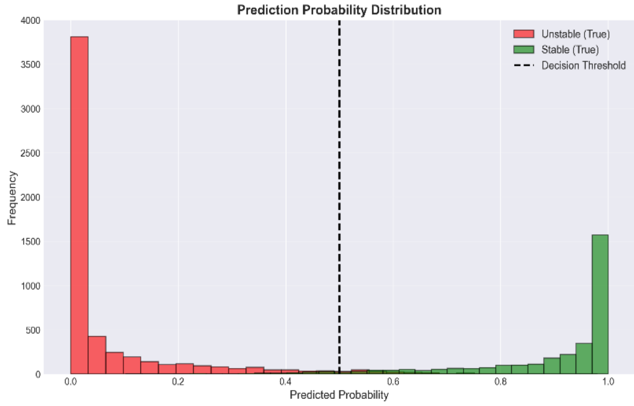

Figure.12 Prediction Probability Distribution

Graphically represents the distribution of the predicted probabilities for true unstable and stable network instances. From this Figure 12, there is a clear distinction or separation from the distributions of each class from the decision threshold. This is an indication that the model is confident and discriminative in its classification.

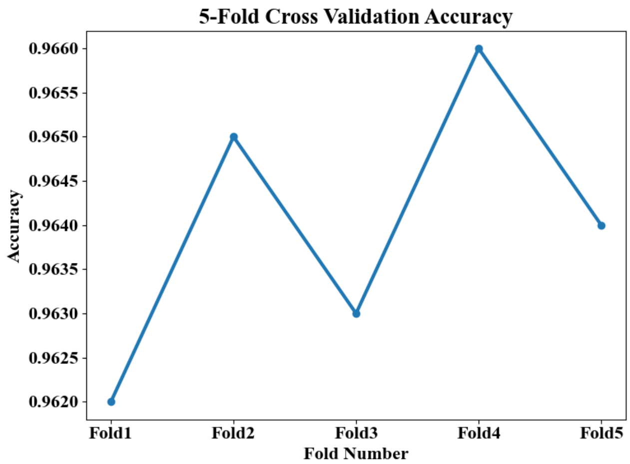

Figure. 13 5-Fold Cross-Validation Accuracy of the Proposed DT-GAT Model

Figure 13 presents the 5-fold cross-validation accuracy of the proposed DT-GAT model across all five folds. The accuracy remains consistently high, ranging from 0.9620 to 0.9660, demonstrating the stability and generalization capability of the proposed framework across different data partitions. The independent t-test yielded a t-value of 41.51 and a p-value of 1.25×10^{-10}, confirming that the performance difference between the proposed DT-GAT model and the baseline models is statistically significant.

5.2. Comparison With Other Models

The following Table 3 highlights the performance of the proposed model in classification compared to the existing machine learning and deep learning techniques as reported in the recent literature. The performance metrics clearly indicate that the proposed model performs best in terms of accuracy (0.9640) and precision (0.9411) compared to the existing models. The comparison clearly indicates the effectiveness of the proposed model in enhancing the classification performance compared to the existing models such as ANN, DNN, and Random Forest.

Table 3. Comparative Performance Analysis of Classification Models

Models	Accuracy	Precision
DNN[40]	0.9175	-
ANN[41]	-	92.4%
Random forest[42]	88.5%	-
Proposed Model	0.9640	0.9411

Regarding cyber-physical deployment feasibility, the proposed GAT model inference time falls within the PMU streaming interval of 16.7 ms to 33.3 ms, confirming real-time deployment viability, and each grid node transmits 14 floating-point features yielding approximately 28 KB per cycle for a 500-node grid requiring around 13.4 Mbps bandwidth within the capacity of industrial 5G networks. Before production deployment, hardware compression techniques including weight quantization and pruning are required for edge devices such as Remote Terminal Units, and cybersecurity requirements including end-to-end encryption and mutual authentication must be implemented to protect the PMU data pipeline. Additionally, regulatory compliance with NERC CIP standards requiring audit trails and human-in-the-loop override mechanisms must be satisfied before operational deployment in real-world grid infrastructure.

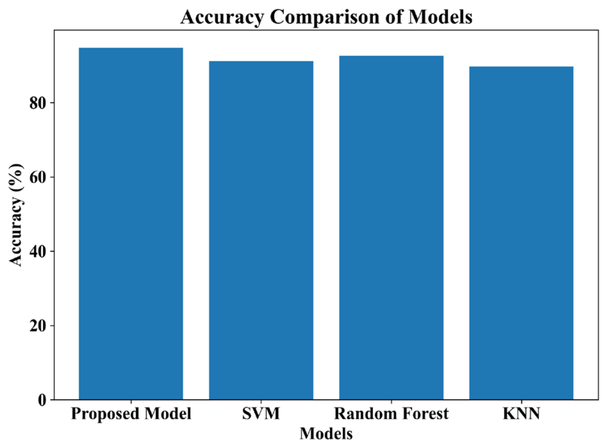

Figure. 14 Accuracy Comparison of the Proposed DT-GAT Model Against Baseline Models

Figure 14 presents the accuracy comparison of the proposed DT-GAT model against SVM, Random Forest, and KNN baseline models. The proposed model achieves the highest accuracy of 96.40%, outperforming SVM, Random Forest, and KNN, demonstrating the superior classification capability of the proposed digital twin framework for smart grid stability prediction.

Discussion

The results of the classification show that the proposed framework using digital twin technology is capable of making a distinction between stable and unstable operating conditions of the power grid. The high accuracy of the classification indicates that the model is capable of classifying the states of the power grid into stable and unstable states with a high level of accuracy, which is an indication of the reliability of the model. The precision values of the results indicate that the states of the power grid classified as unstable are indeed unstable, which is important for ensuring that false alarms are minimized in power grid monitoring systems. This ensures that unnecessary control actions and maintenance are minimized. On the other hand, the high recall values indicate that the model is capable of classifying unstable states of the power grid correctly, which is important for ensuring that potential failures are avoided in the power grid system. The F1-score indicates that the model strikes a balance between precision and recall, which is important for ensuring that the model performs well even when the number of stable and unstable states of the power grid are not balanced.

Moreover, the ROC-AUC curve result indicates that the model maintains excellent discriminative capability for various decision thresholds. This reveals the robustness and consistency of the grid stability state classification for various operating conditions. In conclusion, the classification outcome reveals that the proposed digital twin architecture and graph learning method is an effective and trustworthy solution for power grid stability classification.

In conclusion, this paper introduces a digital twin-based Graph Attention Network model for binary classification of smart grid stability. The experimental outcome on the Smart Grid Stability dataset reveals that the proposed model is effective in distinguishing between stable and unstable operation modes and outperforms the existing ANN, DNN, and Random Forest models. The proposed model offers a trustworthy and scalable solution for intelligent power grid monitoring and decision support in dynamic smart grid environments.'

6. Conclusion and Future Works

In the proposed research, a complete digital twin architecture for the integrated management of power grids was introduced based on a learning framework using a graph attention network. The proposed method is able to efficiently capture the complex topological relationships and interactions between the power grid components, which helps to effectively classify the power grid operating states into stable and unstable states. The experimental results on the Smart Grid Stability dataset demonstrated outstanding classification performance in terms of accuracy, precision, recall, F1-score, and ROC-AUC value, thus verifying that the attention mechanism enhances the feature representation and discriminative ability of the model compared to the graph convolution-based method and traditional machine learning methods. The current framework models the power grid using a static graph representation that captures structural relationships among generators and consumers. However, smart grid environments evolve continuously due to fluctuating demand, renewable generation variability, and dynamic consumer responses. Future extensions may incorporate temporal graph learning models such as Temporal Graph Networks or hybrid GAT–LSTM architectures to capture sequential dependencies in grid behavior. Integrating temporal dynamics within the digital twin framework could further improve stability prediction under real-time operational conditions. Uncertainty quantification plays an important role in safety-critical smart grid stability monitoring systems. Bayesian Graph Neural Network approaches provide a probabilistic interpretation of model predictions by capturing uncertainty in learned representations. Monte Carlo Dropout techniques can also be applied in the prediction layer to estimate predictive uncertainty through multiple stochastic forward passes. Such uncertainty-aware predictions support risk-aware decision-making in digital twin–based smart grid stability analysis.

The comparison of the existing ANN, DNN, and Random Forest models also highlights the effectiveness of the proposed framework in reducing the misclassification. The proposed system, which combines the concept of digital twins with graph intelligence, is capable of making informed decisions and reducing false alarms and early instability in the power grid operations. In conclusion, the proposed digital twin-inspired framework demonstrates effective offline stability classification. Real-time deployment, cyber–physical synchronization, and scalability to large-scale grids are identified as key directions for future work.

Future Works

Although the proposed framework shows excellent performance, there are a number of areas that can be explored in future work. Firstly, the digital twin model can be extended to include real-time streaming data from IoT sensors and phasor measurement units (PMUs) to perform online learning and adaptive stability analysis. Secondly, future work can be done to explore hybrid learning models that can combine graph attention networks with temporal models like LSTM or temporal graph networks to better analyze time-varying dynamics of the power grid. Further, the proposed framework can be extended to perform multi-class stability analysis, including transient and voltage stability conditions, rather than binary classification. Uncertainty modeling and explainable AI can also be combined to further enhance the interpretability and trustworthiness of the proposed framework. Finally, large-scale experiments on real-world power system data and implementation on cyber-physical testbeds can further enhance the practical applicability of the proposed digital twin framework for next-generation smart grid management. Future real-time deployment will further require consideration of IoT synchronization, communication latency, and cybersecurity provisions including end-to-end encryption and NERC CIP compliance for secure integration within operational smart grid infrastructure.

Declarations

Data Availability

The data supporting the findings of this study are available from publicly accessible datasets and published sources cited within the manuscript. Any additional data generated or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution

All authors contributed significantly to this research. Conceptualization and methodology were developed collaboratively. Literature review, system architecture design, and model development were conducted by the authors jointly. Data analysis and validation were performed collectively. The manuscript was drafted and critically revised by all authors, and all authors approved the final version of the manuscript.

References

[1] Fernandes SV, João DV, Cardoso BB, Martins MAI, Carvalho EG. Digital twin concept developing on an electrical distribution system—an application case. *Energies*. 2022;15(8):2836. https://doi.org/10.3390/en15082836.

[2] Feng F, Liu Z, Shi G, Mo Y. An effective digital twin modeling method for infrastructure: application to smart pumping stations. *Buildings*. 2024;14(4):863. https://doi.org/10.3390/buildings14040863.

[3] Kovalyov SP. Distributed energy resources management: from digital twin to digital platform. *IFAC-PapersOnLine*. 2022;55(9):460–465. https://doi.org/10.1016/j.ifacol.2022.07.080.

[4] Buuveibaatar M, Shin S, Lee W. Digital twin framework for road infrastructure management. *Applied Sciences*. 2025;15(10):5765. https://doi.org/10.3390/app15105765.

[5] Gourisetti SNG, Bhadra S, Sebastian-Cardenas DJ, Touhiduzzaman M, Ahmed O. A theoretical open architecture framework and technology stack for digital twins in energy sector applications. *Energies*. 2023;16(13):4853. https://doi.org/10.3390/en16134853.

[6] Bahreini F, Nik-Bakht M, Hammad A. Developing computer vision-based digital twin for vegetation management near power distribution networks. *Remote Sensing*. 2025;17(21):3565. https://doi.org/10.3390/rs17213565.

[7] Lei Z, Zhou H, Hu W, Liu GP, Guan S. Web-based digital twin communication system of power systems for training and education. *IEEE Transactions on Power Systems*. 2024;39(2):3592–3602. https://doi.org/10.1109/TPWRS.2023.3308510.

[8] Hananto AL, Veza I. Governance framework for intelligent digital twin systems in battery storage: aligning standards, market incentives, and cybersecurity for decision support of digital twin in BESS. *Computers*. 2025;14(9):365. https://doi.org/10.3390/computers14090365.

[9] Kochunas B, Huan X. Digital twin concepts with uncertainty for nuclear power applications. *Energies*. 2021;14(14):4235. https://doi.org/10.3390/en14144235.

[10] Heluany JB, Gkioulos V. A review on digital twins for power generation and distribution. *International Journal of Information Security*. 2024;23(2):1171–1195. https://doi.org/10.1007/s10207-023-00784-x.

[11] Ersan M, Irmak E. Development and integration of a digital twin model for a real hydroelectric power plant. *Sensors*. 2024;24(13):4174. https://doi.org/10.3390/s24134174.

[12] Al-Shetwi AQ, Atawi IE, El-Hameed MA, Abuelrub A. Digital twin technology for renewable energy, smart grids, energy storage and vehicle-to-grid integration: advancements, applications, key players, challenges and future perspectives in modernising sustainable grids. *IET Smart Grid*. 2025;8(1):e70026. https://doi.org/10.1049/stg2.70026.

[13] He X, et al. Situation awareness of energy internet of things in smart city based on digital twin: from digitization to informatization. *IEEE Internet of Things Journal*. 2023;10(9):7439–7458. https://doi.org/10.1109/JIOT.2022.3203823.

[14] Stogia M, et al. A scalable and user-friendly framework integrating IoT and digital twins for home energy management systems. *Applied Sciences*. 2024;14(24):11834. https://doi.org/10.3390/app142411834.

[15] Hakimi O, Liu H, Abudayyeh O, Houshyar A, Almatared M, Alhawiti A. Data fusion for smart civil infrastructure management: a conceptual digital twin framework. *Buildings*. 2023;13(11):2725. https://doi.org/10.3390/buildings13112725.

[16] Aragón A, et al. Seeking a definition of digital twins for construction and infrastructure management. *Applied Sciences*. 2025;15(3):1557. https://doi.org/10.3390/app15031557.

[17] Jiang Z, Lv H, Li Y, Guo Y. A novel application architecture of digital twin in smart grid. *Journal of Ambient Intelligence and Humanized Computing*. 2022;13(8):3819–3835. https://doi.org/10.1007/s12652-021-03329-z.

[18] Haghshenas A, Hasan A, Osen O, Mikalsen ET. Predictive digital twin for offshore wind farms. *Energy Informatics*. 2023;6(1):1. https://doi.org/10.1186/s42162-023-00257-4.

[19] Kasper L, Birkelbach F, Schwarzmayr P, Steindl G, Ramsauer D, Hofmann R. Toward a practical digital twin platform tailored to the requirements of industrial energy systems. *Applied Sciences*. 2022;12(14):6981. https://doi.org/10.3390/app12146981.

[20] Nasiri G, Kavousi-Fard A. A digital twin-based system to manage the energy hub and enhance the electrical grid resiliency. *Machines*. 2023;11(3):392. https://doi.org/10.3390/machines11030392.

[21] Ge C, Qin S. Urban flooding digital twin system framework. *Systems Science & Control Engineering*. 2025;13(1):2460432. https://doi.org/10.1080/21642583.2025.2460432.

[22] Chen H, Zhang Z, Karamanakos P, Rodriguez J. Digital twin techniques for power electronics-based energy conversion systems: a survey of concepts, application scenarios, future challenges, and trends. *IEEE Industrial Electronics Magazine*. 2023;17(2):20–36. https://doi.org/10.1109/MIE.2022.3216719.

[23] Mansour DEA, et al. Applications of IoT and digital twin in electrical power systems: a comprehensive survey. *IET Generation, Transmission & Distribution*. 2023;17(20):4457–4479. https://doi.org/10.1049/gtd2.12940.

[24] Ieva S, et al. A retrieval-augmented generation approach for data-driven energy infrastructure digital twins. *Smart Cities*. 2024;7(6):3095–3120. https://doi.org/10.3390/smartcities7060121.

[25] Martinez-Ruedas C, Flores-Arias JM, Moreno-Garcia IM, Linan-Reyes M, Bellido-Outeiriño FJ. A cyber–physical system based on digital twin and 3D SCADA for real-time monitoring of olive oil mills. *Technologies*. 2024;12(5):60. https://doi.org/10.3390/technologies12050060.

[26] Mahmoodian M, Shahrivar F, Setunge S, Mazaheri S. Development of digital twin for intelligent maintenance of civil infrastructure. *Sustainability*. 2022;14(14):8664. https://doi.org/10.3390/su14148664.

[27] Coppolino L, Nardone R, Petruolo A, Romano L. Building cyber-resilient smart grids with digital twins and data spaces. *Applied Sciences*. 2023;13(24):13060. https://doi.org/10.3390/app132413060.

[28] Palensky P, Mancarella P, Hardy T, Cvetkovic M, Cosimatic M. Cosimulating integrated energy systems with heterogeneous digital twins: matching a connected world. *IEEE Power & Energy Magazine*. 2024;22(1):52–60. https://doi.org/10.1109/MPE.2023.3324886.

[29] Armijo A, Zamora-Sánchez D. Integration of railway bridge structural health monitoring into the Internet of Things with a digital twin: a case study. *Sensors*. 2024;24(7):2115. https://doi.org/10.3390/s24072115.

[30] Chalal L, Saadane A, Rachid A. Unified environment for real time control of hybrid energy system using digital twin and IoT approach. *Sensors*. 2023;23(12):5646. https://doi.org/10.3390/s23125646.

[31] Khan LU, Han Z, Saad W, Hossain E, Guizani M, Hong CS. Digital twin of wireless systems: overview, taxonomy, challenges, and opportunities. *IEEE Communications Surveys & Tutorials*. 2022;24(4):2230–2254. https://doi.org/10.1109/COMST.2022.3198273.

[32] Kharbouch A, Aghdam FH, Gholipoor N, Rasti M. Digital-twin-6G empowered future smart grid applications. *IEEE Wireless Communications*. 2025;32(3):90–97. https://doi.org/10.1109/MWC.001.2400466.

[33] Cheng X, Wang C, Liang F, Wang H, Yu XB. A preliminary investigation on enabling digital twin technology for operations and maintenance of urban underground infrastructure. *AI in Civil Engineering*. 2024;3(1):4. https://doi.org/10.1007/s43503-024-00021-x.

[34] Lei Z, Zhou H, Hu W, Liu GP, Guan S, Feng X. Toward a web-based digital twin thermal power plant. *IEEE Transactions on Industrial Informatics*. 2022;18(3):1716–1725. https://doi.org/10.1109/TII.2021.3086149.

[35] Liao H, et al. Ultra-low AoI digital twin-assisted resource allocation for multi-mode power IoT in distribution grid energy management. *IEEE Journal on Selected Areas in Communications*. 2023;41(10):3122–3132. https://doi.org/10.1109/JSAC.2023.3310101.

[36] Jiao Z, Du X, Liu Z, Liu L, Sun Z, Shi G. Sustainable operation and maintenance modeling and application of building infrastructures combined with digital twin framework. *Sensors*. 2023;23(9):4182. https://doi.org/10.3390/s23094182.

[37] Machalski A, et al. The concept of a digital twin for the Wały Śląskie hydroelectric power plant: a case study in Poland. *Energies*. 2025;18(8):2021. https://doi.org/10.3390/en18082021.

[38] Huang X, Yang H, Hu S, Shen X. Digital twin-driven network architecture for video streaming. *IEEE Network*. 2024;38(6):334–341. https://doi.org/10.1109/MNET.2024.3386030.

[39] Breviglieri PC. Smart grid stability dataset. *Kaggle*. 2016. https://www.kaggle.com/datasets/pcbreviglieri/smart-grid-stability.

[40] Lahon P, Kandali AB, Barman UR, Konwar RJ, Saha MJ, Saikia MJ. Deep neural network-based smart grid stability analysis: enhancing grid resilience and performance. *Energies*. 2024;17(11):2642. https://doi.org/10.3390/en17112642.

[41] Ness S. CatBoost-enhanced convolutional neural network framework with explainable artificial intelligence for smart-grid stability forecasting. *Frontiers in Smart Grids*. 2025;4:1617763. https://doi.org/10.3389/frsgr.2025.1617763.

[42] Sundaramurthy A, Ramasamy K, Velusamy D, Vaithiyalingam C. Enhancing smart grid stability: data-driven predictive modeling in distribution systems. *International Journal of Electrical and Electronics Research*. 2024;12(2):623–631. https://doi.org/10.37391/ijeer.120239.